Deep learning-based Edge-aware pre and post-processing methods for JPEG compressed images

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Abstract—We propose a learning-based compression scheme that envelops a standard codec between pre and post-processing deep CNNs. Specifically, we demonstrate improvements over prior approaches utilizing a compression-decompression network by introducing: (a) an edge-aware loss function to prevent blurring that is commonly occurred in prior works & (b) a super-resolution convolutional neural network (CNN) for post-processing along with a corresponding pre-processing network for improved rate-distortion performance in the low rate regime. The algorithm is assessed on a variety of datasets varying from low to high resolution namely Set 5, Set 7, Classic 5, Set 14, Live 1, Kodak, General 100, CLIC 2019. When compared to JPEG, JPEG2000, BPG, and recent CNN approach, the proposed algorithm contributes significant improvement in PSNR with an approximate gain of 20.75%, 8.47%, 3.22%, 3.23% and 24.59%, 14.46%, 10.14%, 8.57% at low and high bit-rates respectively. Similarly, this improvement in MS-SSIM is approximately 14.08%, 50%, 36.36%, 23.08%, 64.70% and 64.47%, 61.29%, 47.06%, 51.52%, 16.28% at low and high bit-rates respectively. With CLIC 2019 dataset, PSNR is found to be superior with approximately 16.67%, 10.53%, 6.78%, and 24.62%, 17.39%, 14.08% at low and high bit-rates respectively, over JPEG2000, BPG, and recent CNN approach. Similarly, the MS-SSIM is found to be superior with approximately 72%, 50%, 36.36%, 23.08%, 64.70%, 64.47%, 61.29%, 47.06%, 51.52%, 16.28% at low and high bit-rates respectively. With CLIC 2019 dataset, PSNR is found to be superior with approximately 16.67%, 10.53%, 6.78%, and 24.62%, 17.39%, 14.08% at low and high bit-rates respectively, over JPEG2000, BPG, and recent CNN approach. Similarly, the MS-SSIM is found to be superior with approximately 72%, 50%, 36.36%, 23.08%, 64.70%, 64.47%, 61.29%, 47.06%, 51.52%, 16.28% at low and high bit-rates respectively.

Index Terms—Edge aware loss, deep learning, CNN, compression-decompression, edge detector, HED, super-resolution network, codec compatible

I. INTRODUCTION

EVERY day an enormous amount of data is continuously transmitted and stored. Mostly the transmission happens through the web, and the images on the internet are of high resolution and larger in size. So to improve the efficacy of the transmission and storage, reducing the size of these files is a compulsion and an issue of big concern. Hence, image compression is widely used for storage & transmission which aims at reducing the different types of redundancies present in the image. A higher compression ratio reduces the size of the image to be stored as bits-per-pixel (bpp) allotted decreases, but it heavily affects the reconstruction quality of the image due to the loss that occurred during compression. So, there is a trade-off between the compression ratio and the quality of the image. Among alternative compression formats, the Joint Photographic Experts Group (JPEG) standard is by-far dominant; currently, almost all pictorial images are stored and communicated in JPEG format. Given the extensive utilization of JPEG, modern SmartPhone & tablet devices commonly include hardware support for JPEG compression & decompression. Methods that can improve compression performance, while maintaining compatibility with the JPEG format are, therefore, of strong research interest. Theoretically, JPEG, the standard algorithm, which is a discrete cosine transform (DCT) based emphasizes low-frequency components while processing the image for the task of image compression. JPEG2000 [2], on the other hand, being lossless & lossy both, is a region of interest (ROI) based compression scheme based on multi-scale decomposition into sub-bands through discrete wavelet transform (DWT). As compared to JPEG, JPEG2000 produces only ringing effects near the edges in the image. However, at high bit-rates, these artifacts become less visible or almost imperceptible. Later on, many techniques like BPG & WebP came into existence which provided a significant quantitative & qualitative improvement with respect to reconstructed image quality. Nowadays, deep learning is producing interesting & eye-catching results in the field of biometrics & computer vision, it has started proving itself in the image compression domain also. Some of the best compression algorithms are discussed in the next sections.

A. Deblocking and Post-processing methods

Various post-processing modules have been proposed in the literature. Modeling of the image-prior, based on maximum a posteriori (MAP) criteria is used in [3], but it is found to be quite more expensive than handcrafted models. The post-processing method in [4] based on the adaptive DCT method is quite good, but failed to generate sharp images. The notion of Wiener filtering for denoising used in [5] was novel, however, the images generated contained highly visible noise at the edge regions. Similarly, the modeling of image prior and quantization is found to be expensive in [6]. Ren et al. [7] combined the local sparsity image prior model and non-local similarity model for artifacts reduction using low-rank minimization and patch clustering proposed in [3] and [6] respectively. Dictionary learning and variational regularization used in [8] for restoring images outperformed the other decompression method but consumed substantial computational time. Weighted nuclear norm minimization

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https://developers.google.com/speed/webp/

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(WNNM) concept used in [9] being complex, outperformed Dabov et al. [5] approach while preserving the local structure and reducing visual artifacts taking more computation time. The deblocking method, given in [10] using a non-convex low rank constrained model was a good optimization of the problem. The denoising method proposed by Zhang et al. [11] helped in reducing artifacts but with the lack of retaining edge information in reconstructed images. The benchmark deblocking method ARCNN, proposed by Dong et al. [12] outperformed the above-discussed methods used for image compression. All these deblocking and post-processing models aimed to improve the reconstruction quality while ignoring the joint optimization of the traditional codec with encoder-decoder structure.

B. Down and Upsampling based CNN methods

Recent work [13], [14] has demonstrated promising results with deep learning methodologies for compression. Specifically, the work in [13] proposed an “end-to-end” compression framework wherein pre & post-processing DNN is introduced around a standard compression codec. However, the training procedure did not take care of high-frequency components (i.e. edges) due to optimization with mean square error (MSE) resulting in smooth reconstructed images. Moreover, the author did not present the rate-distortion analysis for the JPEG codec, which is needed to compare the compression performance based on bit-rates. Like [13], the approach in [14] uses jointly trained CNNs for the pre-processing and post-processing stages. These stages incorporate resolution reduction only for low JPEG quality factor (QF) and maintain resolution for higher QF. On the other hand, the work in [15] is based on investigating different downsampling networks and super-resolving or upsampling networks along with different training strategies. The sequential training of downsampling CNN with upsampling CNN only has been considered, without the consideration of any codec in-between.

C. Recent State-of-the-Art Algorithms

In 2016, Toderici et al. [16] introduced an RNN based full resolution compression exploiting the principle of progressive encoding-decoding of images. In 2017, Balle et al. [17] proposed to use generalized divisive normalization based local gain control method with the use of additive uniform noise to make non-differentiable quantization function a continuous function. Theis et al. [18] developed an algorithm to use a single autoencoder for providing variable bit-rate image compression by just tweaking with the size of latent space representation before quantization. Basically, the work in [16], [19], [20] is based on the calculation of the probability of binary representation for context-adaptive coding. Basically, Johnston et al. [20] extracted binary information for maximizing the entropy. In 2018, Li et al. [21] came up with a compression model based on content prediction with the help of importance map generation through CNN. Later on, Balle et al. extended the work in [17] by exploiting spatial dependencies for variable rate image compression in [22]. Similarly, Lee et al. [23] extended the work in [22] by proposing a context-adaptive entropy model by incorporating bit-consuming and bit-free contexts. On the other hand, the approach reported by Minnen et al. [24] was based on weighted auto-regressive and hierarchical priors for contextual image compression. Mentzer et al. [25] proposed to focus on rate-distortion trade-offs by learning a conditional probability model of latent space distribution in a 3D-CNN autoencoder. Later on in 2019’s, Choi et al. [26] proposed a variable bit-rate image compression in the hierarchy of having one compression module for providing multiple bit-rates. In early 2020’s, the model proposed by Yang et al. [27] was based on multi-layer feature modulation which reduced the problem of lower performance at low bit-rates. Chen et al. [28] proposed to learn a single CNN model at high bit-rates and then scaling the bottleneck by some factor for low bit-rates.

Motivated by the discussions on downsampling/upsampling based CNN methods, we utilize an “end-to-end” deep compression framework compatible with the traditional codec by utilizing pre & post-processing DNNs. Different from prior works, however, we:

- introduce an edge-aware loss function during compression, which significantly improves compression performance. The edge-aware loss function is motivated by the need to minimize edge distortion in compression, which the MSE loss function in [13] does not emphasize.
- for the low bit-rate regime, utilize a super-resolution network in the post-processing stage.
- prefer to use direct image-to-image learning over patch-to-patch learning criteria which is generally practiced in previous compression algorithms. The later scheme degrades the training performance, prediction efficiency, and lead to distortions in the output image.

In the proposed approach, we utilize the enhanced deep super-resolution (EDSR) network [29], which is a multi-scale network designed for specific super-resolution scaling that reduces model size and training time using residual learning compared with alternative approaches. The residual learning used in the super-resolution network helps in preserving the detail components. Because the quantization in the codec represents a non-differentiable operation, we use progressive training that co-optimizes the pre & post-processing modules in an “end-to-end” manner by appropriately approximating the codec. The super-resolution is chosen to improve the quality of the JPEG-compressed output by reducing blocking artifacts at the time of post-processing. In-fact, super-resolution which is a process of converting a low-resolution image into its high-resolution counterparts is exactly equivalent to image decompression which aims to improve the quality of the decoded image by adding more high-frequency details. Hence, the image super-resolution mechanism can be called a special case of an image compression-decompression algorithm. Different from [13], [14], the proposed network uses an edge-aware loss function to optimize the pre-processing module. In addition to that, it uses EDSR module instead of VDSR [30] module (used in [13]) & 5 layer encoder-decoder network (used in [14]) as post-processing module. The proposed algorithm is quite different from the work reported in [14], [15] in terms
of the pre-processing module and post-processing module exploited. Moreover, the algorithm presented in [14], [15] exploited switching between one network to another when investigating compression performance from low bit-rates to high bit-rates, which does not seem optimal. Also, the author did not compare the work reported in [15] with any DNN based image compression algorithms.

The remaining sections of the paper are organized as follows. Section II presents the proposed approach covering details of the post-processing DNN & the edge-aware loss function [31], [32] that we introduce. Section III discusses for the datasets used and other experimental setup details. In Section IV comparison between different experiment strategies and modules has been shown. Section V throws light on the comparison of the final proposed algorithm with the state-of-the-art algorithms. Section VI finally summarizes the effectiveness of the proposed algorithm reported in this paper.

II. Edge-Aware Codec Compression

The proposed architecture with complete layer-wise details for the three separate modules is shown in Fig. 1. The image to be compressed, \( f(x, y) \), goes through an image pre-processing network \( P_rN \) that generates the input image \( Y = P_r(f, \phi_1) \) for the standard codec (here, JPEG), where \( \phi_1 \) are the network weights, i.e., the learned parameters, of \( P_rN \). Decompression is performed by first decoding the image from its coded JPEG representation to obtain the image \( \hat{f}_c = C_o(Y, \theta) \), where, \( C_o(.) \) represents the codec function, \( \theta \) denotes the JPEG QF. The reconstructed image \( \hat{f}(x, y) \) is then obtained by post-processing the image \( \hat{f}_c \) through the post-processing network \( (P_oN) \); this operation is represented as \( \hat{f}(x, y) = P_o(\hat{f}_c, \phi_2) \), where \( \phi_2 \) are the network weights of \( P_oN \). In this process: (a) for \( P_r \) (CR) (proposed edge-aware compression algorithm based on compact resolution (CR) network), the image \( Y \) produced by \( P_rN \) is a CR (scaled down in size by 2 along each dimension by using a stride of 2 in the final convolutional layer), & \( P_oN \) includes an upsampling layer that scales up the resolution by a factor of 2 along each dimension & (b) for \( P_r \) (FR) (proposed edge-aware compression algorithm based on full resolution (FR) network), the resolution is held constant by the processing by \( P_rN \) & \( P_oN \). \( P_rN \) uses an arrangement of layers identical to [13], except that the second convolutional layer consists of 32 filters instead of 64 filters in [13]. Accordingly, to make the downscaled image to be as informative as possible, \( P_rN \) uses stride 2 in the last CNN layer (different from Li’s). We defer using the batch normalization (BN) (as used in [13]) for better generalizability, stable training, and consistent performance. Firstly, normalizing features with the mean and variance of batch during training generate artifacts, if the statistical characteristics of the training and testing datasets largely differ [29], [33]. Secondly, in PSNR oriented tasks, like image enhancement, image super-resolution & image compression, BN gives rise to unpleasing artifacts when the CNN network is deeper. Thirdly, feature normalization reduces range flexibility which is also experimentally proven in [29]. Lastly, BN layers consume the same amount of memory as the preceding convolutional layers, this elimination also significantly reduces the network parameters & GPU memory usage. The post-processing network \( P_oN \) uses an adaptation of the EDSR network [29], with an upsampling layer at the output when a CR representation is used. The use of this upsampling layer is dropped when the FR representation is used. The upsampling layer in CR representation replaces the bicubic interpolation that was used in [13] to recover a full-size image from CR representation. Fully connected layers have not been used in the proposed network making it a fully convolutional network (FCN) in nature.

We stress upon the fact that, while the approach of reducing the codec input to a lower (compact) resolution is beneficial
at low rates (correspondingly, lower reconstruction quality), at higher rates, better rate-distortion performance is obtained by retaining the original or full resolution instead of using the reduced resolution.

Structural and textural details are the important features that are highly correlated to human visual perception. Training a DNN with MSE produces smooth images at the output while ignoring the fine structural features, which are also important details for human visual perception. The edges present in the images which are mainly responsible for structural features should also be considered and given some weight while training the network. Accordingly, the edge-aware loss function is defined as,

\[ L_{\text{edge-aware}} = \alpha \times L_{\text{MSE}} + \gamma \times L_{\text{edge weighted MSE}} \]  

where, \( \gamma = 1 - \alpha \) & \( \alpha \) decides the weight for the two components in Eq. (1). The first component in Eq. (1) is basically MSE and the second component is the edge-preserving loss function (weighted MSE) which helps to restore edges or structural information in the image. Learning high-quality edges ensures the good quality of the reconstructed images.

Accordingly, for the \( P_o N \) module, a novel edge aware loss function for an image \( f \) is introduced as in Eq. [2],

\[
L_r(\phi_1, f) = \alpha \left\| P_o(\hat{f}_2, P_r(\phi_1, f)) - f \right\|^2 \]

\[
+ \gamma \left\| E \circ (P_o(\hat{f}_2, P_r(\phi_1, f)) - f) \right\|^2 \]  

where \( \| \cdot \|_2 \) denotes the \( \ell \)-2 vector norm, \( E \) denotes the edge weight map (binary map representing edge at 1 & no edge at 0) obtained by applying the edge detector to the input image, & \( \circ \) denotes pixel-wise multiplication.

The post-processing network \( P_o N \) uses the MSE loss function as given in Eq. [3] as,

\[
L_o(\phi_2, f) = \left\| P_o(\phi_2, c_o(P_r(\phi_1, f), \theta)) - f \right\|^2 \]  

Also, Fig. 2 clearly shows the progressive learning workflow for the proposed algorithm. Initially, both the CNN modules are initialized with the learning parameters \( \phi_1^0 \) & \( \phi_2^0 \) with training as a simple autoencoder, as shown in step 1. Then, the CR (in case of \( P_E \) (CR)) or FR representation (in case of \( P_E \) (FR)) is predicted using weights of \( P_o N \) module as in step 2. This representation is compressed with JPEG for a particular QF, as in step 3. Now, we define any arbitrary variable \( f_c, \) codec output, acting as input to \( P_o N \) module.

Accordingly, for an image \( f, \) codec output \( \hat{f}_c \) can be written as in Eq. (4) as,

\[
\hat{f}_c = C_o(P_r(\phi_1, f), \theta) \]  

Hence, further to optimize \( P_o N \) module for batch of images, the learning parameter \( \phi_2 \) can be obtained as in Eq. (5),

\[
\hat{\phi}_2 = \arg \min_{\phi_2} \left( \sum_{k=1}^{N} \left\| P_o(\phi_2, C_o(P_r(\phi_1, f_k), \theta)) - \hat{f}_k \right\|^2 \right) \]  

For batch of images, Eq. (5) can be modified using using Eq. (4) to,

\[
\hat{\phi}_2 = \arg \min_{\phi_2} \left( \sum_{k=1}^{N} \left\| P_o(\phi_2, \hat{f}_c) - \hat{f}_k \right\|^2 \right) \]  

where Eq. (5), implies that the codec output \( \hat{f}_c \) in Eq. (4) and ground truth \( f_k \) are then used to optimize the \( P_o N \) training parameter \( \phi_2 \) as in step 4. With \( \hat{\phi}_2, \) \( P_r N \) module is optimized by back-propagating error through \( P_r N \) module to obtain \( \hat{\phi}_1 \) in step 5 as in Eq. (7) as,

\[
\hat{\phi}_1 = \arg \min_{\phi_1} \left( \alpha \sum_{k=1}^{N} \left\| A \right\|^2 \right) + \arg \min_{\phi_1} \left( \gamma \sum_{k=1}^{N} \left\| E \circ A \right\|^2 \right) \]  

where, \( A \) in Eq. (7) can be written as,

\[
A = P_o(\phi_2, c_o(P_r(\phi_1, f_k), \theta)) - f_k \]  

Since to optimize the weights of \( P_o N, \) codec is excluded in the back-propagation path, accordingly, on putting the value of \( A, \) finally it can be deduced that,

\[
\hat{\phi}_1 = \arg \min_{\phi_1} \left( \alpha \sum_{k=1}^{N} \left\| P_o(\phi_2, P_r(\phi_1, f_k)) - f_k \right\|^2 \right) \]

\[
+ \arg \min_{\phi_1} \left( \gamma \sum_{k=1}^{N} \left\| E \circ (P_o(\phi_2, P_r(\phi_1, f_k)) - f_k \right\|^2 \right) \]  

Note that codec is used in the forward path only to predict the input to \( P_o N, \) the flow can also be called predicting (testing) while training. In every epoch, the weights of \( P_o N \) are fine-tuned according to the JPEG decoded output at a particular QF. Then the weights of \( P_r N \) are fine-tuned by fixing the weights of \( P_o N. \) Hence, it is clear that the training of both the CNN modules depends upon JPEG QF \( \theta, \) as all the intermediate outputs \( Y & \hat{f}_c \) depends upon \( \theta. \) Hence, it is deduced that the codec JPEG also plays a role in CNN weight learning of \( P_r N & P_o N. \) Here, we have used the JPEG codec, however, the framework is generalized to use any codec.

### III. IMPLEMENTATION DETAILS

#### A. Dataset

The proposed compression-decompression model is trained on 400 images \((256 \times 256)\) of the ImageNet dataset \([34]\). In order to compare the results with \([14]\), we have assessed the algorithm on various datasets namely Live 1 \([33]\), Set 14 \([36]\), Set 5 \([37]\) & Set 7 (same as built up in \([14]\)). These datasets have different attributes which also help
in the better generalization of the proposed scheme. Live 
1 dataset has twenty-nine diversified generic PNG images 
with sizes ranging from 438 × 634 to 720 × 480. These 
images contain high resolution and high-quality, sharp images. 
Set 14 contains fourteen low-frequency PNG images with 
size ranging from 250 × 361 to 768 × 512. Set 5 contains 
five edge centered luminance images. These are images with 
high-frequency domination where size varies from 280 × 280 
to 512 × 512. Apart from these three standard test sets, a 
test of 7 images named Set 7 is prepared (as in [14]) to 
compare the results with Zhao’s approach [14]. This special set 
contains both smooth and sharp images with size 
256 × 280, 512 × 512 & 512 × 768, and reported as challenging for 
image compression application. To compare with the recent 
techniques, the proposed algorithm is also assessed on Kodak 
benchmark dataset [38] and CLIC challenging dataset [39]. 
Kodak dataset contains uncompressed true-color PNG images, 
with a size of 768 × 512 or 512 × 768. CLIC 2019 consists of 
high-resolution and high-quality images with size ranging 
from 512 × 768 to 2048 × 1646. Moreover, to compare the 
deblurriness effect of the proposed algorithm, we have also 
tested Classic 5 [40] & General 100 [41] datasets. Classic 5 contains five BMP gray images of 512 × 512 size. General 
100 contains a hundred images in BMP format with zero com-
pression, which makes it highly suitable for the compression 
task. It contains good quality images with clear sharp edges 
but fewer smooth regions. The image dimensions range from 
131 × 112 to 710 × 704.

B. Hyperparameter Tuning

Both the CNN modules are trained for five iterations in each 
epoch. Adam optimizer is used to optimize the weights of the 
network that has shown very good performance as reported in [42]. Initially, \( \alpha = 0.01 \) was selected as the learning rate, 
but the loss observed was very high. Then we decreased the 
learning rate to \( \alpha = 0.001 \), due to which loss also decreased 
substantially. On further decreasing the learning rate, we did 
not get much improvement. Hence, we finalized the learning 
rate at \( \alpha = 0.001 \). The momentum parameters are selected as 
\( \beta_1 = 0.9, \beta_2 = 0.999 \) & \( \epsilon = 1 \times 10^{-7} \), which are 
reported to yield good results as in [13, 29, 43] to find the 
global minima. The batch size depends upon the computational 
platform used for the implementation of the CNN based algorithm. It should fit into the memory specification of CPU 
or GPU based architecture. Generally, training on small batch 
sizes speeds up the learning process at the cost of low accuracy 
on account of noise in the training process. On the other hand, 
with large batch size, the learning process converges slowly 
with better prediction or estimation. Accordingly, we have 
set a mini-batch size of 10, suitable for the used platform. 
We have finalized training epochs to be 50, as, after that, 
the performance was not improving. All the experiments have 
been conducted using Python with Tensorflow & Keras deep 
learning framework on TITAN X (Pascal)/PCIe/SSE2 16 GB 
CPU RAM, 12 GB GPU enabled system.

3The results of Cavigelli et al. [55] are not given at QF=30.
Fig. 4. (a), (c) & (e): \( P_{CE} (CR) \); (b), (d) & (f): \( P_{CE} (FR) \) compression performance on “Kodim 04” image of Kodak dataset at QF of 6 (row 1), 10 (row 2) & 50 (row 3). Compression performance is (a) 6, 0.042, 27.19, 0.8789, 27.19, 0.1832; (b) 6, 0.1238, 28.79, 0.8466, 28.79, 0.3756; (c) 10, 0.0528, 28.46, 0.7931, 0.9135, 28.46, 0.2071; (d) 10, 0.1832, 32.01, 0.8954, 32.01, 0.4856; (e) 50, 0.1144, 31.71, 0.8554, 31.72, 0.3848; (f) 50, 0.4925, 37.58, 0.9600, 37.58, 0.6839. The four images in each sub figure represents \( f, Y, \hat{f}_c \) and \( \hat{f} \) respectively. It is clear that FR network performed quite better at high bit-rate & CR network performed better at low bit-rate. Visually, at low rates, the proposed algorithm is also be seen to reduce blocking artifacts. The numbers for each sub figure specify the QF, Rate (bpp), PSNR (dB), SSIM, MS-SSIM, PSNRB (dB) and mIoU.

Fig. 5. Left: At QF: 10, JPEG decoded image with bpp=0.1026, PSNR=27.78, SSIM=0.7623, MS-SSIM=0.9182, Middle: Post-processed image using proposed CR image representation based algorithm with bpp=0.06, PSNR=25.17, SSIM=0.7546, MS-SSIM=0.8896, Right: Post-processed image using proposed FR image representation based algorithm with bpp=0.2074, PSNR=29.97, SSIM=0.8892, MS-SSIM=0.9485. Both the CR & FR image representation network produce images with a quite reduction in blocking artifacts by preserving edges & textures as compared to JPEG.
### Table I
Performance evaluation (PSNR (dB)/SSIM/MS-SSIM) showing the efficacy of HED detector over Canny Edge detector, when tested on Kodak dataset.

| Algorithm          | QF  | 10   | 20   | 10   | 20   |
|--------------------|-----|------|------|------|------|
|                   |     | Canny Edge Detector (CED) | HED |
| $P_E(CR)$         |     | 24.57/0.752/0.8946 | 24.80/0.764/0.9055 | 26.13/0.7679/0.9131 | 27.63/0.8067/0.9483 |
| $P_E(FR)$         |     | 28.99/0.876/0.9328 | 30.86/0.9077/0.9633 | 30.07/0.8983/0.9574 | 32.24/0.9261/0.9764 |

### Table II
Performance evaluation (PSNR (dB)/SSIM/MS-SSIM) showing the efficacy of EDSR over VDSR post-processing module, when tested on Kodak dataset.

| Networks          | QF  | 10   | 20   | 30   | 40   |
|-------------------|-----|------|------|------|------|
|                   |     | Codec + $P_E(CR)$ | Codec + $P_E(FR)$ |
| $P_{EDSR}(CR)$    |     | 24.61/0.626/0.8559 | 25.59/0.680/0.9098 | 26.04/0.7106/0.9304 | 26.35/0.7296/0.9418 |
| $P_{EDSR}(FR)$    |     | 27.76/0.700/0.9290 | 29.70/0.847/0.9679 | 31.54/0.8795/0.9791 | 32.31/0.8983/0.9844 |
| $P_{EDS1}(CR)$    |     | 26.13/0.7679/0.9131 | 27.63/0.8067/0.9483 | 28.25/0.8304/0.9612 | 28.52/0.8305/0.9685 |
| $P_{EDS1}(FR)$    |     | 30.07/0.8983/0.9574 | 32.24/0.9261/0.9764 | 33.55/0.9451/0.9862 | 34.76/0.9507/0.9898 |

### Table III
Performance evaluation (PSNR (dB)/SSIM/MS-SSIM) to check the effect of Pre ($P, N$) & Post Processing Networks ($P_n,N$), when tested on Kodak dataset.

| Networks          | QF  | 10   | 20   | 30   | 40   |
|-------------------|-----|------|------|------|------|
|                   |     | Codec + $P_E(CR)$ | Codec + $P_E(FR)$ |
| $P, N + Codec (CR)$ |     | 26.88/0.7419/0.9258 | 27.68/0.7996/0.9644 | 27.83/0.8198/0.9758 | 27.90/0.8288/0.9808 |
| $P, N + Codec + P_E (CR)$ |     | 26.13/0.7679/0.9131 | 27.63/0.8067/0.9483 | 28.25/0.8304/0.9612 | 28.52/0.8365/0.9685 |
| $P, N + Codec (FR)$ |     | 28.01/0.7792/0.9291 | 31.18/0.8466/0.9678 | 31.60/0.8801/0.9795 | 32.53/0.8990/0.9849 |
| Codec + $P, N$ (CR/FR) |     | 26.56/0.7520/0.9413 | 31.22/0.8630/0.9717 | 32.30/0.8900/0.9810 | 33.17/0.9061/0.9856 |
| $P, N + Codec + P_E (FR)$ |     | 30.17/0.8983/0.9574 | 32.24/0.9261/0.9764 | 33.55/0.9451/0.9862 | 34.76/0.9507/0.9898 |

### Table IV
Mean intersection over union showing effectiveness of edge aware loss function over MSE loss function at QF: 10 & 50. $P_M$: Proposed algorithm with training of both modules on MSE loss. $P_E$: Proposed algorithm with training of $P_E$ modules on Edge and MSE loss respectively.

| Dataset       | Set7 | Set14 | Live 1 | Set5 | Kodak | CLIC 2019 | General 100 | Classic 5 | Average |
|---------------|------|-------|--------|------|-------|-----------|-------------|-----------|---------|
| QF            |      |       |        |      |       |           |             |           |         |
| $P_M(CR)$     | 0.3571 | 0.2847 | 0.2503 | 0.3063 | 0.2343 | 0.2496 | 0.2952 | 0.2734 | 0.2814 |
| $P_M(FR)$     | 0.5775 | 0.5163 | 0.5063 | 0.5105 | 0.4970 | 0.4816 | 0.5373 | 0.5066 | 0.5225 |
| $P_E(CR)$     | 0.3589 | 0.2815 | 0.2539 | 0.3000 | 0.2375 | 0.2531 | 0.2993 | 0.2759 | 0.2823 |
| $P_E(FR)$     | 0.6068 | 0.5279 | 0.5322 | 0.5347 | 0.5252 | 0.5020 | 0.5575 | 0.5264 | 0.5391 |
| QF            |      |       |        |      |       |           |             |           |         |
| $P_M(CR)$     | 0.5332 | 0.4418 | 0.4066 | 0.4880 | 0.3868 | 0.4185 | 0.4853 | 0.4246 | 0.4474 |
| $P_M(FR)$     | 0.6413 | 0.5776 | 0.5622 | 0.5393 | 0.5478 | 0.5362 | 0.6093 | 0.5754 | 0.5736 |
| $P_E(CR)$     | 0.5154 | 0.4257 | 0.3900 | 0.4613 | 0.3771 | 0.4041 | 0.4612 | 0.4282 | 0.4329 |
| $P_E(FR)$     | 0.7676 | 0.7066 | 0.7137 | 0.7134 | 0.7031 | 0.6984 | 0.7393 | 0.7257 | 0.7209 |

### Table V
Performance evaluation (PSNR (dB)/SSIM/MS-SSIM) showing the effectiveness of edge aware loss function over MSE loss function, when tested on Kodak dataset.

| Algorithms       | QF  | 10   | 20   | 30   | 40   |
|------------------|-----|------|------|------|------|
| $P_M(CR)$        |     | 24.30/0.759/0.8959 | 26.55/0.804/0.9463 | 27.04/0.813/0.9542 | 26.65/0.818/0.9644 |
| $P_M(FR)$        |     | 26.13/0.7679/0.9131 | 27.63/0.8067/0.9483 | 28.25/0.8304/0.9612 | 28.52/0.8365/0.9658 |
| $P_E(FR)$        |     | 26.09/0.888/0.9464 | 31.77/0.834/0.9585 | 31.86/0.923/0.9660 | 33.67/0.941/0.9799 |
| $P_E(FR)$        |     | 30.07/0.8983/0.9574 | 32.24/0.9261/0.9764 | 33.55/0.9451/0.9862 | 34.76/0.9507/0.9898 |
tested the classical Canny Edge Detection \cite{49} and learning-based edge detector. For learning-based edge detection, we have chosen the Holistically-Nested Edge Detection technique (HED), which has been set as a benchmark technique for edge detection after the development in the CNN architectures. HED is a learning-based end-to-end edge detection system that uses a trimmed VGG-like CNN for an image to image prediction task. It is based on multi-scale and multi-level feature learning and claims to learn rich hierarchical features which are crucial. However, Canny edges are not directly connected and produce some spatial shifts and inconsistencies. It makes use of the side outputs of intermediate layers to learn edges synchronizing with the contextual information leaving undesired and false edges. Since the feature maps generated at each layer are of different sizes, it effectively looks at images at different scales. Generally, edge detectors are supposed to assume 90% of the ground truth as non-edge, but HED uses a class balancing weight to make a balance between edge & non-edge region, to find the true & strong edges much effectively as shown in Fig. 3. To implement it, we have used the code provided at \cite{4} for exploiting edge map predictions obtained through training the modified VGGNet with BSDS500 \cite{50}. HED seems to produce better compression performance than CED as shown in Table \ref{tab1}.

### B. Comparison for learning the proposed network separately with VDSR & EDSR post-processing module

In \cite{13}, the VDSR module has been used as the post-processing module. However, we have used the EDSR module to remove the blocking effects generated after JPEG decoding. To show the efficacy of the EDSR module, we have implemented the proposed algorithm considering the VDSR post-processing module. The compression with the EDSR module achieves significant improvement over compression with the VDSR module as shown in Table \ref{tab1}.

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**Table VI**

| Stride 2 | QF | 10 | 20 |
|----------|----|----|----|
| At first layer | PSNR (dB) | 26.33/0.7372/0.9095 | 27.55/0.7876/0.9436 |
| At last layer | SSIM | 26.13/0.7679/0.9131 | 27.63/0.8067/0.9483 |

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Fig. 6. Performance comparison showing the applicability of proposed CR & FR networks based algorithm.

Fig. 7. Objective (PSNR) & Subjective parameter (SSIM) comparison of proposed algorithm with standard & downsampling method on (a) Live 1 (b) Set 14 (c) Set 7 (d) Set 5 datasets.

\[\text{https://github.com/senliuy/Keras\textunderscore HED\textunderscore with\textunderscore model}\]
C. Comparison for impact of Pre & Post-processing module separately on codec compression with full framework

To check the individual contribution of each sub-module i.e., pre & post-processing module, we have trained the network considering $P_E$ & $P_N$ individually. In fact, these individual implementations are the special cases of proposed $P_E (\text{FR})$. From Table III, it is inferred that traditional codec compression followed by the post-processing network $P_N$ produces better results than pre-processing module $P_E$. Moreover, adding both these modules with the codec compression added further gain in compression performance.

D. Comparison for learning the network on Edge aware loss & comparison with the MSE loss function

The training of $P_E$ on edge-aware loss forced the network to retain structural and sharp details while compressing the images. Also, the tuning parameter $\alpha = 0.75$ worked best for training the network to preserve edges in the reconstructed images. The first term in Eq. (2) ensures high PSNR by minimizing MSE while preserving edges. Preserving edges via the second term in Eq. (2) ensures the preservation of structural information and hence maximize SSIM & MS-SSIM. High mIoU value in Table IV indicate to retain edges with edge loss.
Fig. 9. Objective (PSNR) & Subjective parameter (MS-SSIM) comparison of proposed algorithm with standard & recent state-of-the-art approaches on CLIC 2019 dataset.

### TABLE IX

| Algorithm       | PSNR (DB) | SSIM   |
|-----------------|-----------|--------|
| DnCNN-3         | 29.40     | 0.806  |
| ARCNN           | 29.05     | 0.817  |
| DPW-SDNet       | 29.74     | 0.814  |
| **P_E (FR)**    | 30.18     | 0.918  |

PSNR (DB)/SSIM COMPARISON OF VARIOUS DEBLOCKING & POST-PROCESSING METHODS WITH THE PROPOSED ALGORITHM ON CLASSIC 5 DATASET.

### TABLE X

| Algorithm       | PSNR (DB) | SSIM   |
|-----------------|-----------|--------|
| DnCNN-3         | 29.19     | 0.823  |
| ARCNN           | 28.98     | 0.821  |
| DPW-SDNet       | 29.53     | 0.830  |
| CASCNN          | 29.44     | 0.833  |
| Galteri's       | 29.45     | 0.834  |
| **P_E (FR)**    | 30.27     | 0.900  |

PSNR (DB)/SSIM COMPARISON OF VARIOUS DEBLOCKING & POST-PROCESSING METHODS WITH THE PROPOSED ALGORITHM ON LIVE 1 DATASET.

### TABLE XI

| Algorithm       | BD-RATE | BD-PSNR |
|-----------------|---------|---------|
| JPEG            | -68.04/5.71 | -56.67/5.96 |
| JPEG2000        | -44.99/2.67 | -33.54/2.71 |
| Zhao's [14]     | -47.62/2.97 | -33.72/2.85 |
| **P_E (CR)**    | -66.59/4.45 | -57.15/5.70 |
| **P_E (FR)**    | -35.25/1.51 | -29.50/2.39 |

BD-RATE (IN %)/BD-PSNR (DB) FOR CODING GAIN OBTAINED COMPARING PROPOSED ALGORITHM WITH RECENT STATE-OF-THE-ART TECHNIQUES.

(\(P_E\)) as compared to MSE loss function (\(P_M\)), ultimately ensuring the edge-preserving property. Also, it indicates that an FR network can recover images with quite a higher mIoU than a CR representation network. In addition to this, we have trained both the modules with MSE and the results are given in Table V. The results show that training of \(P_E\) with
edge-aware loss function leads to better results than training with MSE. Apart from that, Li et al. [15] use a resolution decrement parameter (layer with stride 2) at the first CNN layer. But, we believe it should be placed at the last CNN layer (as used in the proposed algorithm) because gradual or delayed downsampling help in learning more features as compared to sudden downsampling just after the first layer. This sudden downsampling may lose learning of some features which are crucially required. To support this statement, a small experiment is conducted first by taking stride 2 in the first layer, then in last and the results are shown in Table [VI].

With multiple sets of experiments, we finalize the training of $P_rN$ & $P_eN$ module on edge-aware & MSE loss functions, respectively. It was found that training with edge-aware loss functions performed well with comparatively more bit saving.

### E. Comparison of CR learning framework with FR learning framework

The results in Fig. 4 stressed upon the point of more appropriate learning of features showing the superiority of the FR over CR image representation in terms of compression gain and performance measures. From the highlighted region in the image given in Fig. 5 it is quite evident that at low bit-rates, the proposed $P_e$ (CR) & $P_r$ (FR) reduces the blocking artifacts more effectively compared to JPEG, due to super-resolution network introduced to post-process the image. However, it is noted that better performance at low bit-rates using CR network representation is obtained at the cost of performance saturation at high bit-rates which can be seen from Fig. 6.

### V. COMPARISON WITH STATE-OF-THE-ART ALGORITHMS

We have compared the proposed algorithm with JPEG and Jiang’s [13] for QF of 5 & 10 on Set 5, Set 14, Live 1 & General 100 dataset. It is observed that the proposed $P_e$ (FR) has outperformed the mentioned approaches with a significant margin as shown in Table [VII]. Specifically, we have compared the proposed algorithm with various deblocking and post-processing based algorithms and again found $P_e$ (FR) to overcome the approaches shown in Table [VII]. Here also, the contribution of each module $P_rN$ & $P_eN$ can be seen as demonstrated separately.

When tested on Classic 5 & Live 1 dataset, the proposed algorithm clearly outperformed the work reported in [11], [12] as shown in Table [X] & Table [X] respectively. The proposed algorithm is effectively seen as to remove blocking artifacts which are confirmed when comparing PSNRB with standard artifacts reduction techniques as shown in Table [XI] & Table [XII].

When tested with Live 1, Set 14, Set 7 & Set 5 dataset, the proposed algorithm has effectively outperformed JPEG, JPEG2000 & Zhao’s [14] as shown in Fig. 7. For plotting rate-distortion curves, the bit-rate for a file is obtained by dividing the file size of codec compressed bit-stream with the respective original image dimension. With the proposed algorithm, the improvement in PSNR is approximately 25%, 3.77%, 10%, and 22.73%, 12.5%, 19.12% at low and high bit-rates respectively, compared to JPEG, JPEG2000, and Jiang’s algorithms on Live 1 dataset. This improvement in SSIM is approximately 45.6%, 15.28%, 16.9%, and 10.11%, 6.5%, 6.52% at low and high bit-rates respectively, compared with the same approaches. When tested on the Set 14 dataset, the improvement in PSNR is 26.67%, 9.61%, 9.61%, and 20.31%, 13.24%, 11.59% at low and high bit-rates respectively, compared to JPEG, JPEG2000 and Jiang’s algorithms. Similarly, the increase in SSIM is approximately 41.67%, 16.44%, 19.72%, and 11.90%, 6.67%, 5.49% at low and high bit-rates respectively, compared with the same approaches. On the Set 7 dataset, the improvement in PSNR is approximately 30.43%, 11.11%, 15.38%, and 16.92%, 7.04%, 8.57% at low and high bit-rates respectively, compared to JPEG, JPEG2000 and Jiang’s algorithms. Similarly, the improvement in SSIM is 31.82%, 12.99%, 8.75%, and 6.59%, 5.43%, 3.19% at low and high bit-rates respectively, compared with the same approaches. The proposed algorithm outperformed JPEG, JPEG2000, and Jiang’s with PSNR with an approximate gain of 38.30%, 12.07%, 16.07%, and 19.40%, 12.68%, 12.68% at low and high bit-rates respectively, on Set 5 dataset. The improvement in SSIM is approximately 42.59%, 3.90%, 7.3%, and 7.87%, 3.23%, 2.13% at low and high bit-rates respectively, compared with the same approaches. As shown in Fig. 8 when tested on Kodak benchmark dataset, the proposed algorithm outperformed JPEG, JPEG2000, BPG, and the work reported in [17], [18], [21], [22], [23], [26].

In terms of PSNR by an approximate improvement of 20.75%, 8.47%, 3.22%, 8.47%, 14.29%, 4.17%, 4.92%, 3.23%, 3.23%, 5.26% and 24.59%, 14.46%, 10.14%, 13.43%, 16%, 13.64%, 11.76%, 8.57%, 8.57%, 14.94% at low and high bit-rates respectively. Similarly the improvement in MS-SSIM is approximately 71.43%, 50%, 36.36%, 23.08%, 56.52%, 40.63%, 63.64%, 50%, 70%, 25.93%, 9.09%, 6.5%, 13.04%, 67%, 64.70%, 41.67% and 64.47%, 61.29%, 47.06%, 51.52%, 60.26%, 43.68%, 78.57%, 51.52%, 32.35%, 27.78%, 21.95%, 35.14%, 42.86%, 69%, 16.28%, 35.29% at low and high bit-rates respectively, when compared with JPEG, JPEG2000, BPG, WebP algorithms and the work reported in [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27].

When tested on CLIC 2019 challenging dataset as shown in Fig. 9, the proposed algorithm outperformed JPEG, JPEG2000, BPG and the work in [17], [22], [27] by approximately 20.73%, 8.85%, 10.53%, 16.24%, 11.70%, 6.78% and 23.08%, 14.94%, 17.39%, 22.73%, 19.12%, 14.08% at low and high bit-rates respectively. Similarly the improvement in MS-SSIM is approximately 72%, 45.45%, 39.13%, 33.33%, 23.08%, 52.38%, 18.52% and 71.43%, 50%, 41.18%, 33.33%, 29.73%, 37.14%, 17.07% at low and high bit-rates respectively, when compared to JPEG, JPEG2000, BPG and the work in [17], [22], [27], [28]. More gain in terms of objective (PSNR) & subjective (MS-SSIM) evaluation has been achieved at lower as well as higher bit-rates due to the use of a super-resolution network that uses residual learning. The edge-aware loss function also helped to reduce the bit-rate while maintaining the same quality of decompressed images. The coding gain of the proposed algorithm (BD metric calculation) concerning various state-of-the-art methods is also found to be quite high as given in Table [XIII]. High
TABLE XIV
SIMILARITY TESTS (AVERAGE VALUE) BETWEEN TRAINING SET (BSD400) AND TESTING SETS USED.

| Datasets | Set 5 | General 100 | Set 7 | CLIC 2019 | Set 14 | Kodak | Live 1 | Classic 5 |
|----------|-------|-------------|-------|-----------|--------|-------|--------|----------|
| Correlation Coefficient | 0.0488 | 0.0985 | 0.109 | 0.1106 | 0.1164 | 0.126 | 0.1521 | 0.2475 |

TABLE XV
RUN TIME COMPLEXITY (IN SEC) OF PROPOSED ALGORITHM WITH VARIOUS STATE-OF-THE-ART ALGORITHMS FOR COMPRESSION OF 256 x 256 SIZE IMAGE AT QF:10.

| Algorithm | Time (CPU/GPU) | Algorithm | Time (CPU/GPU) |
|-----------|----------------|-----------|----------------|
| ARCNN     | 106564 (417 KB)| Zhang's   | 10.109         |
| Johnston's | 708674         | DnCNN-3   | -0.0157        |
| Zhao's    | 19968768       | Balle's   | 0.73           |
| DnCNN-3   | 1112192        | Lee's     | -7.5           |
| Rensch's  | 36/-           | DPW-SDNet | -1.2 ~ 2       |
| ArcTV     | 53/-           | CASCNN    | -2.4           |
| WNNM      | 230/-          | Proposed CR/FR | -0.081 |

TABLE XVI
TRAINING PARAMETERS OR MODEL SIZE COMPARISON OF PROPOSED ALGORITHM WITH VARIOUS STATE-OF-THE-ART METHODS.

| Algorithm | Parameters | Algorithm | Parameters |
|-----------|------------|-----------|------------|
| ARCNN     | 106564 (417 KB)| Li et al. | 257557187 |
| Johnston's | 708674         | Balle's   | 4.76 million |
| Zhao's    | 19968768       | Mentzer's | 9561472 |
| DnCNN-3   | 1112192        | Yang's    | 10.27 million |
| Toderici's | 7457472        | Chen's    | 261.803 MB |
| Balle's   | 16.1 million   | DPW-SDNet | 1700736 |
| Theis's   | 2742112       | CASCNN    | 5144000 |
| Johnston's | 9917504        | Galleri's | 7128160 |
| Proposed CR/FR | 7960986/648386 |           |            |

the-art techniques, the approach yields very good results with only a few training images. The testing time when using the proposed algorithm is also less i.e., 0.081s, making it practically implementable. Table [XV] and Table [XVI] show the comparison between the run-time complexity and number of training parameters for the proposed algorithm. Both the testing time and training parameters being feasible to make the proposed algorithm real-time applicable.

VI. CONCLUSION

The end-to-end compression-decompression framework centered on super-resolution preserves the quality of the images both at low & high bit-rates along with reducing artifacts while reconstructing the images. The edge-aware loss function introduced using HED is used to prevent the blurriness & artifacts which are generally caused by training the network with MSE. We reported on extensive experiments conducted to evaluate the proposed approach on several compression datasets. The results demonstrate that compared to the various state-of-the-art method, both the super-resolution post-processing network & the edge-aware loss function provide significant gain concerning deblocking, rate-distortion performance, compression performance (PSNR, PSNRB, SSIM, MS-SSIM), and coding gain in terms of BD-Rate & BD-PSNR.

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