ISNN 3030-3907

2026/3
VOLUME 7

DEVELOPMENT OF SCIENCE

ILMIY JURNAL



Development of science

Ilmiy jurnal

2026/3 VOLUME 7

ISSN 3030 -3907

Ilmiy jurnal OAK rayosatining 2024 yil 27 sentabrdagi 361-son qaroriga asosan 02.00.00 kimyo fanlari hamda 2025 yil 12 fevral 367- son qaroriga asosan 05.00.00 texnika fanlari bo‘yicha falsafa doktori (PhD) va fan doktori (DSc) ilmiy darajasiga talabgorlarning dissertatsiya ishlari yuzasidan dissertatsiyalari asosiy ilmiy natijalarini chop etish tavsiya etilgan milliy ilmiy nashrlar ro‘yxatiga kiritilgan.

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ISSN 3030-3907

Development of science ilmiy jurnali 2024 yil 15 aprel kuni №256445 sonli guvohnoma bilan Davlat ro‘yxatidan o‘tgan.

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ISSN 3030-3907

DEEP PERCEPTUAL IMAGE QUALITY ASSESSMENT FOR COMPRESSION

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Abstract. Lossy Image compression is necessary for efficient storage and transfer of data. Typically the trade-off between bit-rate and quality determines the optimal compression level. This makes the image quality metric an integral part of any imag- ing system. While the existing full-reference metrics such as PSNR and SSIM may be less sensitive to perceptual quality, the recently introduced learning methods may fail to general- ize to unseen data. In this paper we propose the largest image compression quality dataset to date with human perceptual preferences, enabling the use of deep learning, and we de- velop a full reference perceptual quality assessment metric for lossy image compression that outperforms the existing state-of-the-art methods. We show that the proposed model can effectively learn from thousands of examples available in the new dataset, and consequently it generalizes better to other unseen datasets of human perceptual preference. The CIQA dataset can be found at https://github.com/google- research/google-research/tree/master/CIQA

Keywords: Full-reference Image Quality Assess- ment, Image Compression, Compression Quality Metric, Perceptual Quality Dataset

Annotatsiya. Ma'lumotlarni samarali saqlash va uzatish uchun tasvirni yo'qotmasdan siqish zarur. Odatda bit tezligi va sifat o'rtasidagi kelishuv optimal siqish darajasini belgilaydi. Bu tasvir sifati ko'rsatkichini har qanday tasvirlash tizimining ajralmas qismiga CIQA ma'lumotlar to'plamini https://github.com/google-research/google-research/tree/master/CIQA saytidan topishingiz mumkin. To'liq mos yozuvlar tasvir sifatini baholash, tasvirni siqish, siqish sifati ko'rsatkichi, idrok etishaqolada biz inson idrokiga oid afzalliklarga ega bo'lgan, chuqur o'rganishdan foydalanishga imkon beruvchi eng katta tasvirni siqish sifati ma'lumotlar to'plamini taklif qilamiz va biz tasvirni yo'qotmasdan siqish uchun mavjud bo'lgan eng zamonaviy usullardan ustun bo'lgan to'liq mos yozuvlar idrok sifatini baholash ko'rsatkichini ishlab chiqamiz. Biz taklif qilingan model yangi ma'lumotlar to'plamida mavjud bo'lgan minglab misollardan samarali

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o'rganishi mumkinligini va natijada u insonning idrok etish afzalliklariga ega bo'lgan boshqa ko'rilmagan ma'lumotlar to'plamiga yaxshiroq umumlashtirilishini ko'rsatamiz. CIQA ma'lumotlar to'plamini https://github.com/google-research/google-research/tree/master/CIQA saytidan topishingiz mumkin

Kalit so'zlar: To'liq mos yozuvlar tasvir sifatini baholash, tasvirni siqish, siqish sifati ko'rsatkichi, idrok etish sifati ma'lumotlar to'plami

Аннотация. Сжатие изображений с потерями необходимо для эффективного хранения и передачи данных. Как правило, оптимальный уровень сжатия определяется соотношением между скоростью передачи данных и качеством. Это делает показатель качества изображения неотъемлемой частью любой системы обработки изображений. В то время как существующие полнофункциональные показатели, такие как PSNR и SSIM, могут быть менее чувствительны к качеству восприятия, недавно внедренные методы обучения могут оказаться неспособными обобщить невидимые данные. В этой статье мы предлагаем самый большой на сегодняшний день набор данных о качестве сжатия изображений с учетом предпочтений человека, позволяющий использовать глубокое обучение, и разрабатываем полный эталонный показатель оценки качества сжатия изображений с потерями, который превосходит существующие современные методы. Мы показываем, что предложенная модель может эффективно извлекать уроки из тысяч примеров, доступных в новом наборе данных, и, следовательно, она лучше обобщается на другие невидимые наборы данных о предпочтениях человеческого восприятия. Набор данных CIQA можно найти по адресу https://github.com/google- research/google-research/tree/master/CIQA

Ключевые слова: Оценка качества полноэкранного изображения, Сжатие изображений, Показатель качества сжатия, Набор данных о качестве восприятия

INTRODUCTION

Compressed image data make up a very large portion of data stored in data centers around the world. At the rapidly in- creasing scale of data storage, compression techniques are more important now than ever. Even a marginal change in ef- ficiency can have large impact on data storage. While image compression techniques are vital for efficiently storing enor- mous quantities of data, they have remained relatively static over the years [1].

Lossy image compression is a family of techniques for digital images, where bits are discarded when compression takes place resulting in a possible degradation in quality per- ceived by a human. The degree of compression or bit rate is directly proportional to file size. There is an inherent trade- off between the bit-rate and

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distortion of a compressed image [2]. Currently, some of the the main metrics used for adjust- ing bit-rate of an encoder is MSE (mean squared error), PSNR (peak-signal-to-noise-ratio), or other similar quality metrics.

* equal contribution

ΔPSNR = -4.2dB, ΔSSIM = -0.011, ΔLPIPS=-0.059, **ΔOurs = -0.02**



ΔPSNR = 3.1dB, ΔSSIM = 0.015, ΔLPIPS = 0.044, **ΔOurs = 0.41**

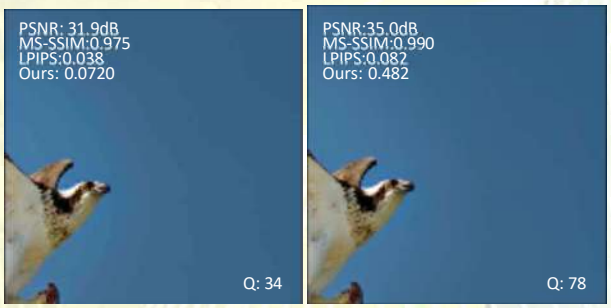


Fig. 1. Examples of CIQA pairwise comparisons with la- beled JPEG Q factor, PSNR, SSIM, LPIPS and our model output. PSNR and SSIM do not adequately correlate with visible distortions in the compressed image. For each metric the Δ is taken as *Metric*(*Image*$_2$, *Reference*) − *Metric*(*Image*$_1$, *Reference*).

However, it has been shown that large PSNR values do not necessarily mean a high perceptual quality. For instance, the JPEG encoder can generate artifacts such as color banding or blockiness, that are not well-captured by PSNR [3]. In addition, other popular baseline metrics such as SSIM [4] and MS-SSIM [5] do not show a consistently high correlation with human perceptual quality preferences. Assessing compres- sion quality based on these metrics can lead to sub-par performances [6]. This leads to low confidence in the results of compression with adjusted bit rates or to the use of a catch- all bit-rate for the encoder to minimize the perceptual quality loss for the vast majority of images [6].

Learning based methods are the logical next step. These methods do show a significant improvement on correlation with human preferences [7, 8]. The LPIPS metric [7] has very promising results correlating with human perceptual preferences in measuring similarity of images that have very differ- ent and obvious perturbations. However, since most of these models are developed to address generic quality assessment, they may not perform well outside of their main

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objective and do not generalize consistently to unseen data. This creates need for a perceptual quality metric that can be used for image compression. Such a metric should not only correlate well with human perceptual preferences but also generalize well to new datasets, robust to unseen data in the wild. To this aim, we first introduce the largest set of hu- man perceptual preference labels for compressed image pair- wise comparisons that is better suited for the creation of deep learning networks for compression image quality assessment (IQA). Since 72.4% of all websites on the internet use images with JPEG standard [9], we focus on this compression for-mat. Our proposed CIQA is 3× larger than previous datasets enabling semantic information to be more general with more examples and allows the model to focus on compression arti- facts during training. Secondly, this paper introduces a deep learning full-reference, perceptual quality metric, trained on CIQA for image compression IQA that correlates strongly with human perception and preference. This model not only outperforms current state-of-the-art (SOTA) metrics on the dataset used for training but also generalizes well to SOTA performance with unseen datasets, namely LIVE-Wild [10] and FG-IQA [11].

RELATED RESEARCH

In recent years, there has been a resurgence in interest for im- age compression techniques particularly in IoT and robotics applications [12, 13], particularly with the advance in ma- chine learning, which introduces the capability for person- alized or smart compression as a way to increase efficiency while minimizing perceptual quality loss.

COMPRESSION

Storing digital images is subject to an important tradeoff be- tween compression file size (bit-rate), perceptual quality (dis- tortion) [2]. Different domains emphasize the tension be- tween different pairs of these goals.

The most well studied obvious is the bit-rate distortion tradeoff. MSE, PSNR, SSIM, MS-SSIM [5] etc., are the dominant metrics used for measuring distortion resulting from compression. Recent work in this domain advances the search for a metric and method for maintaining a high quality after compression [14, 15]. In [16] discusses the importance of a perceptual quality metric that can be used to train a deep compression model.

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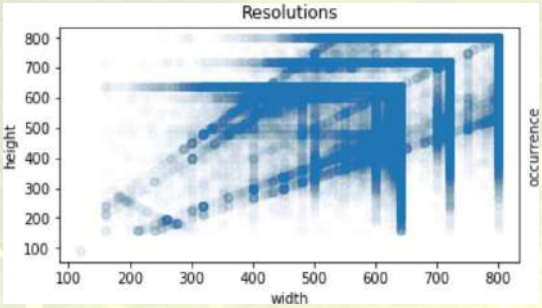


Fig. 2. Resolution of images sampled for the CIQA dataset showing diversity in heights and widths

Compressed Image Quality Assessment

Image quality assessment broadly has been accelerated by the release of large scale datasets that include image labels of hu- man perceptual ratings. Data sets such as AVA [17], TID2013 [3], KonIQ-10k [18] and WILD [10] have enabled the use of deep learning for this task. Image compression perceptual quality datasets, however, are still somewhat limited in size limiting the use of deep learning due to likely over-fitting.

Two prominent datasets [10, 11] and associated analysis have been performed in image quality assessment (IQA) for compressed images. [10] created the LIVE-Wild in which 100 reference images were compressed to different degrees using different encoders and the compressed images were rated using single stimulus ranking. [11] introduces the fine- grained image quality assessment dataset, a much larger-scale image database used for fine grained quality assessment not- ing the preference of human raters to more subtle changes in compression.

METHODS

The current perceptual quality datasets for image compres- sion, FG-IQA and LIVE-Wild [10, 11], are well suited for the evaluation of baseline methods, but fall short when training deep learning models due to the limitations in the number of training examples resulting in over-fitting of the network.

The Aesthetic Visual Analysis dataset (AVA) is well suited for deep learning applied to perceptual IQA proven by its successful implementation in the NIMA, NR-IQA model,

[8] and others [19]. AVA contains ~ 255, 000 images rated based on aesthetic quality by amateur photographers [17], and its size and semantic content distribution may be attributed to its success in deep learning applications. In order to mir- ror this success to the field of compression perceptual IQA, we introduce the Compression Image Quality Assessment (CIQA) dataset with 6,667 (6400/267 train/test split) unique images sampled from AVA, whose new labels are used to compare quality between images compressed to different JPEG Q values.

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Table 1.

Summary of current Compression IQA Datsets

Database	No. Ref Images	No. Distortions	No. Distinct Comparisons	Number of Ratings
LIVE-Wild	29	779	780	single stimulus (20-29 per image)
FGIQA	100	1,200	3600	54,000 (15 per pair)
CIQA	6,667	13,868	7808	249,856 (32 per pair)

Because these images are stored using JPEG compression, only the subset of images with a JPEG Q factor of 99 or more (essentially uncompressed) were sampled and subsequently compressed at random JPEG quality factors. The original dataset contained semantic labels in addition to perceptual quality labels, and the distribution images from each of the semantic groups was preserved. Semantics labels for each of animal, architecture, cityscape, floral, food/drink, land- scape, portrait, and still life each have almost equal occur-rence (∼ 6.25%) and the category of 'generic' has an oc- currence of 50%. This was done to ensure the diversity of sampled images and to be a more accurate representation of general perceptual image quality. Similarly, Figure 2 shows the distribution of resolution from the sampled images which includes ranges from 200 × 200 to 800 × 800, not necessarily always of equal height and width. The distribution of image area (*height* × *width*) followed close to a normal distribution with a mean of ∼ 300, 000 pixels and a standard deviation of ∼ 100, 000 pixels.

The aforementioned study was a forced choice pairwise comparison study [20, 21] and consisted of human raters who were presented with two images derived from the same refer- ence, compressed to different degrees, and were asked to se- lect which image has the better perceptual quality. The rater was asked to select an image at random when unsure.

This resulted in 7,808 pairwise comparisons were gener- ated and each was rated by 32 individual participants. Pairs were chosen by compressing the reference image to two ran- dom quality factors in [10,100]. 13,868 compressed images were generated from the 6,667 reference images, 2 for each image in the train set and 4 for each image in the test set.

PERCEPTUAL QUALITY METRIC FOR COMPRESSED IMAGES

As shown in Figure 3, we propose a full-reference CNN model architecture that leverages a partial weight matrix pre- trained on ImageNet [22]. The base CNN corresponds to the first N layers from one of, EfficientNet-b0 [23] (73 layers), EfficientNet-b7 (157 layers), DenseNet [24] (121 layers),

ResNet50-v2 [25] (32 or 44 layers) or VGG16 (7 layers). Both images are

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fed through a base CNN model to extract features separately up to some some hidden layer l. Both features are then fed through a 1 × 1 convolution filter with 2 features maps to reduce the dimensional of the original features, namely the bottleneck. Next, we concatenate these

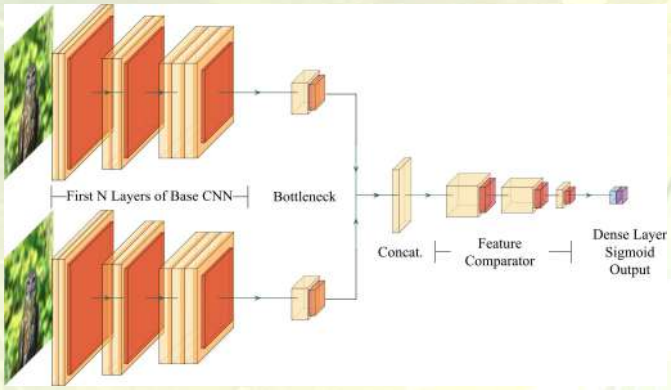


Fig. 3. Architecture used for our proposed deep learning model to predict perceptual IQA preference. The output cor- responds to the proportion of raters prefer JPEG2

Features, and feed it into the feature comparator, a two layer 1x1 convolutional layer with 256 hidden feature maps and a 1 feature map output. Finally, we apply a global average pooling, an affine transform, and a sigmoid activation, which represents our final prediction. The output is a number be- tween 0 and 1 corresponding to the predicted preference of the second JPEG. A value of 0.5 corresponds to an indis- tinguishable change in perceptual quality between the two images, and a prediction approaching 0 or 1 corresponds to the respective image being of higher quality.

The neural network based models this architecture de- scribed above are trained on our CIQA labels and then evalu- ated on FG-IQA and LIVE-Wild datasets. Then the current best methods used pervasively including PSNR, MS-SSIM and Q2StepQA are used on the same evaluation set of the three datasets.

Implementations of PSNR, MS-SSIM and NIQE differ slightly with their implementations in their respective papers as we used the readily available TensorFlow implementation where available. This table includes Q2StepQA which is equal to MS-SSIM multiplied with the negative inverse of NIQE [10].

EXPERIMENTAL RESULTS

The proposed CNN architecture was trained on the new aug- mented CIQA dataset using multiple base models and subse- quently evaluated on FG-IQA and LIVE-Wild to test gener- alizability in the wild. The results of the CNN model com- parison are presented in Table 3. *N* layers of the base CNN

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Table 2.

Pearson correlation coefficient of popular and best performing baseline models on Major compression IQA datasets. Ours corresponds to the neural network model trained on CIQA and evaluated on all three datasets.

Models	LIVE-WILD	FG-IQA	CIQA
PSNR	0.51	-0.29	-0.35
MS-SSIM	0.76	0.81	0.44
Q2StepQA	**0.79**	0.53	0.41
LPIPS	0.70	0.55	0.81
Ours	0.76	**0.89**	**0.91**

Table 3.

Pearson correlation coefficient results from various base CNN models

Base CNN	Train correlation	Test correlation
EfficientNet-b7	0.95	0.92
EfficientNet-b0	0.90	0.88
DenseNet121	0.85	0.85
ResNet50-v2	0.87	0.82
VGG16	0.88	0.87

Model were integrated into our architecture. EfficientNet was the best performing CNN by a considerable margin, and the EfficientNet-b0's first 73 layers was chosen due to its perfor- mance and lesser complexity when compared to EfficientNet- b7's first 159 layers, also tested.

The two most important criteria for a compression IQA metric are high correlation with human labels (Accurate) and consistent results across a diverse set of unseen examples (Re- liable). For this purpose we use the Pearson Correlation Coef- ficient. The baseline models show high variability in correla- tion between datasets and, in some cases, low correlation with labels. Both these qualities indicate a poor real correlation with human perception and a real opportunity for improve- ment. Table 2 shows the correlation of our proposed model using the

ISSN 3030-3907

efficientnet-b0 backbone, trained on CIQA and sub- sequently evaluated on both CIQA, FG-IQA, and LIVE-Wild compared with the other baseline models tested.

Our proposed model outperforms SOTA for the FG-IQA and our CIQA datasets while remaining competitive when evaluated on the LIVE-Wild dataset achieving similar to MS- SSIM and Q2stepQA.

The LIVE-Wild dataset used single stimulus scores and the correlation is computed from the difference in the mean opinion scores (DMOS) for the images in the pairwise com- parisons giving the labels a different meaning and uses more noticeably compressed images. The model as well as FGIQA and CIQA have labels that represent which is the higher qual- ity image and the degree to which the distinction is clear. The LIVE-Wild labels use a ranking system such that even if the degradation in one image is clear and there is a clear ”higher quality image” the magnitude of of the DMOS score depends on more than the two images being compared. The CIQAmtrained model rates the noticeably distorted images all very low and rates the minimally distorted images in a more linear fashion, which explains the lower correlation with the datasets labels, which is linear across the whole set.

The use of this neural network approach increases the time cost per pixel, but there remains a high potential for op- timization. The following inference time is reported for our TensorFlow implementation on an Intel(R) Xeon(R) CPU at 2.30GHz. PSNR: 0.0144 ms/kpixel, LPIPS: 0.215 ms/kpixel, SSIM 0.763 ms/kpixel and our model: 0.675 ms/kpixel.

Our model’s input image size of 400 × 400 was produced using random cropping with the possibility for zero padding along dimensions smaller than 400 pixels which is standard in network based image processing. Training was conducted for 15 epochs of 150 steps each with a batch size of 64 and at a learning rate of 0.001. L_2 regularization, weight decay, and dropout were not successful in increasing generalizability and were not used.

DISCUSSION

In this work we compare with LPIPS, a SOTA perceptual dis- tance metric, and we evaluate it as a perceptual quality metric, which may not be its intended use. However, the variability seen between datasets is noteworthy. This model is based on human perception and its variance across three datasets sup- ports the need for more training data.

The proposed model performs at or above SOTA for the three evaluated datasets. The performance of the model trained on the new CIQA data fulfils the two requirements maximizing correlation with perceptual preference and re- ducing variance across unseen data.

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Our proposed model is not necessarily a compression ar- tifact detection algorithm and dataset. The model performs well but not at SOTA when detecting compression artifacts that are difficult for humans to detect. This fact may be a ben- efit rather than a limitation. Figure 1 shows in its first example how a large Q value difference can result in an indistinguish- able perceptual result (∼ 0.5) even though the two images differ greatly in file size. This may lead to the potential to use our model as a loss function for the degree of compression or to measure the rate/distortion trade-off.

CONCLUSION

The new CIQA dataset is the largest available dataset cur- rently available, opening the possibility for further improve- ments in deep learning applications to compression IQA. This new augmented database performs significantly better than the current standards when training deep neural networks, leading to less substantial over-fitting and greater generaliza- tion. Using this data we were able to train a deep model that outperformed SOTA models across 3 datasets.

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ISSN 3030-3907