# Neural Image Decompression: Learning to Render Better Image Previews

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### Abstract

A rapidly increasing portion of Internet traffic is dominated by requests from mobile devices with limited- and metered-bandwidth constraints. To satisfy these requests, it has become standard practice for websites to transmit small and extremely compressed image previews as part of the initial page-load process. Recent work, based on an adaptive triangulation of the target image, has shown the ability to generate thumbnails of full images at extreme compression rates: 200 bytes or less with impressive gains (in terms of PSNR and SSIM) over both JPEG and WebP standards. However, qualitative assessments and preservation of semantic content can be less favorable. We present a novel method to significantly improve the reconstruction quality of the original image with no changes to the encoded information. Our neural-based decoding not only achieves higher PSNR and SSIM scores than the original methods, but also yields a substantial increase in semantic-level content preservation. In addition, by keeping the same encoding stream, our solution is completely inter-operable with the original decoder. The end result is suitable for a range of small-device deployments, as it involves only a single forward-pass through a small, scalable network.

#### **1. Introduction**

Compression of high-quality thumbnails is an active area of research [36, 33, 1, 18, 3] as the demand for image content over connections of all speeds continues to quickly rise. In addition to the decreased download latency and bandwidth consumption that is particularly important to the "next billion users" (NBU), reducing the compressed-image size also helps with storage requirements for the billions of thumbnails needed for rapid access [13, 6, 16].

Two standard measures of compression quality are PSNR and SSIM [35]. However, at such high-compression rates (200 bytes per thumbnail image, which is 0.033 bpp for  $221 \times 221$  thumbnails), we have found that these metrics

do not adequately reflect subjective preferences. Therefore, in addition to using PSNR and SSIM, we measure how well semantic information, in terms of recognizable objects and scenes, is preserved.

Similarly, at these extreme-compression rates, JPEG and other standard approaches do not fare well. Usually, when extreme compression is required, it is addressed with domain-specific techniques: for example, faces [5], satellite imagery [15], smooth synthetic images [25], or surveillance [39]. For non-specialized image-compression, *WebP* [13] is a leading compression format. When used on small images, WebP yields better compression than both JPEG and JPEG2000 standards [12, 14].

The fundamental operation of both WebP and JPEG is a subdivision of the image into a set of blocks. Alternative approaches have used triangulation [4, 9, 11, 22]. The most recent of these, [22], has shown promising results on a wide variety of natural images. Their approach creates an adaptive Delaunay [10] triangulation of the target image, based on the underlying entropy of the local pixel distributions. The result is a mesh in which a larger number of triangles are devoted to the complex (high-entropy) regions, while smooth patches of the image are approximated with fewer triangles. After transmission, the decoder renders the triangles by interpolating the vertex colors.

The performance of the triangulation method in [22] provides a strong encoder that works well precisely in the regime of interest: transmission of images under 200 bytes. At that small size, image previews can be easily transmitted as part of the original page-load process on mobile devices or on bandwidth limited connections [6, 22]. When measured in terms of PSNR or SSIM [35], the triangulation method significantly outperformed JPEG and WebP. However, when the images were visually inspected, their visual quality was very uneven: see Figure 1 (row b) for examples. Though some of the images appear very well reconstructed (Figure 1 left columns), others are unrecognizable when viewed without the reference. Other images resulted in spurious edges formed by the triangulation boundaries (Figure 1 right columns). To address these shortcomings,



Figure 1: Images represented in ~200 bytes. Five original images (row a) are compressed by the state-of-the-art triangulation method from [22] (row b) and by our neural decoder (row c). A variety of qualitative results were intentionally selected — from good (left 2 columns) to poor with many visual artifacts (right 2 columns). The middle column is acceptable, though many extraneous "jagged" artifacts are visible. See the appendix for more examples.

we replace the decoder with a deep convolutional neural network. We ensure that the network remains relatively modest in size for ease of deployment. The decoder inputfeature representations played a crucial role for good performance: we provide details in Section 3. The results, presented in Section 4, reveal not only improved PSNR and SSIM scores, but also semantic-content preservation that is quantitatively measured as far superior.

Deep neural networks for compression have been studied in a variety of configurations, from shallow [8, 20, 18] and deep feed-forward auto-encoders [3, 26, 32, 2] to recurrent neural nets/LSTMs for variable-length encodings [33, 34]. Others have taken approaches more closely tied in spirit to ours: employing established encodings as the inputs and using neural networks as the basis for a new decoder with improved performance. These techniques effectively learn a mapping from decompressed patches back to the original image, for example to remove JPEG compression artifacts [37, 30, 7]. Finally, though we do not explore generative adversarial networks (GANs) in this paper, we will briefly address how they can easily be used in a manner similar to other super-resolution and compression studies [21, 1].

## 2. Triangulation of Images: Encoding & Decoding

In this section, we review the triangulation approach presented in [22]; this yields a state-of-the-art compressed encoding that is used (indirectly) as the input for our neural decoder (presented in the next section).

In [22], the compressed representation of an image describes a list of colored vertices and a color table. The vertices lie on a regular grid of size  $M \times M$  and the edges of the grid lie on the edges of the image. The vertex color is an index into the color table. Their "triangle-based" decoder constructs a Delaunay triangulation of the vertices on a raster image of size  $N \times N$  where  $M \ll N$ . Each raster pixel in a triangle is colored using a linear interpolation of the colors of its triangle's vertices.

Their encoder uses a stochastic-hillclimbing optimizer to find the vertices and color table that optimize the output of their decoder, i.e., that produce a good Delaunay triangulation and raster pixel colors from their decoder algorithm. In this way, the encoder is optimized specifically for their decoder.

We built our decoder to directly operate on the output of the state-of-the-art encoder presented in [22] because of



Figure 2: Visualizing the results vs. image byte size. For each of the two original images (left-most column), the image is shown after compression with WebP at two levels (roughly 400 & 100 bytes) and five compression levels for the triangulation approach. The grid-size (M) is also given. Figure adapted with permission [22].

its good performance across a wide variety of natural images. and because that encoder has been proposed as a profile in the next-generation WebP standard [23]. By strictly adhering to this as our input with no modifications, wide deployment becomes substantially easier. Ensuring this interoperability of decoders is an important feature since some very low-end devices may not support even our light-weight decoding network; therefore, we need to be able to seamlessly back-off to [22]'s decoder. For those devices that can support forward propagation through our simple network, we will demonstrate substantially improved images in both reconstruction quality and recognizability. Unlike other profile-based compression approaches, this interoperability ensures that the encoder does not need to know which decoder that the client is using. In fact, if necessary, a mix of different decoders can all be supported by exactly the same bit-stream.

Increasing the vertex grid size (making M larger) increases the encoded rate while reducing distortion. Figure 2 shows sample decompressed images with grid sizes ranging from  $15 \times 15$  to  $76 \times 76$  and compressed sizes ranging from 100 to 400 bytes. In the examples shown in Figure 2, the types of errors that the triangle-shading codec introduces become evident. As each triangle needs to encode more of the image, the jagged edges of the triangles introduce spurious features and misalignments (see the car's front grill in Figure 2). Nonetheless, it is interesting to note that even at these extreme compression levels many colors and much of the shading remain intact. More examples are presented in Figure 6 and the appendix; see the "interpolated" column.

To provide insight into the actual triangulations computed, see Figures 3 (right column) and 4 ("edges" column). As can be seen, triangles are more densely concentrated in the high-entropy regions of the image. In contrast, the uniform regions of the input image are adequately represented by fewer triangles.

### 3. Neural Decoding

Let us examine a few sample triangulations in detail to see where there is room for improvement: see Figure 3. The most salient observations are: (1) there are severe jagged edges in the image (see both images) and (2) discontinuities in straight lines appear (see the boat-deck outline). These are caused by triangle boundaries. Recall that each triangle is in-painted using only the colors of its own vertices. However, vertices of nearby triangles have the potential to contain valuable information - especially when they are assigned the same (or nearly same) color. For example, in the toy-dial image, notice that many triangles encode subtle shading differences. It should be possible to use this consistency information across triangles in re-rendering the image.

One can imagine a variety of simple techniques to overcome the jagged edges in the decoded image. However, designing the rules to best employ information from close triangles will likely result in a number of ad-hoc heuristics and thresholds. Instead, we use a deep neural network to implicitly create the rules to address both of these shortcomings, based on image statistics. To train the network, we start with exactly the same inputs from the triangulation procedure that were used to render the images shown above. For the target output, we use the original image. Training proceeds using samples from Imagenet's training set [28].

### 3.1. Architecture and Inputs

A variety of deep convolutional networks have been driving recent computer-vision research, for example in object



Figure 3: Two sample triangulations, shown enlarged. Note the jagged edges and discontinuities introduced. Also note that triangles with similar color vertices may yield information about shading and color consistency along inferrable directions; this is not taken into account when triangles are shaded independently.

detection and recognition (e.g. the Imagenet challenge [28] and activity recognition [29]). For this application, however, the goal is to take an extremely sparse input and generate a full image. We formulate this problem as an *imagetranslation* task. As described by Isola *et. al.*, Image translation is the task of "translating one possible representation of a scene into another, given sufficient training data … the setting is always the same: predict pixels from pixels" [17].

Unlike the more common object-identification tasks, where the end result is a classification, here the result is a full image. Therefore, it is important to be able to recreate details from the inputs while allowing for non-spatially-local influences to direct larger features and impose global consistency. The need to have both details from the original image and potentially global coordination of the generated image has resulted in a variety of fine $\rightarrow$ coarse $\rightarrow$ fine architectures such as "hourglass" and "u-net" [17, 27]. These architectures pass the inputs through a series of convolution layers that progressively downsample the image. After the smallest layer is reached, the process is reversed and the image is expanded back to the desired size.

One of the largest differences between the previous image-to-image translation work and ours is that our inputs are not the typical 3-channel images. Instead, they are composed of 8 channels (Figure 4): (channel 1) the edge image - a binary image showing the edges created by the Delaunay triangulation; (channel 2) the binary vertex-presence image; (channels 3-5) the reconstruction using the original system's bilinear-interpolation approach [22]; and (channels 6-8) the RGB color-vertex image showing the color

assigned to each vertex (with black everywhere else).<sup>1</sup>

Beyond good reconstruction performance, an equally important consideration for this study was the simplicity/size of the final decoding network - keeping computation requirements manageable is crucial for large-scale device deployment. An enormous number of architectures and a variety of approaches were empirically examined. Because of space limitations, we provide a brief summary of them here. We tried architectures ranging from imagetranslation (e.g. pix2pix [17], cycle-gan [38]), to shapeencoding/decoding networks (e.g., where the bottleneck is a set of geometric descriptions), to progressive-completion networks [33, 34]. The approach that provided the best trade-off, in terms of reconstruction quality vs. simplicity, was the stacked hourglass network described below. The hourglass network is also simple enough to meet the NBUapplications requirements since, in NBU areas, processor computational limitations are prevalent in the available mobile devices. As a secondary benefit, the number of hourglass networks (e.g. stack size) can be adjusted according to computational availability, though, as will be described in the experiments, even a single hourglass provides substantial benefits.

<sup>&</sup>lt;sup>1</sup>The decision to use images as inputs into the network is not the only possible approach. For example, after decoding the transmission, the series of vertex+color tuples could be directly used. We did not pursue this avenue since, in addition to learning the image-translation problem, it would require the network to learn how to triangulate and how to map between the real-value inputs and coordinates. Further, more complex measures would be required to handle the variable number of vertices. All of these are avoided by using the eight-channel, image-like input in which the spatial information is explicitly maintained and the triangulation's edges directly given.



Figure 4: Eight input channels. Left: Original Image (not used as input, only shown for reference). Channel 1: Delaunayedge map (binary image). Channel 2: Binary vertex-location map (visibility enhanced for printing). Channels 3-5: Linearinterpolation reconstruction. Channels 6-8: Colored vertex-location map. (Channel 2 is also given, in order to correctly represent pure-black vertex colors.)

The remainder of this study uses the most promising of these: the hourglass network. The input images have a resolution of  $256 \times 256$  with 8 channels and a batch size of 32. The output is an RGB image of the same resolution. Our network (Figure 5) is based on the Stacked Hourglass in [24]. We apply a Conv2d(size=7x7,filters=256,stride=2) to the  $256 \times 256 \times 8$  input, then a Conv2d(3x3,f256,s2) to bring the dimensions to  $64 \times 64 \times 256$ . This feeds into an Hourglass as described in [24] except 1) when downscaling, each MaxPool layer is replaced by a layer that stacks the values of each  $2 \times 2$  spatial block depth-wise (a Space-ToDepth(2x2) layer) followed by a Conv2d(3x3,f256,s1) and, 2) when upscaling, each nearest neighbor upsampling is replaced by a DepthToSpace(2x2), the inverse of a Space-ToDepth, followed by a Conv2d(3x3,f256,s1). The Hourglass output is added to the Hourglass input and passed to the next Hourglass. We stacked two Hourglass networks.

To apply intermediate supervision as described in [24], we split an intermediate Loss Module off the output of every Hourglass. It is a DepthToSpace(4x4) and a Conv2d(1x1,f3,s1) with a Tanh activation to get us to a  $256 \times 256$  RGB image. During training, we apply a meansquared-error loss between this and the original ground truth image to maximize PSNR. During inference, the network's prediction is the  $256 \times 256$  RGB image in the second (final) Hourglass's Loss Module. Every layer is followed by Batch Norm and Relu except the final layer (with the Tanh). We use the Adam Optimizer [19] with learning rate of 0.1.

#### 4. Experimental Results

The network described in the previous section was trained for 2.2 million steps on five asynchronous GPUs: this was approximately 15 days of continuous training. Testing was conducted on 20,000 images drawn from the ImageNet validation set; these were not used elsewhere in training.

In addition to Figure 1, Figure 6 and the appendix provide more comparisons to the interpolated images and their respective PSNR and SSIM (Structural Similarity Index [35]) scores. Overall, when measured on the entire testing set, we are able to outperform the triangulation approaches in both PSNR and SSIM.

• For PSNR: Triangulation scored 20.7 dB and our neural approach scored 21.7 dB. In this range, a 1-dB PSNR increase is extremely valuable. Out of the 13,000 examples examined, 12,810 (98.5%) showed improved PSNR via the neural decoding. Comparing the two approaches using a standard *t*-test on the PSNR, p < 0.0001.



Figure 5: Modified Stacked-Hourglass network from [24], including intermediate loss.

For SSIM: Triangulation scored 0.51 and our neural approach scored 0.54. Out of the 13,000 examples examined, 12,255 (94.2%) were improved via the neural decoding. Comparing the two approaches using a standard *t*-test on SSIM, *p* < 0.0001.</li>

Importantly, recall that the triangulation method [22] also outperformed JPEG and WebP, which, in turn, equals or outperforms JPEG2000 [12, 14].

To better understand what the network was encoding, an extensive grid search was also performed to determine which channels were actually necessary. For space reasons, we cannot recreate all of the results here. A few salient findings, however, are worth noting: (1) The best performing network was one that received all the eight channels as input; (2) If we removed the interpolated image (as created by [22]) from the inputs, the PSNR performance drops approximately 0.75 dB; (3) Interestingly, if we used only the interpolated as input, the PSNR performance drops 0.5 dB; (4) Finally, while we used 2 stacked Hourglasses in this work, the results with 1 Hourglass or 3 stacked Hourglasses were almost identical; any variation was likely due to the stochasticity in the training procedure. On a mobile or computationally constrained device, a single Hourglass can be used. This decision on the complexity of the decoder can be made on a pre-device basis and all will work on exactly the same encoding.

#### 4.1. Semantic Content Preservation

The quantitative results, in terms of PSNR and SSIM, reveal a significant improvement for extremely compressed images. Despite the numeric improvements, however, it is important to assess whether the images are qualitatively better. The simplest, though resource-consuming, method is to employ human raters. We propose a novel technique using a well-trained classification network as an automated proxy. For our experiments, we employ a pre-trained state-ofthe-art classifier, Inception ResNet v2 (IR2), which produces a 1000-dimension "classification vector" prior to the final soft-max layer representing the classification of the objects in the image. On the ImageNet challenge, IR2 has has a top-1 single-crop error rate of 19.9% on the 50,000 image validation set, and a top-5 error rate of 4.9% [31]. For each of our test images, we use the original image, the interpolated image and the neural decoded image:  $t^{\text{orig}}$ ,  $t^{\text{interp}}$ , and  $t^{\text{nnDec}}$ . Passing each of these through IR2 produces classification vectors  $c^{\text{orig}}$ ,  $c^{\text{interp}}$ , and  $c^{\text{nnDec}}$ . We measure the similarity between  $c^{\text{orig}}$  and  $c^{\text{interp}}$  and between  $c^{\text{orig}}$  and  $c^{\text{nnDec}}$  in two ways: (1) the  $L_2$  difference between the classification vectors, and (2) whether the top classification in  $c^{\text{orig}}$  appears in the top-1, -5, and -10 positions of  $c^{\text{interp}}$  and  $c^{\text{nnDec}}$ .

Note that this is *not* equivalent to checking the groundtruth classification. The goal of our compression task is not to alter the original image to make a wrong classification correct, it is to achieve the *same* classification as the original. Finally, we remark that with such aggressive compression rates, we do not expect all images to be recognized; for example, images in which the object of interest does not cover a large portion of the image, the object may be lost. Nonetheless, for images in which the object is large, these metrics elucidate how recognizable the object remains.

The results are presented in the first two rows of Table 1. There is more than a 10% decrease in the  $L_2$  error using the neural-network decoding. However, the largest benefit comes when looking at the recall measures. Looking at recall in the top-1 position, the results are **300% improved** ( $3\times$ ) and at top-10, they remain approximately 2.5× improved. This large gain indicates that the content of the image remains far more recognizable using our neuralnetwork decoder.

Upon first glance at our decoded neural-network images,

Figure 6: Seven results comparing decoding via [22] (interp.) and our neural network (nn) decoding. Rows A-E are good quality reconstructions. Rows F-G show examples where both methods do poorly. Also given with each image pair are the PSNR and SSIM scores without (left) and with (right) neural network decompression. Additional examples (plus WebP results) can be found in the appendix.

Detailed notes:

A: Note the jagged lines along the window.

B: Both images are recognizable, but our method provides cleaner lines. C: Note the severe artifacts

in the vertical lines.

D: Note the smooth shading from the lights and the hair lines.

E: Note the problem with the two thin triangles starting from the upper left corner.

F: Neither method provides a good reconstruction but our decoder gives a slightly better rendition.

G: Compression rate is too extreme for either method to provide recognizable results.



|                         | $\begin{array}{c} (Lower \ Better) \\ L_2 \ Error \end{array}$ | Recall Top-1 | (Higher Better)<br>Recall Top-5 | Recall Top-10 |
|-------------------------|----------------------------------------------------------------|--------------|---------------------------------|---------------|
| interpolated [22]       | 39.5                                                           | 0.05         | 0.13                            | 0.15          |
| nn-Decoded (our method) | <b>36.0</b>                                                    | <b>0.17</b>  | <b>0.33</b>                     | <b>0.38</b>   |
| interpolated+Blur x1    | 39.5                                                           | 0.11         | 0.26                            | 0.30          |
| interpolated+Blur x5    | 43.0                                                           | 0.08         | 0.18                            | 0.22          |

Table 1: Semantic Similarity: Comparing Classification Vectors of Original and Compressed Images

it is tempting to wonder if much of the recognition improvement is coming from simply blurring the triangulated image. Though we would not expect an improvement in PSNR or SSIM from additional blurring, it is possible that the Inception-Resnet-V2 network is not robust to the types of edges seen in Figure 6. We explicitly checked that possibility, to ensure that the network is not acting as an overly complex approach to a simple blur operation. Instead of decoding with a neural network, we use the method from [22] followed by Gaussian blurring (r=2). We create two new test sets: the first with a single pass of a blur filter and the second with 5 sequential passes. The last two rows of Table 1 show the performance after the added blurring. The results, though improved, do not match those our NNbased decoding. And, as expected, the PSNR and SSIM rates decline for both sets over the base triangulation results reported above (PSNR: blur1: 20.6, blur5: 19.6, SSIM: blur1: 0.50, blur5: 0.46). Visually, it appears that the neural approach is smoothing the harsh color transitions created by the triangulation. However, based on the PSNR/SSIM scores and the similarity of the classification vectors, the neural network's effect is well targeted: the edges and details required to maintain the object identity and similarity to the original image are preserved.

### 5. Discussion & Future Work

The application of neural networks to image decompression is not only of interest to researchers and practitioners, as witnessed by the vast amount of neural image compression literature, but also will have a large and socially important impact: allowing efficient discovery/browsing of visual content for the "next-billion users" whose bandwidth is limited and expensive. We have found that the impact of using neural networks in place of the current triangle-shading decoder results in consistent and very significant quantitative and qualitative improvements to the final image quality.

By casting the task of decompression into an image-toimage-translation problem, we were able to generate images that, when compared to recently released state-of-theart compression techniques, more closely resemble the original image in terms of the standard quantitative metrics such as PSNR and SSIM. More importantly, they far exceeded the previous method [22] in preserving *semantic* quality. The results come in an operating regime of extreme compression where there is large practical interest, but existing compression schemes do not fare well.

These improved results are somewhat surprising since, on each encoding, the encoder is explicitly optimizing for the best results from the triangle-based decoder in [22]. Yet, we are able to provide better reconstructions with neural decompression *without changing the encoder at all*. This points the way for efforts to replace full H.264 decoders with neural approaches without changing the already deployed video encoders.

This study leads to many avenues of future work. First, simultaneously to the development of this study, Generative Adversarial Networks were in parallel developed for compression [1]. Beyond using GANs for error signals, they also make clever use of the ability for GANs to synthesize, rather than compress. Though they operate on larger images at higher bit rates, many of the same approaches, including using GANs to augment the objective functions, can easily be incorporated.

Second, although not discussed in this paper, an interesting side finding was early evidence that it is possible to train a network to infer a Delaunay triangulation given just the vertex points. In preliminary studies, the network fared much better than expected in not only finding the same connections, but also in creating relatively straight edges between the vertices (the output was a  $256 \times 256$  image). If these results hold true, this has potentially broad applicability as the operation of triangulation could then be integrated into a fully differentiable system.

Third, we should consider that if we know that semantic recall, as measured by IR2, is important, should it be included as an extra error term during training? The answer may not be straightforward – if it is used, it is possible that the examples generated will take advantage of small inconsistencies in the training, in the same way that adversarial attacks are remarkably plentiful and easy to find. On the other hand, if we train and test on distinct semantic models, perhaps the semantic recall will improve without falling into model-specific traps.

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### A. Additional Examples

We provide additional examples of the neural-decoding method's best and worst performance on both PSNR and SSIM. Images are from the ImageNet test set, reported in the paper.

Ten examples of each have been provided in the tables below along with their metrics and a comparison to the bi-linear-interpolated, non-neural-network approach and WebP. Because WebP could not target the same rates on  $256 \times 256$  resolution images, the input images were resized to 4 or more times smaller in each dimension, compressed with WebP, decompressed, and then upscaled to bring it back to source resolution.





### 

13.5967 PSNR, 0.3586 SSIM







13.2259 PSNR, 0.2121 SSIM



12.6962 PSNR, 0.1356 SSIM

12.4848 PSNR, 0.2032 SSIM







Ground Truth



Ground Truth



Ground Truth







12.7520 PSNR, 0.2868 SSIM











Interpolated







12.1248 PSNR, 0.2400 SSIM





WebP



Figure 9: Worst PSNR

**Neural Decoded** 

13.4038 PSNR, 0.1157 SSIM

13.4994 PSNR, 0.1541 SSIM

13.1843 PSNR, 0.0973 SSIM

13.4025 PSNR, 0.1437 SSIM













**Neural Decoded** 



12.8032 PSNR, 0.3029 SSIM



Ground Truth



Ground Truth



Ground Truth



Ground Truth



13.1887 PSNR, 0.2672 SSIM

13.6563 PSNR, 0.3064 SSIM





**Original Image** 













13.0452 PSNR, 0.1211 SSIM











12.0996 PSNR, 0.2213 SSIM





13.2473 PSNR, 0.1040 SSIM





Ground Truth

25.5729 PSNR, 0.9287 SSIM

33.2967 PSNR, 0.9612 SSIM

26.4886 PSNR, 0.9374 SSIM

## Figure 13: Worst SSIM Interpolated

**Neural Decoded** 



15.6083 PSNR, 0.0734 SSIM







18.3455 PSNR, 0.1022 SSIM



16.6109 PSNR, 0.1014 SSIM 16.7528 PSNR, 0.1111 SSIM Figure 14: Worst SSIM



15.5354 PSNR, 0.0735 SSIM



16.5516 PSNR, 0.0860 SSIM



16.4033 PSNR, 0.08411 SSIM



18.0795 PSNR, 0.0917 SSIM



16.4989 PSNR, 0.0962 SSIM



**Original Image** 

Ground Truth

Ground Truth

Ground Truth



Ground Truth



15.5495 PSNR, 0.0659 SSIM

16.5936 PSNR, 0.0833 SSIM

18.2631 PSNR, 0.0962 SSIM







16.5101 PSNR, 0.0944 SSIM







WebP

## Figure 15: Worst SSIM Interpolated Neur

**Neural Decoded** 



Ground Truth



Ground Truth



Ground Truth



Ground Truth



Ground Truth



16.0347 PSNR, 0.0777 SSIM

17.7205 PSNR, 0.0933 SSIM



16.5107 PSNR, 0.1072 SSIM



16.1087 PSNR, 0.0814 SSIM



17.7716 PSNR, 0.0935 SSIM



13.6928 PSNR, 0.1000 SSIM





16.6494 PSNR, 0.1148 SSIM





15.9726 PSNR, 0.0765 SSIM



17.7348 PSNR, 0.0909 SSIM



13.4264 PSNR, 0.0754 SSIM



34.9583 PSNR, 0.9679 SSIM



16.0610 PSNR, 0.0815 SSIM