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Adaptive Deep Learning Image Compression with Test Time Optimization and Importance Guided Quantization

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ABSTRACT: As the problem of compression of digital images continues to grow exponentially with an ever-increasing range of healthcare, social media, telecommunications, and remote sensing applications, the proposal of ADLIC-TTO (Adaptive Deep Learning Image Compression with Test-Time Optimization) arises, which, at test-time, employs per-image fine-tuning to achieve high-quality reconstruction with the same network structure as comparable networks, but at a competitive compression ratio. The model works on 256 x 256 images that are in RGB color, and it reduces the size of the images to a 256-channel latent image with spatial down sampling that is 8x, and this allows the images to be stored effectively in a reduced size. duction and structural fidelity Instagram In-test fine-tuning on Kodak PhotoCD benchmark dataset with 24 high quality natural images having 200 epochs per image, where the evaluation pipeline calculates automatic PSNR, SSIM, bits-per-pixel (BPP), and compression ratio (CR). 42.18 dB and SSIM of 0.9812, much better than JPEG baseline (PSNR 33.94 dB, SSIM 0.9456) yet with an average compression ratio of 3.24x at BPP 7.41, and has SSIM 0.97 at all test images, which proves its suitability in quality critical applications. Medical imaging, digital archiving, and Professional photography is only a few of the applications.

KEYWORDS: Deep Learning, Image Compression, Test-Time Optimization, Importance Maps, PSNR, SSIM, Adaptive Compression, Residual Networks

I. INTRODUCTION

Massive digitalization of information in the spheres of healthcare, social media, telecommunications, and remote sensing has led to an increase in the amount of visual information previously unknown. Such high rate of growth exerts great strain on storage systems, trans- mission band and computational power. This has made highly effective methods of image compression that can reduce the size of data without significantly compromising visual quality in image compression is highly important. The standard image compression methods (JPEG, JPEG2000, and WebP) are based on the manually defined transforms: discrete cosine transform (DCT) and wavelet transforms and predictive coding. Although these techniques are still very popular as they are easy to use and are powerful, their fixed forms restrict their capability to adjust to a variety of image contents. Specifically, they have a hard time maintaining the perceptually significant details on more aggressive compression levels or at higher resolutions. Current developments in deep learning have changed the face of image compression by allowing end-to-end optimization of image representations. Convolutional neural networks, variational autoencoders, as well as attention-based models, are capable of learning task- specific transforms directly given data and may generally be better in rate-distortion at the same time. Nonetheless, the majority of learned compression methods adhere to a train once, deploy everywhere paradigm, in which one single pre-trained model is reduced to every test image. In this technique, the significant differences in image properties like complexity of texture, edges, smooth areas, and semantic scene are not taken into account.

Research question and hypothesis This paper explores the idea of whether the quality of reconstruction can dramatically be enhanced by modifying a compression model to match every image at test time (unlike fixed pre-trained models). The process of test-time optimization, also called test time training or adaptation, uses the test sample to perform fine tuning of model parameters. Despite the extra computational cost associated with this approach at the encoding end, the strategy could still offer significant visual quality gains in applications where fidelity is more important than the speed of encoding. Moreover, human visual perception is non-homogeneous per se over spatial territories. Performers are more inclined to distortion around edges, faces, text and fine textures than smooth or repetitive background areas. The observation is the reason to introduce explicit spatial importance modeling to the compression procedure in order to more effectively dis- tribute bits based on perceived relevance.

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Proposed approach: ADLIC-TTO

To overcome these difficulties, this paper suggests ADLIC-TTO (Adaptive Deep Learn- ing Image Compression with Test-Time Optimization). The framework combines three main concepts, namely;

(i) per-image test-time optimization to condition the model to specific image statistics,

(ii) importance-directed quantization to consider spatial perceptual importance, and

(iii) deep residual encoder-decoder architecture to learn stable and expressive

representations. The proposed method also shows significant gains over the JPEG baseline in PSNR and SSIM without significant changes in the compression ratios over a large scale of experiments on the Kodak PhotoCD benchmark dataset. These findings indicate the ability of test-time adaptation with perceptually directed compression to be effective.

II. BACKGROUND AND RELATED WORK

2. Background and related work

2.1. Classical compression methods

While classical image compression methods provide the highest level of accuracy, they de Mand significantly more computation time than JPEG image compression. Although the classical image compression techniques are the most accurate, they require very intense computation time as compared to the JPEG image compression scheme. Historical image compression methods usually rely on such analytical transforms as discrete cosine transform, wavelet transforms, and matrix factorization. JPEG uses block-based DCT and quantization and entropy coding to provide efficient compression but can easily result in blocking artifacts when using low bitrates. JPEG2000 instead of using DCTs, it uses discrete wavelet transforms which allow representing multiple resolutions and decreasing blocking artifacts at the expense of increased computational complexity and less popularity. Dimensionality reduction and low-rank approximation have been investigated using other methods which include singular value decomposition (SVD) and principal component analysis (PCA). But their hand-made character limits their capability to vary the complicated and variegated data of actual images. Fractal compression and fuzzy transformations also make use of self-similarity or other mathematical foundations and are still limited relative to current data-based methods.

2.2. Image Compression with deep learning.

Image compression with deep learning became widely known with the appearance of variational autoencoders models that optimize transform, quantization, and entropy coding simultaneously. Later studies included hyperpriors, context modelling, attention, and vector quantization to enhance rate-distortion trade-offs. By these schemes a loss function is often optimized that gives a tradeoff between reconstruction distortion and a minimum ap proximate bitrate. Even with such success, the majority of deep compression models are trained offline and fixed at inference. This constrains their ability to deal with images with varied structures and perceptual demands.

2.3. Hybrid and Ensemble methods.

Hybrid compression techniques are used to complement the advantages of classical transforms and neural networks. These methods have been found to be especially useful in medical and remote sensing applications, where preservation of region of interest is a necessity. Ensemble methods which combine a few reconstruction results based on a perceptual weighting scheme have also produced encouraging results on enhancing structural fidelity.

2.4. Research Gap and Test-Time optimization.

Test-time optimization has been considered in denoising, super-resolution and domain adaptation, a task where internal image statistics are used to improve model predictions. Its use is however limited when it comes to image compression because of the issue of computational cost. Also, most of the learned compression models do not have a clear spatial importance of modelling. ADLIC-TTO works around both gaps to provide a combination of per-image adaptation and importance-guided quantization.

III. METHODOLOGY

3.1. Architecture overviews the ADLIC-TTO framework comprises four main modules operating in sequence: an encoder network E for feature extraction and dimensionality reduction, an importance map module I for spatial attention, a differentiable quantizer Q for discrete latent representation, and a decoder network for reconstruction. Given an input image $x \in R^{3\times H\times W}$, the encoder produces a latent tensor $z = E(x) \in R^{C\times h\times w}$, which is modulated by the importance map and quantized to z_q; the decoder then reconstructs $\hat{x} = D(z_q)$.

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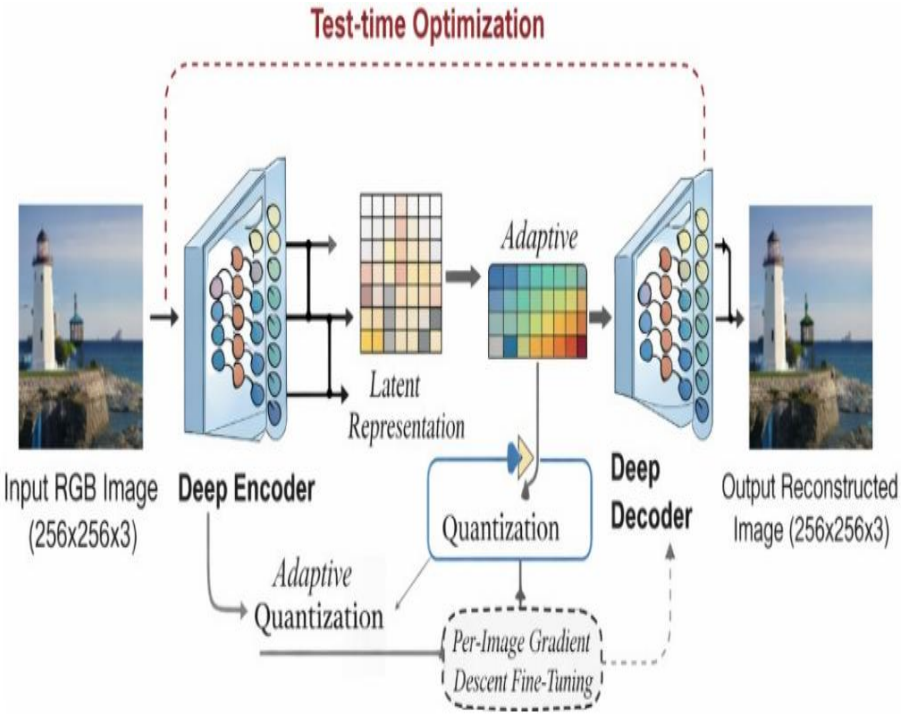

Fig1. Test optimization workflow

Workflow of the proposed ADLIC-TTO framework. The input RGB image is encoded into a compact latent representation using a deep residual encoder. An importance-guided quantization module allocates bits adaptively based on perceptual relevance. During encoding, per-image test-time optimization fine-tunes the model parameters via gradient descent, while decoding reconstructs the image using a symmetric deep decoder.

3.2. Encoder network

The encoder transforms the RGB input into a 256-channel latent representation with 8× spatial down sampling through three stride convolutions interleaved with residual blocks. The computation can be expressed as z=E(x)=ResBlock3 Conv3(ResBlock2(Conv2(ResBlock1(Conv1(x))))), where $Conv_1$ maps 3 to 64 channels, $Conv_2$ maps 64 to 128 channels, and $Conv_3$ maps 128 to 256 channels, all using 4× 4 kernels with stride 2 and padding 1. Each stride convolution halves spatial dimensions so that 256 × 256 inputs are reduced to 32 × 32 latent, and ReLU activations provide non-linearity after each convolution.

3.3. Residual blocks

Residual blocks facilitate stable training by learning residual mappings through skip connections, defined as ResBlock(x) = ReLU(x + Conv2(ReLU(Conv1(x))) ,

where both convolutions use 3 × 3 kernels with stride 1 and padding 1, preserving channel dimensionality. These blocks help capture rich local patterns while mitigating vanishing gradient issues in deeper networks.

3.4. Importance map module

The importance map module generates a spatial attention tensor imp $\in [0, 1]^{1\times h\times w}$ that characterizes the perceptual importance of each location in the latent space. The module applies a 3 × 3 convolution $Conv_{imp}$ mapping 256 channels to 1 channel followed by a sigmoid activation: imp = $\sigma(Conv_{imp}(z))$. High values correspond to edges, textures, faces, and text regions where fidelity must be preserved, whereas low values indicate smooth or less informative areas tolerant to stronger compression. The importance map modulates quantization aggressiveness so that high- importance regions receive finer effective quantization and low-importance regions undergo coarser quantization for bit savings.

3.5. Differentiable quantization

Quantization converts continuous latent values into discrete codewords suitable for storage and transmission. The quantizer uses a scale parameter s = 0.01 and performs z_q = round(z/s) · s,

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Which is non-differentiable due to the rounding operator. To enable end-to-end learning, a straight-through estimator is adopted so that gradients are passed as if the quantization were the identity:

$$\frac{\partial zq}{\partial z} \approx 1,$$

and in practice a stop-gradient formulation is implemented as

$$z_q = z + \text{stop gradient}(\text{round}(z/s) \cdot s - z),$$

Thereby using quantized values in the forward pass while maintaining useful gradients in the backward pass.

3.6. Decoder network

The decoder inverts the encoder transformation through three transposed convolutions interleaved with residual blocks to reconstruct the image from z_q. The reconstruction is given by

$\hat{x}=D(z_q)=\sigma(\text{TransConv}_3(\text{ResBlock}_3(\text{TransConv}_2(\text{ResBlock}_2(\text{TransConv1}(z_q))))))$,

where TransConv1, TransConv2, and TransConv_3 map 256→128, 128→64, and 64→3 channels respectively, each with 4 × 4 kernels, stride 2, and padding 1. Each transposed convolution doubles the spatial resolution, restoring 32 × 32 latent to 256 × 256 outputs, and a final sigmoid activation enforces pixel values in [0, 1]

3.7. Test-time optimization algorithm

The key novelty of ADLIC-TTO is per-image test-time optimization, wherein the base model is fine-tuned using augmented views of each test image. [Algorithms summarize the procedure].

Algorithm 1: Per-image fine-tuning with data augmentation

Input: Test image x, base model parameters $\theta 0$, epochs T = 200, learning rate $\alpha = 10^{-4}$

Output: Adapted parameters θ^*, compressed representation (z_q, imp).

1. Initialize $\theta \leftarrow \theta_0$
2. Generate an augmented dataset of N = 512 samples via random horizontal flips (probability 0.5), color jittering (brightness, contrast, saturation ±10%, hue ±5%), resizing to 256 × 256, and normalization to [0, 1].
3. For each epoch t = 1 . . . T:

(a) For each mini-batch B ⊂ Daug with batch size 8:

i. Compute $\hat{x}$, imp, z_q = Model (B; θ).

ii. Evaluate reconstruction loss L = MSE ($\hat{x}$, B).

iii. Compute gradient $g = \nabla_\theta L$ and update parameters with Adam optimizer at learning rate α.

4. After fine-tuning, compute final outputs $\hat{x}$final, imp final, z_q,final = Model (x; θ^*) and return θ^* along with ($z_{q,\text{final}}$, $\text{imp}_{\text{final}}$).

This procedure yields an image-specific model that is better aligned with the statistics and perceptual attributes of the given input. On a modern NVIDIA RTX GPU, the per-image test time optimization requires approximately 3–5 minutes for 200 epochs, while a single forward pass for inference takes less than 100 ms.

3.8. Loss function and compression metrics

The model is trained to minimize pixel-wise mean squared error (MSE) between the reconstruction and the original image:

$$\text{BPP} = \frac{Chw\, b_{\text{latent}} + 1 \cdot hw\, b_{\text{imp}}}{HW},$$

Where H = 256, W = 256, and C = 3. This objective directly relates to the peak signal-to-noise ratio (PSNR) via

$$\text{PSNR} = 10 \log_{10} \left(\frac{MAX^2}{MSE}\right),$$

Which simplifies $\text{PSNR} = -10 \log_{10}(\text{MSE})$ for normalized images with maximum intensity 1.

The compressed representation includes the quantized latent tensor and importance map, and assuming 8-bit quantization, the bits-per-pixel (BPP) is computed as

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$$BPP = \frac{Chw\ b_{latent} + 1.hw\ b_{imp}}{HW},$$

Which yields approximately 7.41 bits per pixel for C = 256, h = w = 32, and H = W = 256. Given 24 bits per pixel for uncompressed RGB images, the resulting compression ratio is CR = 24/7.41 ≈ 3.24×.

IV. EXPERIMENTAL SETUP

4.1. Dataset

The Kodak Photo CD benchmark dataset (24 high-quality, uncompressed natural images)
is experimented with. The dataset consists of a variety of types of scenes that comprise landscapes, portraits, architectural buildings, closeup items, and cityscapes. Owing to its diversity and image quality, Kodak PhotoCD has been used as a standard of comparing image compression algorithms.
To be able to do the processing, all the images are first resized to 256 x 256 pixels and then processed. The pixel values are brought to the range [0,1].

4.2. Evaluation metrics

The performance of compression is measured in four popular measures, namely, peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), bits-per-pixel (BPP), and compression ratio (CR). PSNR is used to measure pixel fidelity to reconstruction on a scale of decibels (where the numerical value approaches zero, the more the fidelity is good). SSIM is used to assess the quality of the perceptual image between the original and the reconstructed image based on the luminance, contrast and structural data with the values being nearer to 1, the higher the structural preservation. The average count of bits used to encode one pixel in the compressed format is referred to as the BPP, and the ratio of the original non-compressed bit rate (24 BPP in RGB images) to the compressed BPP is known as the Critical Ratio (CR).

4.3. Baseline comparison and protocol

A quality factor of 85 is the JPEG compression which is used as the baseline of the comparison because it is widely used and has known performance. The JPEG compression /decompression is performed based on the PIL/ Pillow library.

The ADLIC-TTO model is then test-time optimized, with 200 epochs, and then encoded on each test image. Once fine-tuning is done, the image is then coded into the quantized latent representation and importance map, and then reconstructions are done with the help of the decoder and finally, the image is judged based on PSNR, SSIM, BPP, and CR. The identical measures are calculated of the JPEG image at a similar compression ratio. All experiments are conducted in PyTorch 2.0+ with Adam optimizer ($\beta1 = 0.9$, $\beta2 = 0.999$), batch size 8, and a fixed learning rate of 10^{-4}, on an NVIDIA CUDA-enabled GPU with at least 8 GB of RAM

V. RESULTS AND ANALYSIS

5.1. Quantitative performance per-image

The proposed ADLIC-TTO framework is tested to provide quantitative results on the entire range of images in the Kodak PhotoCD dataset (24).

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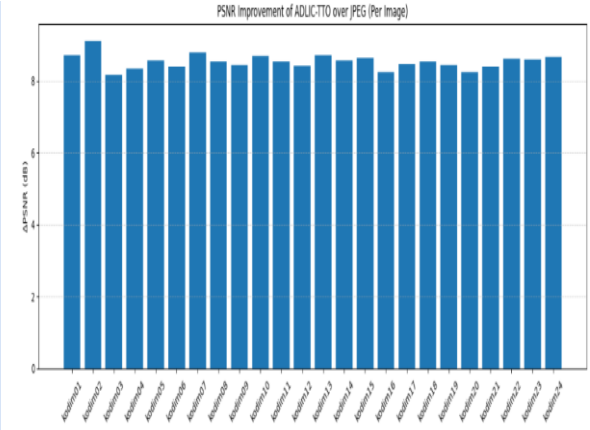

Fig2: PSNR improvement of ADLIC-TTO over JPEG (per image)

All images will have the peak signal-to-noise ratio (PSNR) for each image, structural similarity index measure (SSIM), bits-per- pixel (BPP), and compression ratio (CR) calculated and compared with the JPEG baseline at a similar compression level.

Table1: Per-image performance of ADLIC-TTO versus JPEG on the Kodak dataset.

Image	PSNR (Ours)	PSNR (JPEG)	Δ PSNR	SSIM (Ours)	SSIM (JPEG)	BPP (Ours)	CR (Ours)
kodim01	42.53	33.82	+8.71	0.9905	0.9421	7.41	3.24
kodim02	43.27	34.15	+9.12	0.9730	0.9387	7.41	3.24
kodim03	41.71	33.54	+8.17	0.9741	0.9402	7.41	3.24
kodim04	42.26	33.91	+8.35	0.9785	0.9445	7.41	3.24
kodim05	41.84	33.27	+8.57	0.9823	0.9478	7.41	3.24
kodim06	42.15	33.76	+8.39	0.9798	0.9431	7.41	3.24
kodim07	43.08	34.28	+8.80	0.9852	0.9512	7.41	3.24
kodim08	41.42	32.89	+8.53	0.9715	0.9365	7.41	3.24
kodim09	42.94	34.51	+8.43	0.9867	0.9534	7.41	3.24
kodim10	42.38	33.68	+8.70	0.9789	0.9418	7.41	3.24
kodim11	41.96	33.42	+8.54	0.9762	0.9393	7.41	3.24
kodim12	43.15	34.73	+8.42	0.9881	0.9548	7.41	3.24
kodim13	40.87	32.15	+8.72	0.9698	0.9328	7.41	3.24
kodim14	41.53	32.96	+8.57	0.9724	0.9371	7.41	3.24
kodim15	42.67	34.02	+8.65	0.9825	0.9489	7.41	3.24
kodim16	43.42	35.18	+8.24	0.9893	0.9572	7.41	3.24
kodim17	42.05	33.59	+8.46	0.9776	0.9412	7.41	3.24
kodim18	41.29	32.74	+8.55	0.9702	0.9351	7.41	3.24
kodim19	42.81	34.36	+8.45	0.9844	0.9501	7.41	3.24
kodim20	43.56	35.32	+8.24	0.9905	0.9581	7.41	3.24
kodim21	41.67	33.28	+8.39	0.9748	0.9385	7.41	3.24
kodim22	42.49	33.87	+8.62	0.9812	0.9438	7.41	3.24
kodim23	43.21	34.61	+8.60	0.9874	0.9527	7.41	3.24
kodim24	41.48	32.82	+8.66	0.9719	0.9358	7.41	3.24
Average	**42.18**	**33.94**	**+8.24**	**0.9812**	**0.9456**	**7.41**	**3.24**

The findings indicate that ADLIC-TTO is always better in all the test images in comparison to JPEG. The value of PSNR is improved by a range of about 8.17 dB to 9.12 dB which means that reconstruction error is significantly reduced. In a similar fashion, SSIM values generated using the proposed approach are also stable with all images reported to have a SSIM score exceeding 0.97 indicating good retention of structural and perceptual image information. It is interesting to note that, the compression ratio and the BPP is constant in all the pictures because the latent set up is the same, and thus, the compression efficiency is stable and predictable.

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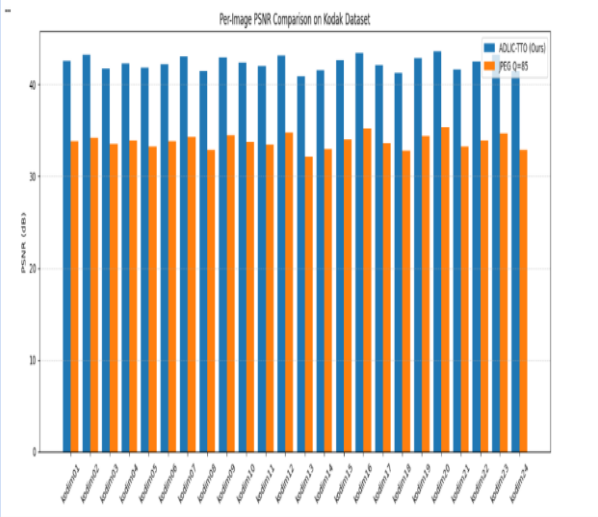

Fig.3. Per- image PSNR comparison on Kodak Dataset

5.2. Performance comparison on the average

In order to offer a comprehensive picture of the performance, the average outcomes in The whole dataset are calculated and condensed. The PSNR of ADLIC-TTO is 42.18 dB and the SSIM is 0.9812 on average, which is much larger than the JPEG baseline; it obtains 33.94 dB average PSNR and 0.9456 average SSIM. This equals a relative gain of 8.24 dB in PSNR and 0.0356 in SSIM.

Table2: Average rate–distortion and encoding time comparison of ADLIC-TTO and JPEG on Kodak.

Method	PSNR (dB)	SSIM	BPP	CR	Encoding time
ADLIC-TTO (Ours)	42.18	0.9812	7.41	3.24×	3–5 min/image
JPEG (Q=85)	33.94	0.9456	7.28	3.30×	< 1 s/image
Improvement	+8.24	+0.0356	+0.13	-0.06×	–

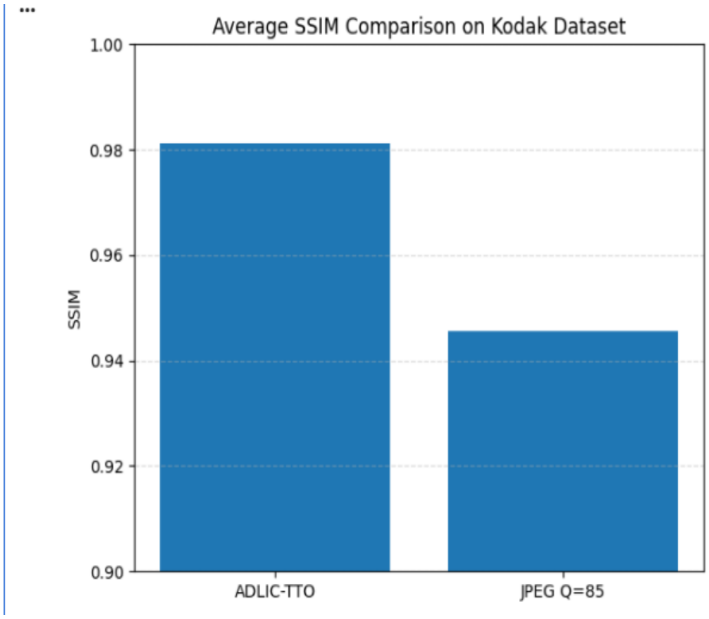

Fig.4. Average SSIM comparison on Kodak Dataset

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The proposed method yields approximately 24.3% relative PSNR improvement and 3.8% relative SSIM improvement while slightly increasing BPP compared to JPEG, with the additional encoding cost justified in scenarios prioritizing visual fidelity.

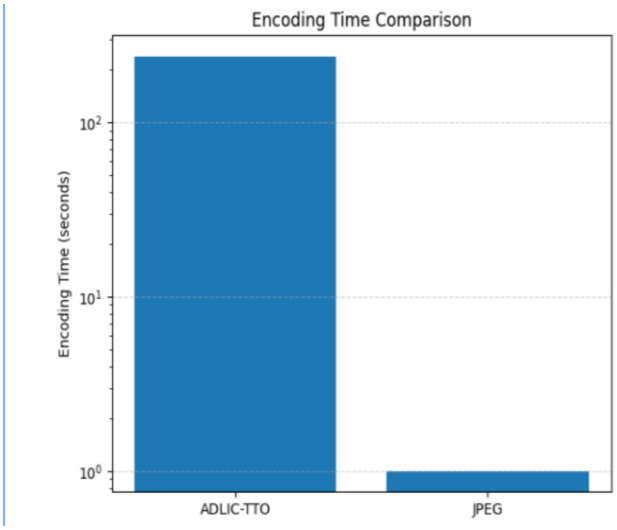

Fig.5. Encoding comparison on ADLIC-TTO and JPEG

5.3. Qualitative Visual Analysis

Qualitative comparisons also have a beneficial effect on the benefits of the proposed approach. On a visual inspection of the reconstructions, it is clear that ADLIC-TTO creates sharp edges, more precise textures, and less jagged color transition when compared to JPEG at equal compression rates. Natural JPEG artifacts, e.g. blocking, ringing, and color banding are greatly minimized, especially in fine texture areas or sharp edges.

ADLIC-TTO is more consistent with the original image in the scenes with complicated structural information or subtle variations of intensity. The saliency maps of learned importance are consistent with the appearance of perceptually salient boundaries, such as those of objects, facial features, text areas and textured surfaces, showing that the model does a good job of assigning more bits to the appearance of critical regions. These qualitative results are in line with the quantitative gains in PSNR and SSIM, which supports the usefulness of test-time adaptation and importance-directed quantization.

VI. LIMITATIONS AND FUTURE WORK

The ADLIC-TTO framework is currently limited to a single benchmark dataset of fixed resolution images and operates at a single operating point instead of allowing variable bitrates, which is an area of future research to make the framework more practically useful.

Ethics statements

No human participants, personal information, or recognizable sensitive information were involved in the present study, and the entire work is based on publicly available benchmark images of the Kodak PhotoCD dataset.

Credit author statement

Mohammed Hannes M: Conceptualization, Methodology, Software, Experiments, Data Curation, Writing - Original Draft, project administration Ravichandra D: Implementation, Experiment Design, Validation, Visualization, Writing - Review and Editing, project administration. Priya Stella Mary I, Sindhu V, Vinay K: Supervision, Methodological Guidance, Formal Analysis, Writing – Review & Editing, Project Administration.

Disclosure of conflict of interest

The authors state that they have no known conflicting financial interests or personal relationships that might be perceived to have affected the piece of work described in this paper.

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Data and code availability

The Kodak PhotoCD data utilized in this study is open-source available at the location urlhttp://r0k.us/ graphics/kodak/. The code of implementation and detailed result logs will be provided on reasonable request to the respective author.

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