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MASTER THESIS

Multi-Scale Super Resolution With Blind De-noising Using Residual Learning For Digital Art

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Abstract

Master in Artificial Intelligence

Multi-Scale Super Resolution With Blind De-noising Using Residual Learning For Digital Art

by Santiago MAZAGATOS PÉREZ

In the fields of illustration and digital art, it is imperative that an image be of high quality when being used for printing, as a wallpaper or for another kind of decorative purpose, however, high resolution, clean images are often unavailable, either because the form in which the original work was rendered is deemed subpar by today's standards, or because all available copies have been subject to lossy compression or downsampling. Super Resolution is an increasingly active field of research in machine learning with the aim of providing a computational model that can achieve what is impractical or impossible with human means, the recreation of available images or other kind of visual data in the highest possible quality, in this work the author makes use of state-of-the-art Super-Resolution methods and denoising methods to try and create a comprehensive solution for all use cases related to digital art restoration.

Super-Resolution, Residual Learning, Deep Learning, Denoising

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Chapter 1

Introduction

Technical limitations are as common to technology as technology itself, what was a vast amount of storage a decade ago is little more than what one would expect from a basic cloud storage plan today, that being the case one often comes face to face with yesterday's limitations, chief among them processing power and storage.

In an era in which the most common removable storage medium had no more than 1.44 Megabytes of space and the average processor had its performance measured in Megahertz and whether or not it had a math co-processor, image use was accompanied by lossy compression, like in the case of JPEG (Hamilton, 1992) files, to save the most amount of space, and cheap downsampling methods that wouldn't overburden the CPU.

Nowadays storing images in PNG (Boutell, 1997) format with its lossless compression and downsizing using methods such as Lanczos resampling (Wikipedia contributors, 2019) to prevent aliasing is a reasonable proposition, but the previous methods of saving space and cycles are still present, and there's no way of knowing whether an illustration created by a digital artist today with a high definition display will end up being dwarfed by screens 10 years into the future.

If one wanted to print an illustration onto a T-shirt, or a poster, or use it as a wallpaper on a 4K display, such file would need to have a very high resolution and no compression artifacts or noise to look good, however such files can often only be sourced from the artist, if they even exist; recreating the work in a way that achieves the required quality would require a substantial amount of time and effort by someone with the skill set to do so, while it would be expensive for someone who lacks it to commission someone for it, furthermore the result might still be unsatisfactory, with the recreated image having a slightly different aesthetic feel to it.

1.1 Waifu2x

Waifu2x (nagadomi, 2019) is a web based application that performs upscaling and denoising of anime style images and photos, however, it uses different models for different levels of noise, relying on the user to select the correct denoising level, and it only allows upscaling up to 2 times the original image size.

While there is a Caffe port of waifu2x (lltcggie, 2019) that supports upscaling beyond 2 times and has an auto-denoising feature, it is not explained how the software determines the best denoising level for a particular image, this port runs on the user's computer and is able to take advantage of any CUDA enabled graphics cards present, making it well suited for batch processing images since the original web application has no such feature and requires a captcha to be resolved for every processed image.

1.2 Goals

The goals of this project are simple, to create a model that is able of upscaling and denoising an image (digital art) without any prior knowledge of level or type of noise (if any) present on the input image/s with results on par or superior to those of the best available alternative (Waifu2x).

Chapter 2

State of the art

2.1 Super-Resolution

Initial works in the world of Super-Resolution relied primarily on Dictionary based approaches, with low resolution and high resolution dictionaries in which a high resolution image is obtained by matching the low resolution representation to items in the LR dictionary and translating those similarities using the HR dictionary to the final HR image.

Dictionary based methods have undergone a great deal of transformation, with a wide array of improvements designed to improve the dictionary learning process (He, Qi, and Zaretzki, 2013), or the LR to HR mapping in terms of speed and memory with approaches like Anchor Neighborhood Regression (Timofte, De, and Gool, 2013), with its subsequent improvements(Timofte, De Smet, and Van Gool, 2015, Timofte, Rothe, and Gool, 2015, Perez-Pellitero, Salvador, Ruiz-Hidalgo, and Rosenhahn, 2016), Sparse Coding (Yang, Wright, Huang, and Ma, 2010, Wang, Liu, Yang, Han, and Huang, 2015) and Super-Resolution Forests (Salvador and Pérez-Pellitero, 2015, Schulter, Leistner, and Bischof, 2015).

Along with all the methods reliant on external information came the ones reliant in information intrinsic to the images being processed (Huang, Singh, and Ahuja, 2015) and more hybrid approaches with external pre-training and internal fine tuning (Wang, Yang, Wang, Chang, Han, Yang, and Huang, 2015.

However, present works rely on less engineered solutions with maps of LR and HR dictionaries and instead have networks learn the mapping functions directly in a non-linear way, the specifics still vary depending on which mapping function has to be learned, the primary example of this new avenue of research is SRCNN (Dong, Loy, He, and Tang, 2016), which has been the subject of some improvements (Shi, Caballero, Huszár, Totz, Aitken, Bishop, Rueckert, and Wang, 2016, Dong, Loy, and Tang, 2016).

As models were made deeper in order to learn more complex mappings, skip connections like the ones displayed in ResNet (He, Zhang, Ren, and Sun, 2015) were added to avoid exploding/vanishing gradients (Tai, Yang, and Liu, 2017, Kim, Lee, and Lee, 2015a, Ledig, Theis, Huszar, Caballero, Aitken, Tejani, Totz, Wang, and Shi, 2016, Lim, Son, Kim, Nah, and Lee, 2017), recursive architectures have also been successfully implemented, among other things as a way to mitigate overfitting (Kim, Lee, and Lee, 2015b), which have then been improved upon (Tai, Yang, and Liu, 2017)

Additionally, new models have been using Generative Adversarial Networks as a way of guiding networks towards producing results belonging to the natural image manifold, avoiding results that are good number-wise (as in having a low Mean Squared Error, or high PSNR and SSIM), but look "soft" and artificial to humans. (Ledig, Theis, Huszar, Caballero, Aitken, Tejani, Totz, Wang, and Shi, 2016, Wang, Yu, Dong, and Loy, 2018, Yuan, Liu, Zhang, Zhang, Dong, and Lin, 2018).

2.1.1 Denoising

Modern denoising methods often double as SISR models, such as TNRD (Chen and Pock, 2017) and RED30 (Mao, Shen, and Yang, 2016), and despite its age, BM3D (Dabov, Foi, Katkovnik, and Egiazarian, 2007) is still relevant and being revisited, either to propose an alternative (Burger, Schuler, and Harmeling, 2012), or a modern adaptation (Yang and Sun, 2018).

2.2 Deep Learning libraries

There are a variety of Open Source machine learning libraries for Python with CUDA support:

- **TensorFlow**: Developed by the Google Brain Team, TensorFlow is a very popular library, especially when used as a backend with Keras, it is in fact taught in this Master's Deep Learning course. (tensorflow, 2019)
- **PyTorch**: Based on Torch and merged with Caffe2, it is developed by Facebook's AI research group. (pytorch, 2019)
- **Theano**: While no longer in development and a relatively minor player, the fact that it was developed by the Montreal Institute for Learning Algorithms might attract those who might be displeased with the corporate ties of other libraries. (Theano, 2019)
- **Microsoft Cognitive Toolkit**: Microsoft's CNTK library has both a Python API and a C# API, which makes it much easier to integrate with Universal Windows Platform, Windows Forms and ASP.NET applications. (Microsoft, 2019)

Chapter 3

Methodology

3.1 Choice: EDSR vs. CinCGAN

At the start of this master thesis project my advisor gave me two papers as good state of the art methods that would do nicely EDSR (Lim, Son, Kim, Nah, and Lee, 2017) and CinCGAN (Yuan, Liu, Zhang, Zhang, Dong, and Lin, 2018) offer fundamentally different approaches to Super Resolution:

EDSR builds on SRResNet (Ledig, Theis, Huszar, Caballero, Aitken, Tejani, Totz, Wang, and Shi, 2016), which is an adaptation of ResNet (He, Zhang, Ren, and Sun, 2015) for SISR, removing Batch Normalization layers, thus reducing the computational and memory burden of the network on hardware and allowing for a deeper architecture and more complex non-linear model to be learned for LR/HR mapping.

CinCGAN uses CycleGAN's (Zhu, Park, Isola, and Efros, 2017) idea of image to image translation to create an unsupervised model that can denoise and upsample images without training with LR/HR pairs by first denoising the input in LR space, and then upscaling it with a state of the art SISR model, in this case EDSR.

While CinCGAN achieves performance comparable to SRGAN, I personally find CinCGAN's results visually un-appealing since it seems to introduce artifacts of its own.

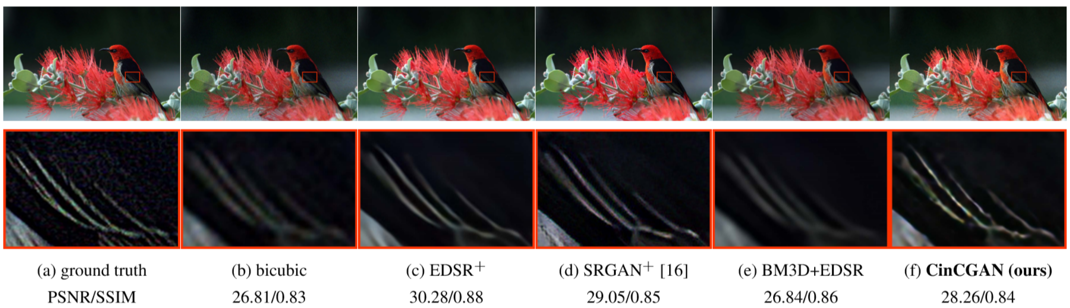


FIGURE 3.1: While SRGAN+'s result is not as sharp as the ground truth or CinCGAN's result, the lines in the latter case look distorted (Taken from the CinCGAN paper)

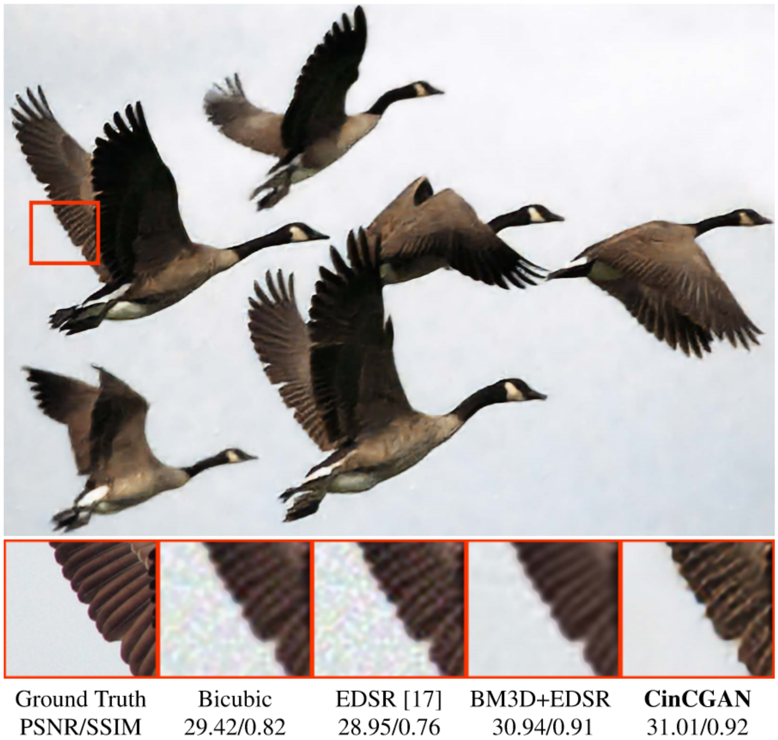


FIGURE 3.2: While Bicubic and EDSR models can't denoise the image and BM3D+EDSR's result looks soft and blurry, the CinCGAN seems to introduce its own noise (Taken from the CinCGAN paper)

Since EDSR already performed the SR task inside CinCGAN and I didn't like the visual quality of the results given by the latter I chose to work with EDSR as a SR method, and would later think of a way of performing denoising.

3.2 Choice: Denoising

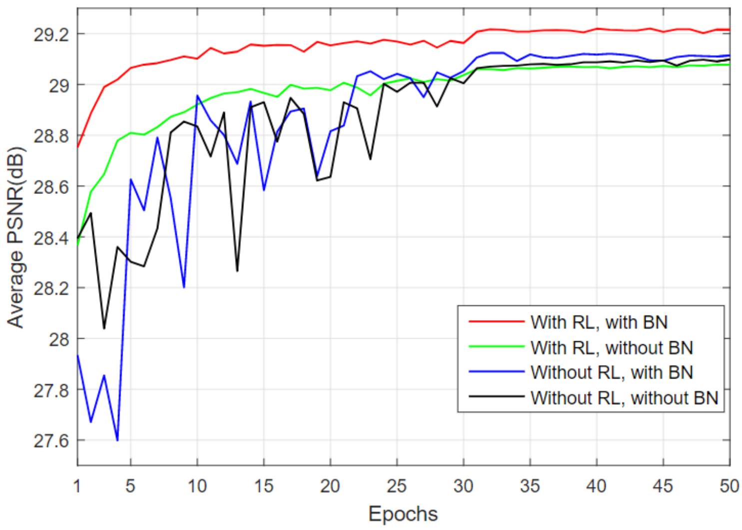
Denoising is a much more established and "stable" field, so when faced with the need to choose a denoising method I chose to look for extensively cited papers first instead of prioritizing state-of-the-art brand new ones.

DnCNN (Zhang, Zuo, Chen, Meng, and Zhang, 2017) is a residual neural network capable of handling gaussian noise and JPEG compression, its architecture according to the authors is a modified VGG (Simonyan and Zisserman, 2015) network, adapting it for denoising instead of image recognition and implementing residual learning (He, Zhang, Ren, and Sun, 2015), the result is strikingly similar to SRResNet, and therefore, to EDSR, although SR tasks in DnCNN are performed by upscaling a LR image to HR size using bicubic interpolation and feeding it to the network.

The way training data is created for DnCNN is to create patches with noise in the ranges of [0,55]σ for gaussian noise and [5,99] quality for JPEG deblocking.

I hypothesized that I could take the training method in DnCNN and use it with the EDSR architecture, since the only major differences were the lack of Batch Normalization layers, and the deconvolution and transpose process at the very end of EDSR, making its output larger than its input.

DnCNN had been tested without Batch Normalization and it was shown that with Adam (Kingma and Ba, 2015), the training and performance impact of not using BN layers was small, so that wouldn't be a significant issue.



(b) Adam

FIGURE 3.3: Impact of training DnCNN with and without BN (Taken from the DnCNN paper)

3.3 Final decision

I chose to use the EDSR architecture with a mixed training approach, the images in the training set would be split into overlapping patches, augmented with 90 degree rotations and then treated randomly in one of three ways (in all cases the HR patch is saved as a PNG intact):

- **Clean save**: the extracted patch would be downscaled using Lanczos resampling and saved as a PNG to preserve its quality.
- **JPEG save**: the extracted patch would be downscaled using Lanczos resampling and saved as a JPEG with a quality varying from 5 to 99.
- **Gauss save**: the extracted patch would be downscaled using Lanczos resampling, gaussian noise would be added to the patch with a standard deviation value between 0 and 55 and then saved as a PNG file.

The network will follow the EDSR architecture and be trained with the Adam optimizer (learning rate: 1e-4, with it being halved every 200.000 updates, momentum: 0.9, variance momentum: 0.999, ϵ: 1e-8) for 300.000 updates with a minibatch size of 16, for the loss function, L2 is used (as in SRResNet) instead of L1 (EDSR).

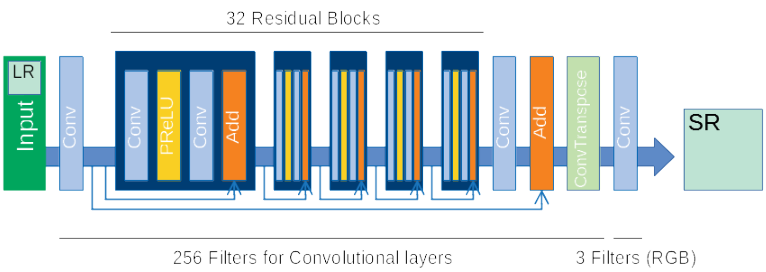


FIGURE 3.4: Implemented Architecture for 2x and 3x scales

This for 4X upscaling has one more ConvolutionTranpose layer, this is especially useful for reusing the 2X model's weights to train a 4X model since the parameters of the layer remain the same.

Chapter 4

Development

4.1 Dataset

To train the model to work with digital art and illustrations a dataset other than the usual photograph based datasets like the ones used on the EDSR paper (DIV2K, Set5, Set14, B100, Urban100), to do that I considered a variety of digital art imageboards: Danbooru, Gelbooru, Yandere, e621, Sankaku Channel and Derpibooru.

I needed images that were in PNG format, for practicality reasons the selected board had to work well with an automatic downloader (Bionus, 2019), the board from which the images were going to be downloaded also needed to have reliable tagging and preferably, an active community that would use the often underutilized scoring system present in (nearly) all imageboards.

Danbooru and e621 were the best candidates among all imageboards considered but due to the prevalence of japanese artists in Danbooru and their infamous censorship practices I chose e621 over Danbooru to ensure no mosaic filters ended up in the training patches.

I downloaded the 1,600 highest scored images on e621 with the assumption that due to their popularity they would be more representative of what the final use case would be.

4.2 Network implementation

Microsoft's CNTK has a greater amount of instructional materials, including examples and tutorials than TensorFlow (in my experience), and has a guide on how to implement various SISR models such as VDSR, DRRN, SRResNet and SRGAN and how to use them later to upscale images (Vukorepa, 2017)

The reason why 1,600 images were downloaded (an excessive amount) is because I initially considered adding a discriminator to EDSR, effectively applying EDSR's improvements over SRResNet to SRGAN and I would use 800 images to train the generator, and 800 to train the GAN, however SRGAN relies on a pre-trained VGG network which is trained on different data (photographs) and training the discriminator from scratch, fine tuning the balance in the loss function between discriminator and generator was a dangerous timesink.

Due to memory constraints on my GTX 1060 (6 GB), the LR patch size for the network had to be reduced to 32 x 32, down from EDSR's LR patch size of 48 x 48.

FIGURE 4.1: Training curve for 2X scale, Training time was: 1 day, 22 hours, 53 minutes

Geometric Self Ensemble as used in Lim, Son, Kim, Nah, and Lee, 2017 and explained in Timofte, Rothe, and Gool, 2015 was implemented, however I haven't used it for testing purposes, my concerns being that each patch needs to be predicted 8 times and the same concerned expressed by Ledig, Theis, Huszar, Caballero, Aitken, Tejani, Totz, Wang, and Shi, 2016 in section 1.1.3, being that averaging all possible solutions for a specific patch might cause a loss of detail and overly smooth the image as a whole, since EDSR doesn't have a discriminator to ensure a good perceptual loss value, this issue is especially relevant.

4.3 Graphical User Interface

Using waifu2x-caffe as an inspiration I created a graphical user interface designed not only to use my EDSR models, but any CNTK model that takes low resolution patches and outputs high resolution ones, the code only needs to know the output patch size and the upscaling coefficient and it will deconstruct input images into appropriately sized patches and reconstruct a high resolution image from the results, additionally, unlike waifu2x-caffe, this GUI presents a real time preview of the upscaling process, a lack of feedback can often be upsetting to users especially if the model is being run on slow hardware.

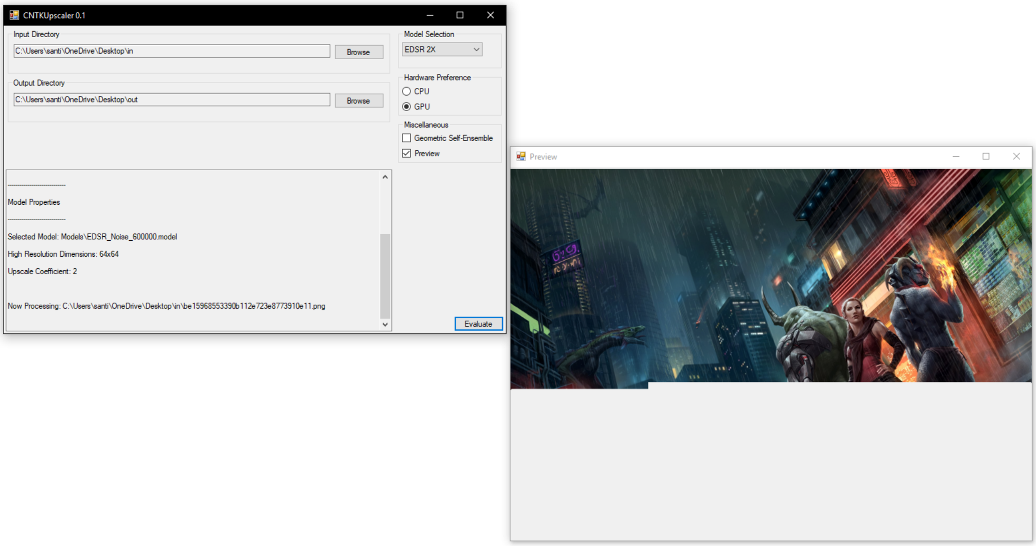


FIGURE 4.2: Screenshot of the CNTK Upscaler GUI

The upscaler also supports using Geometric Self Ensemble since it isn't dependent on the model, and models can be added by placing them on the 'Models' folder of the application along with a JSON file with the necessary information, the application automatically loads all models present in the folder at startup.

```json
{
  "ModelName": "EDSR 2X",
  "File": "EDSR_Noise_600000.model",
  "OutDimensions": 64,
  "UpscaleCoefficient": 2
}
```

FIGURE 4.3: An example JSON file

Chapter 5

Evaluation

To evaluate the trained EDSR with blind-denoising I hand picked 7 pictures with varying styles and complexity and created low resolution versions with specific gaussian noise levels and JPEG qualities; for Gaussian noise the σ values were: 0, 15, 25 and 50. And for JPEG quality levels, the values were: 25, 50, 75 and 100, in total that is 56 low resolution images per model to test.

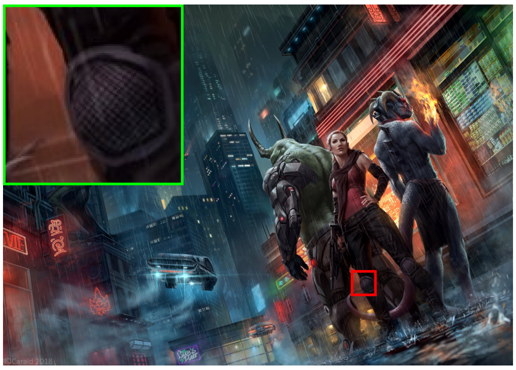
(A) LR image with gaussian noise (25σ)

(B) EDSR result

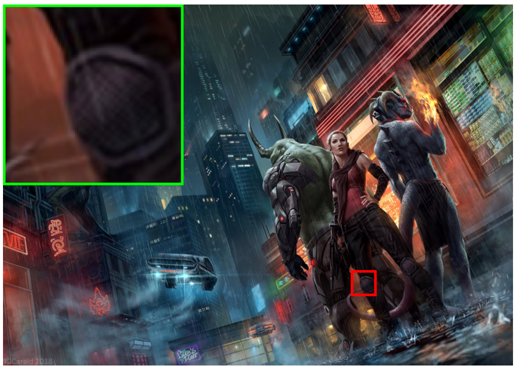
(C) LR image with JPEG noise (50)

(D) EDSR result

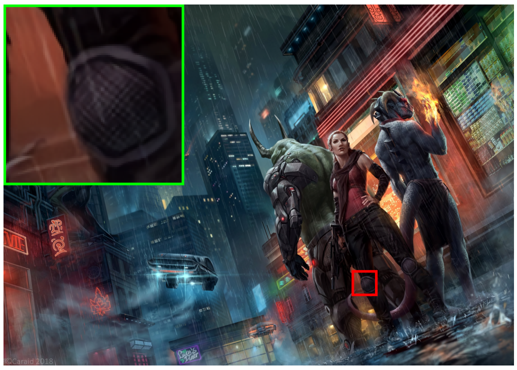
FIGURE 5.1: trained denoising capabilities



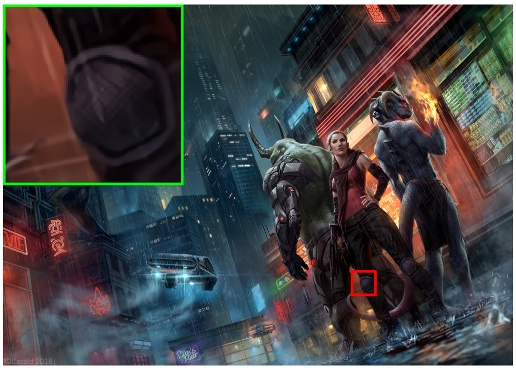
(A) High Resolution



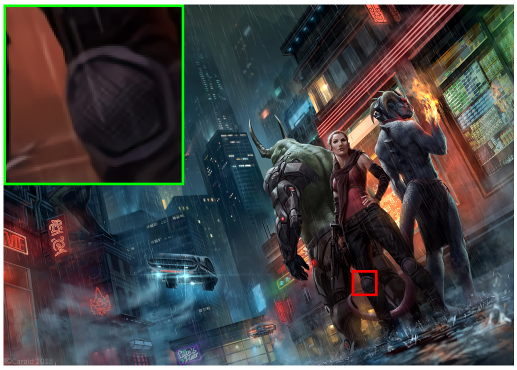
(B) Bicubic



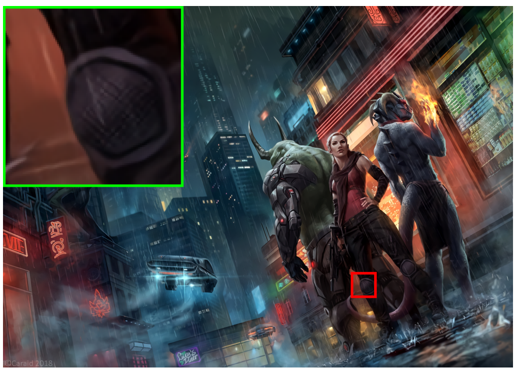
(C) EDSR



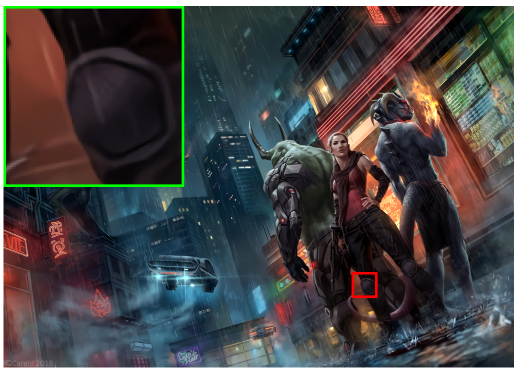
(D) Waifu2x (level 0)



(E) Waifu2x (level 1)



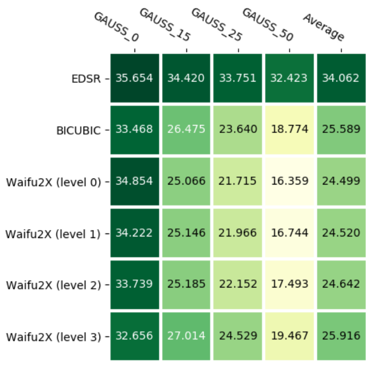
(F) Waifu2x (level 2)



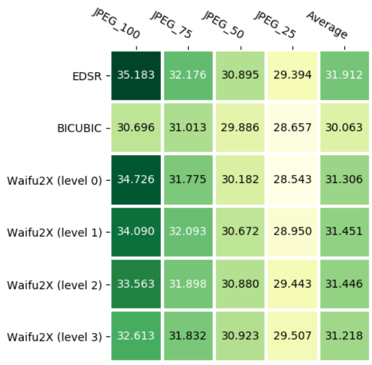
(G) Waifu2x (level 3)

FIGURE 5.2: Results of Waifu2x and my trained model on a clean version (GAUSS_0) of one of the images

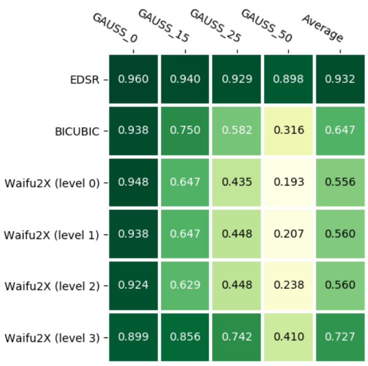
(A) High Resolution



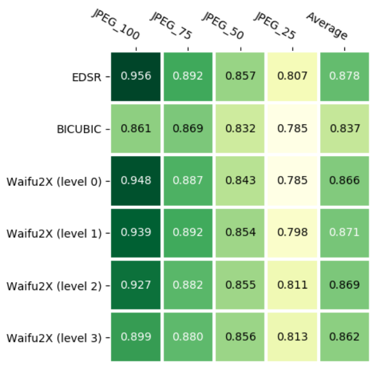
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



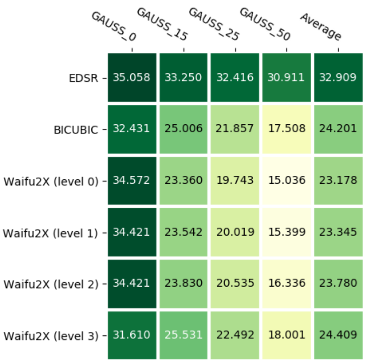
(D) SSIM results with gaussian noise



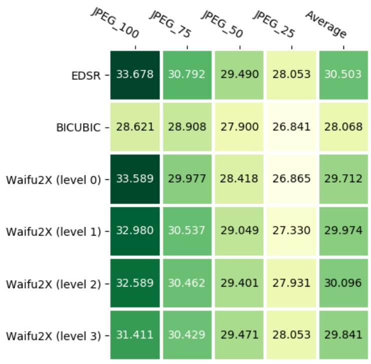
(E) SSIM results with JPEG noise

FIGURE 5.3: PSNR and SSIM results on the shown image

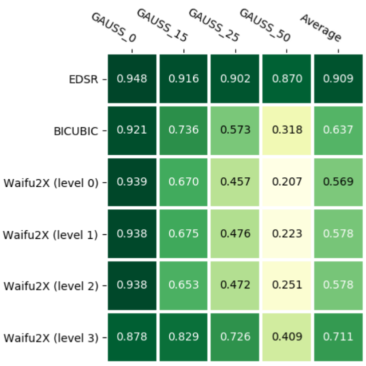
(A) High Resolution



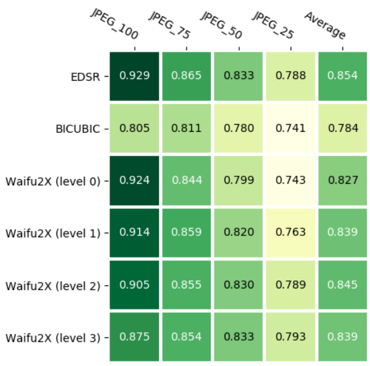
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



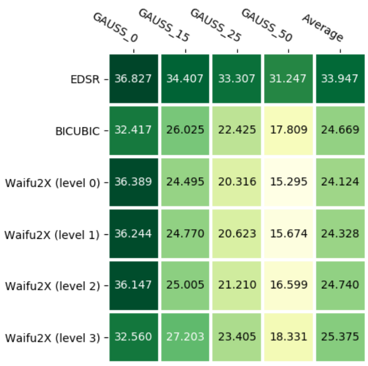
(D) SSIM results with gaussian noise



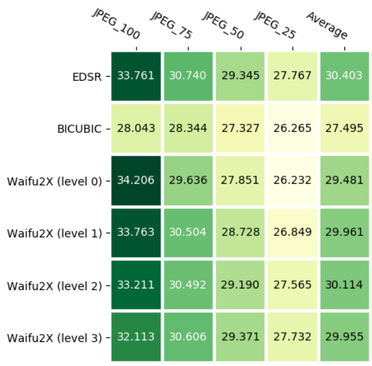
(E) SSIM results with JPEG noise

FIGURE 5.4: PSNR and SSIM results on the shown image

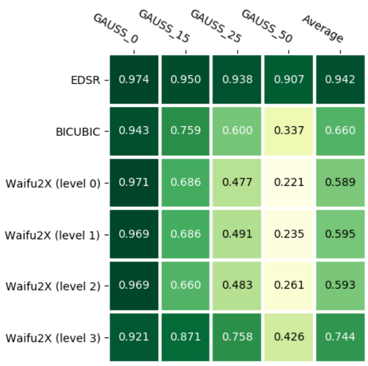
(A) High Resolution



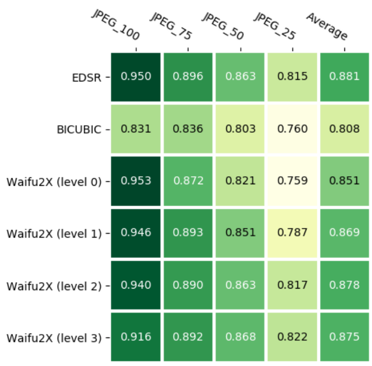
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



(D) SSIM results with gaussian noise



(E) SSIM results with JPEG noise

FIGURE 5.5: PSNR and SSIM results on the shown image

(A) High Resolution

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	43.314	41.144	40.155	38.120	40.683
BICUBIC	39.634	23.934	20.738	16.880	25.296
Waifu2X (level 0)	44.156	21.552	18.299	14.210	24.554
Waifu2X (level 1)	43.405	21.656	18.493	14.519	24.518
Waifu2X (level 2)	43.050	21.717	18.865	15.439	24.768
Waifu2X (level 3)	39.541	23.404	20.546	16.995	25.122

(B) PSNR results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	40.456	37.690	36.033	33.793	36.993
BICUBIC	34.407	34.713	33.529	32.103	33.688
Waifu2X (level 0)	41.605	36.635	34.488	32.247	36.244
Waifu2X (level 1)	40.980	37.706	35.559	32.938	36.796
Waifu2X (level 2)	40.289	37.749	36.218	33.884	37.035
Waifu2X (level 3)	39.143	37.810	36.425	34.174	36.888

(C) PSNR results with JPEG noise

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	0.987	0.977	0.972	0.959	0.974
BICUBIC	0.981	0.690	0.472	0.202	0.586
Waifu2X (level 0)	0.987	0.548	0.309	0.102	0.487
Waifu2X (level 1)	0.985	0.557	0.329	0.114	0.496
Waifu2X (level 2)	0.985	0.516	0.319	0.141	0.490
Waifu2X (level 3)	0.971	0.879	0.710	0.297	0.714

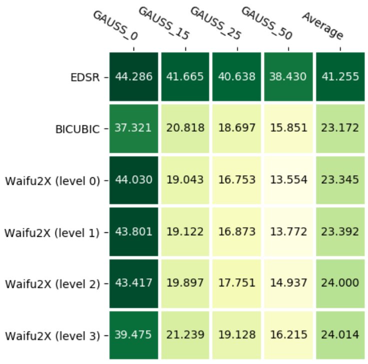
(D) SSIM results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	0.977	0.961	0.950	0.927	0.954
BICUBIC	0.927	0.929	0.916	0.897	0.917
Waifu2X (level 0)	0.980	0.952	0.931	0.901	0.941
Waifu2X (level 1)	0.978	0.961	0.946	0.916	0.950
Waifu2X (level 2)	0.974	0.962	0.953	0.934	0.956
Waifu2X (level 3)	0.970	0.964	0.956	0.939	0.957

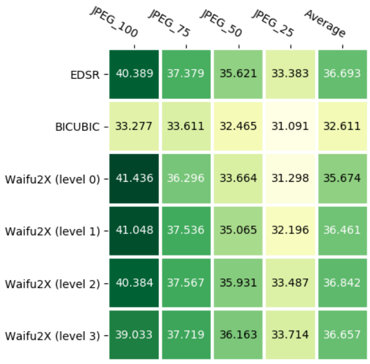
(E) SSIM results with JPEG noise

FIGURE 5.6: PSNR and SSIM results on the shown image

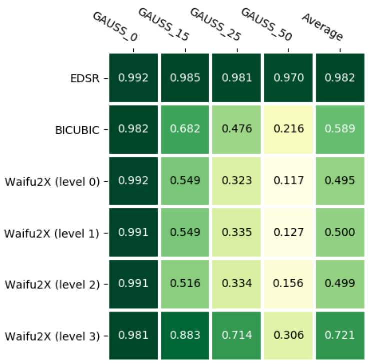
(A) High Resolution



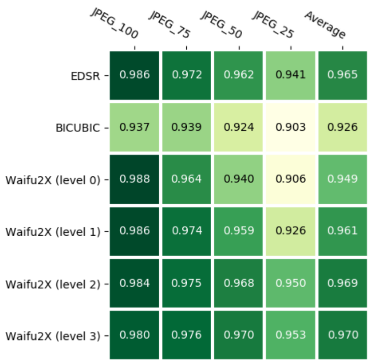
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



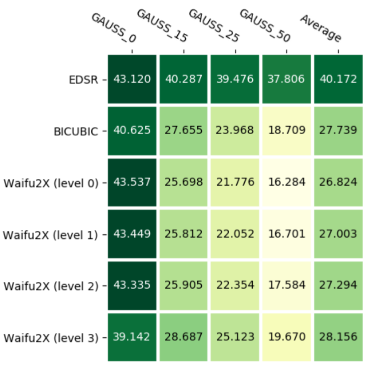
(D) SSIM results with gaussian noise



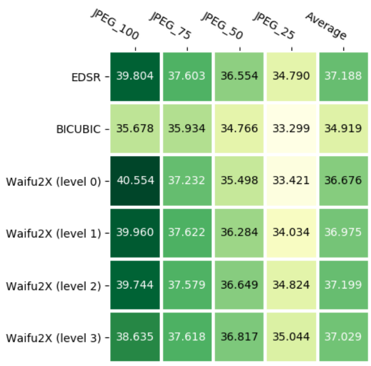
(E) SSIM results with JPEG noise

FIGURE 5.7: PSNR and SSIM results on the shown image

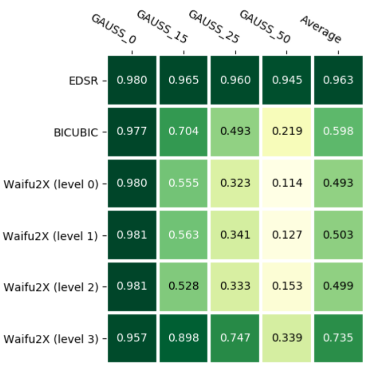
(A) High Resolution



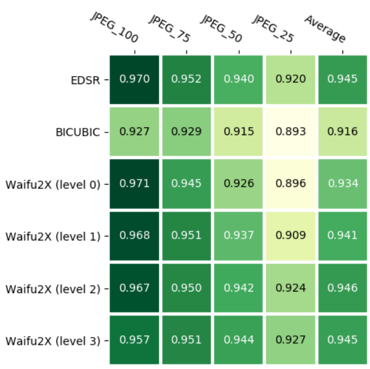
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise

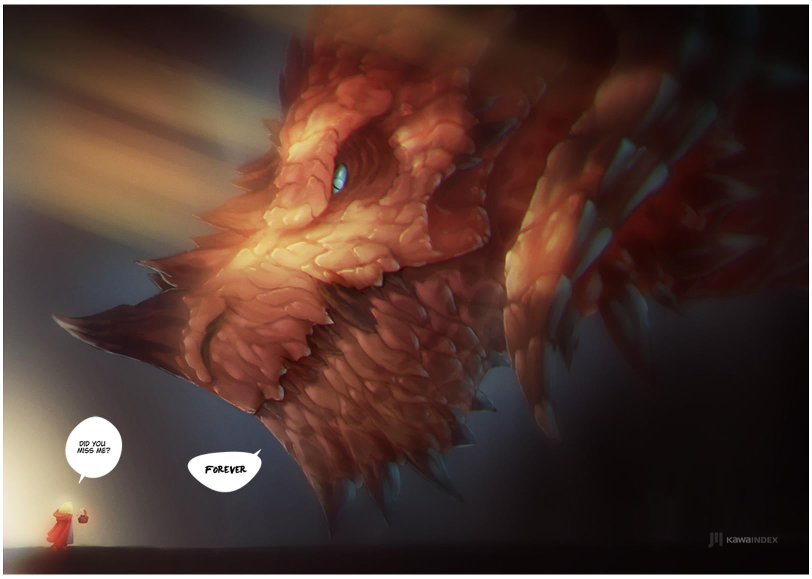


(D) SSIM results with gaussian noise

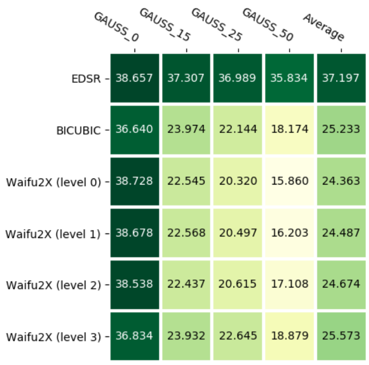


(E) SSIM results with JPEG noise

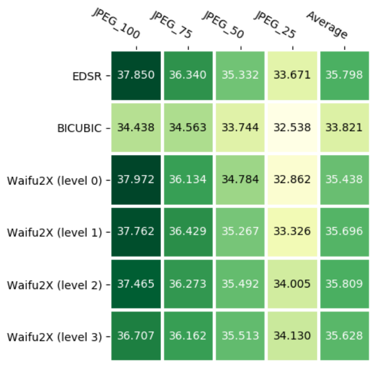
FIGURE 5.8: PSNR and SSIM results on the shown image



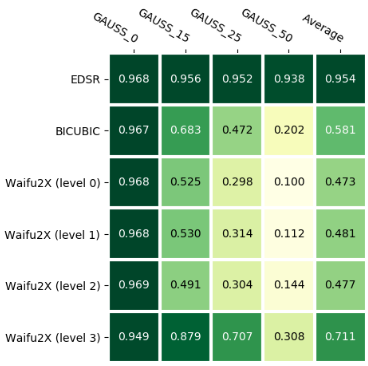
(A) High Resolution



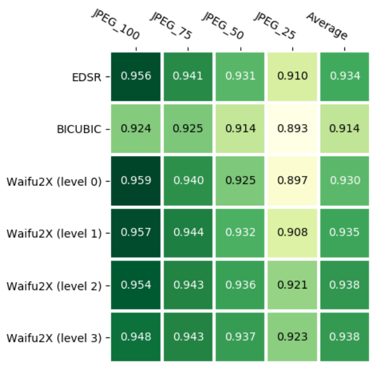
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



(D) SSIM results with gaussian noise



(E) SSIM results with JPEG noise

FIGURE 5.9: PSNR and SSIM results on the shown image

Chapter 6

Conclusion

My model achieves performance comparable to the best waifu2x model match for a given noise level for JPEG tasks, while dominating in gaussian denoising, I suspect the reason why it doesn't consistently outperform it in JPEG denoising (apart from the average score) is that the patch size is overly small (32 x 32), I used the L2 metric as a "safe" option since I was adding new functionality to the network apart from just uscaling, despite L1 having empirically better results (Lim, Son, Kim, Nah, and Lee, 2017) and the lack of Batch Normalization layers, which are proven to degrade performance slightly (Zhang, Zuo, Chen, Meng, and Zhang, 2017), however the fact that my model performs substantially better when the picture has a lot of fine detail 5.2 suggest that there might actually be an overfitting issue, after all EDSR is a highly complex model, and artwork is generally not as complex as photographs.

6.1 Future work

I have found a small handful of images with compression artifacts that differ from JPEG compression, I will try to find the optimizer that generated those artifacts and include it in the training data, as well as other downsampling methods to fix aliasing or other issues that might occur on low resolution images.

List of Abbreviations

CNN	**C**onvolutional **N**eural **N**etwork
GAN	**G**enerative **A**dversarial **N**etwork
GUI	**G**raphical **U**ser **I**nterface
JSON	**J**ava **S**cript **O**bject **N**otation
SR	**S**uper **R**esolution
HR	**H**igh **R**esolution
LR	**L**ow **R**esolution
SISR	**S**ingle **I**mage **S**uper **R**esolution
PSNR	**P**eak **S**ignal to **N**oise **R**atio
SSIM	**S**tructural **SIM**ilarity Index

Acknowledgements

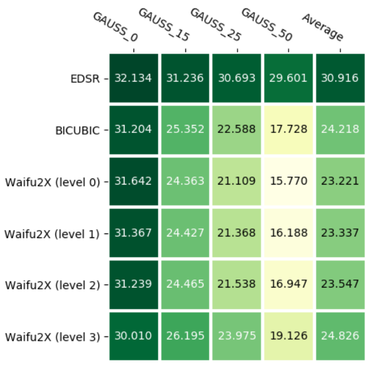
I thank my advisor for pointing me in the right direction with this project when he talked to me about the NITRE challenge and gave me the EDSR and CinCGAN papers to read, as a researcher in the field of Computer Vision he would know about the latest developments in Super-Resolution much better than a master degree student searching on Google Scholar.

I also want to thank my colleague Jordan that left the program after the first semester for making that trial by fire bearable enough for me to get this far.

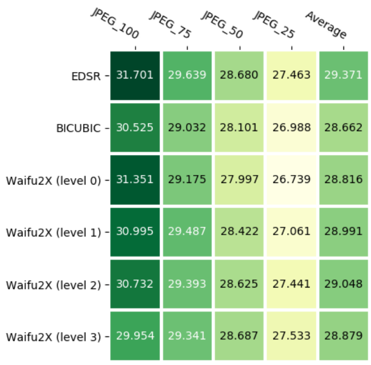
Appendix A

Results for 3X scale

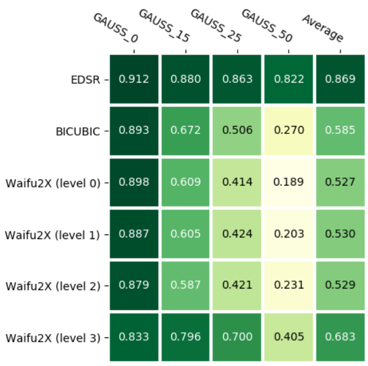
(A) High Resolution



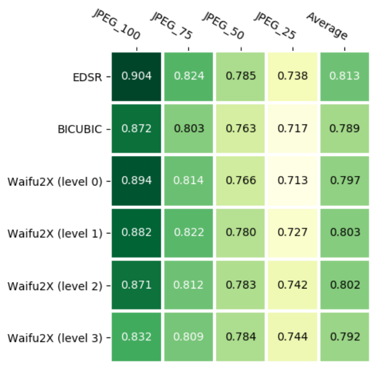
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



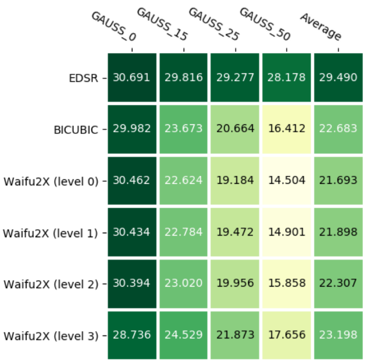
(D) SSIM results with gaussian noise



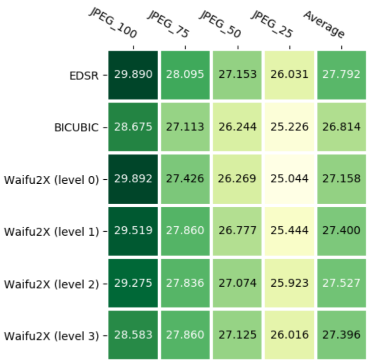
(E) SSIM results with JPEG noise

FIGURE A.1: PSNR and SSIM results on the shown image

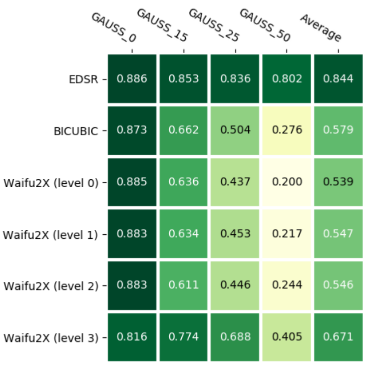
(A) High Resolution



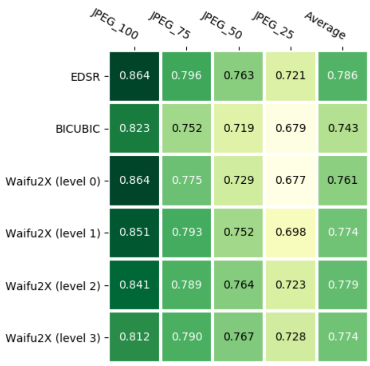
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



(D) SSIM results with gaussian noise



(E) SSIM results with JPEG noise

FIGURE A.2: PSNR and SSIM results on the shown image

(A) High Resolution

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	31.133	30.088	29.401	28.023	29.661
BICUBIC	29.610	24.416	21.114	16.678	22.954
Waifu2X (level 0)	30.971	23.548	19.647	14.735	22.225
Waifu2X (level 1)	30.922	23.756	19.957	15.131	22.441
Waifu2X (level 2)	30.868	23.926	20.445	16.032	22.818
Waifu2X (level 3)	28.937	25.733	22.628	17.923	23.805

(B) PSNR results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	29.775	27.750	26.759	25.515	27.450
BICUBIC	28.016	26.472	25.551	24.488	26.132
Waifu2X (level 0)	29.849	26.921	25.545	24.262	26.644
Waifu2X (level 1)	29.567	27.528	26.248	24.770	27.028
Waifu2X (level 2)	29.288	27.546	26.663	25.351	27.212
Waifu2X (level 3)	28.620	27.623	26.766	25.473	27.120

(C) PSNR results with JPEG noise

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	0.918	0.887	0.871	0.834	0.878
BICUBIC	0.893	0.684	0.525	0.289	0.598
Waifu2X (level 0)	0.919	0.652	0.455	0.212	0.560
Waifu2X (level 1)	0.918	0.647	0.467	0.227	0.565
Waifu2X (level 2)	0.918	0.620	0.456	0.250	0.561
Waifu2X (level 3)	0.851	0.809	0.713	0.417	0.698

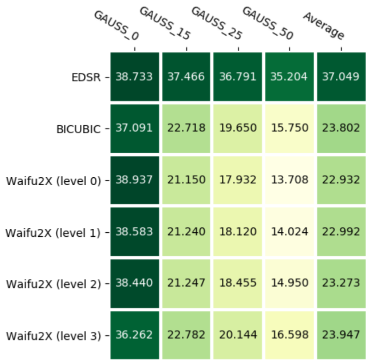
(D) SSIM results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	0.895	0.824	0.788	0.738	0.811
BICUBIC	0.845	0.770	0.730	0.681	0.757
Waifu2X (level 0)	0.894	0.798	0.741	0.678	0.778
Waifu2X (level 1)	0.884	0.822	0.775	0.708	0.797
Waifu2X (level 2)	0.876	0.818	0.789	0.740	0.806
Waifu2X (level 3)	0.845	0.819	0.792	0.744	0.800

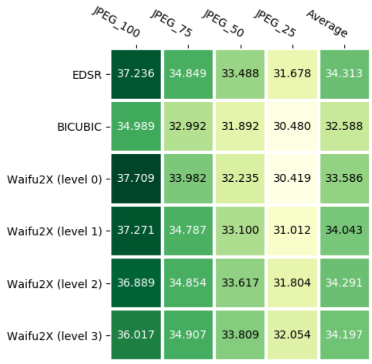
(E) SSIM results with JPEG noise

FIGURE A.3: PSNR and SSIM results on the shown image

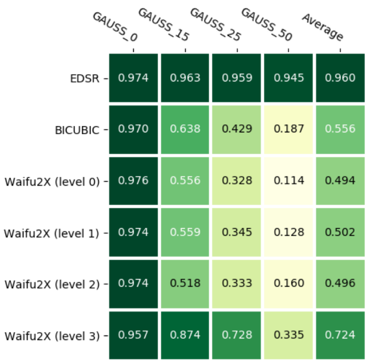
(A) High Resolution



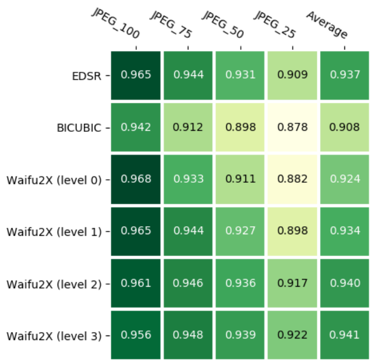
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



(D) SSIM results with gaussian noise



(E) SSIM results with JPEG noise

FIGURE A.4: PSNR and SSIM results on the shown image

(A) High Resolution

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	37.880	36.654	35.982	34.413	36.232
BICUBIC	34.389	19.802	17.668	14.803	21.666
Waifu2X (level 0)	37.442	18.719	16.379	13.101	21.410
Waifu2X (level 1)	37.382	18.806	16.511	13.345	21.511
Waifu2X (level 2)	37.234	19.618	17.416	14.547	22.204
Waifu2X (level 3)	34.941	20.935	18.831	15.933	22.660

(B) PSNR results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	36.149	33.927	32.543	30.841	33.365
BICUBIC	32.988	31.535	30.514	29.200	31.059
Waifu2X (level 0)	36.205	32.915	30.952	29.094	32.292
Waifu2X (level 1)	35.949	33.800	32.109	29.903	32.940
Waifu2X (level 2)	35.568	33.771	32.717	30.987	33.261
Waifu2X (level 3)	34.661	33.849	32.863	31.139	33.128

(C) PSNR results with JPEG noise

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	0.982	0.973	0.969	0.957	0.970
BICUBIC	0.967	0.632	0.434	0.199	0.558
Waifu2X (level 0)	0.982	0.559	0.339	0.127	0.502
Waifu2X (level 1)	0.982	0.552	0.349	0.139	0.505
Waifu2X (level 2)	0.981	0.520	0.347	0.172	0.505
Waifu2X (level 3)	0.966	0.878	0.731	0.340	0.729

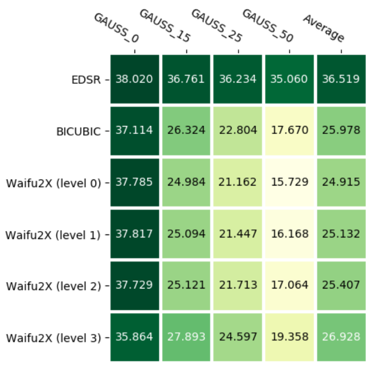
(D) SSIM results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	0.975	0.954	0.940	0.915	0.946
BICUBIC	0.947	0.914	0.895	0.869	0.906
Waifu2X (level 0)	0.976	0.942	0.910	0.872	0.925
Waifu2X (level 1)	0.974	0.957	0.936	0.898	0.941
Waifu2X (level 2)	0.971	0.957	0.948	0.927	0.951
Waifu2X (level 3)	0.965	0.959	0.950	0.930	0.951

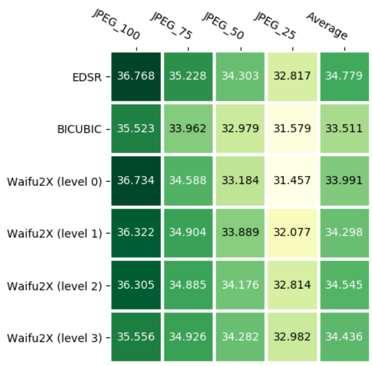
(E) SSIM results with JPEG noise

FIGURE A.5: PSNR and SSIM results on the shown image

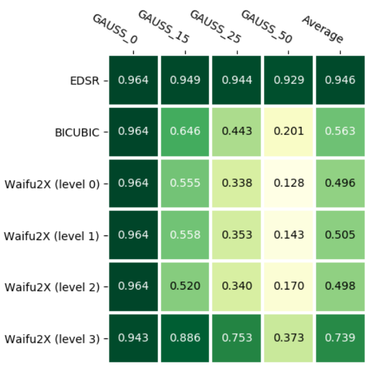
(A) High Resolution



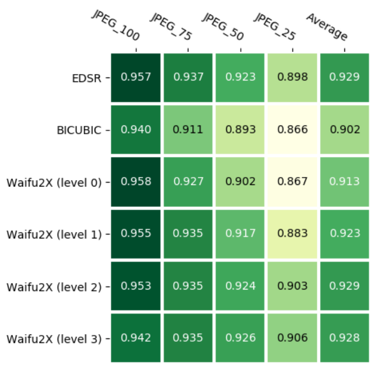
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise

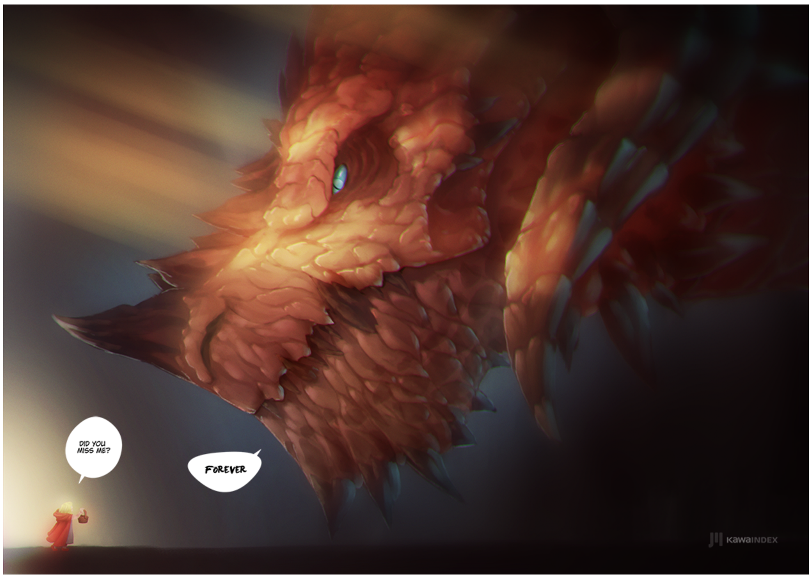


(D) SSIM results with gaussian noise



(E) SSIM results with JPEG noise

FIGURE A.6: PSNR and SSIM results on the shown image



(A) High Resolution

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	36.631	35.677	35.186	34.493	35.497
BICUBIC	35.346	23.382	21.349	17.229	24.326
Waifu2X (level 0)	36.535	22.422	19.967	15.379	23.576
Waifu2X (level 1)	36.500	22.467	20.177	15.761	23.726
Waifu2X (level 2)	36.420	22.532	20.422	16.749	24.031
Waifu2X (level 3)	34.920	24.123	22.646	18.726	25.104

(B) PSNR results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	36.201	34.693	33.674	32.196	34.191
BICUBIC	34.512	33.409	32.564	31.275	32.940
Waifu2X (level 0)	36.004	34.278	32.895	31.290	33.617
Waifu2X (level 1)	35.842	34.556	33.470	31.784	33.913
Waifu2X (level 2)	35.630	34.455	33.785	32.422	34.073
Waifu2X (level 3)	34.835	34.410	33.827	32.539	33.903

(C) PSNR results with JPEG noise

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	0.959	0.948	0.942	0.929	0.945
BICUBIC	0.959	0.631	0.426	0.186	0.550
Waifu2X (level 0)	0.960	0.531	0.315	0.116	0.480
Waifu2X (level 1)	0.960	0.528	0.329	0.130	0.487
Waifu2X (level 2)	0.960	0.488	0.315	0.162	0.481
Waifu2X (level 3)	0.940	0.876	0.722	0.346	0.721

(D) SSIM results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	0.951	0.930	0.919	0.897	0.925
BICUBIC	0.937	0.915	0.901	0.879	0.908
Waifu2X (level 0)	0.952	0.927	0.910	0.882	0.918
Waifu2X (level 1)	0.949	0.932	0.920	0.894	0.924
Waifu2X (level 2)	0.946	0.931	0.924	0.908	0.927
Waifu2X (level 3)	0.939	0.932	0.925	0.910	0.927

(E) SSIM results with JPEG noise

FIGURE A.7: PSNR and SSIM results on the shown image

Appendix B

Results for 4X scale

(A) High Resolution

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	30.715	29.929	29.432	28.413	29.622
BICUBIC	29.740	24.931	22.427	17.660	23.689
Waifu2X (level 0)	30.381	24.220	21.191	15.915	22.927
Waifu2X (level 1)	30.221	24.277	21.435	16.325	23.064
Waifu2X (level 2)	30.159	24.304	21.595	17.049	23.277
Waifu2X (level 3)	28.841	25.712	23.801	19.068	24.356

(B) PSNR results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	30.245	28.438	27.464	26.462	28.152
BICUBIC	29.176	27.833	27.013	26.009	27.508
Waifu2X (level 0)	30.054	28.016	26.879	25.751	27.675
Waifu2X (level 1)	29.738	28.250	27.204	26.039	27.808
Waifu2X (level 2)	29.476	28.164	27.389	26.409	27.859
Waifu2X (level 3)	28.770	28.142	27.462	26.492	27.717

(C) PSNR results with JPEG noise

	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	0.868	0.834	0.815	0.776	0.823
BICUBIC	0.840	0.655	0.510	0.290	0.574
Waifu2X (level 0)	0.853	0.609	0.432	0.210	0.526
Waifu2X (level 1)	0.846	0.604	0.440	0.225	0.529
Waifu2X (level 2)	0.842	0.588	0.436	0.251	0.529
Waifu2X (level 3)	0.784	0.755	0.679	0.422	0.660

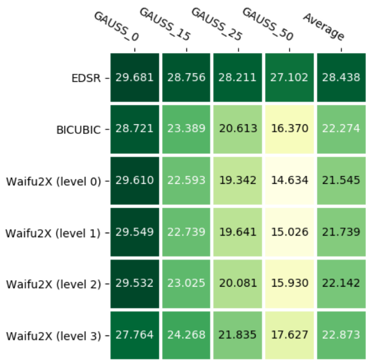
(D) SSIM results with gaussian noise

	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	0.856	0.774	0.737	0.700	0.767
BICUBIC	0.822	0.751	0.715	0.677	0.741
Waifu2X (level 0)	0.845	0.763	0.717	0.672	0.749
Waifu2X (level 1)	0.833	0.771	0.731	0.685	0.755
Waifu2X (level 2)	0.823	0.763	0.735	0.700	0.755
Waifu2X (level 3)	0.782	0.760	0.736	0.702	0.745

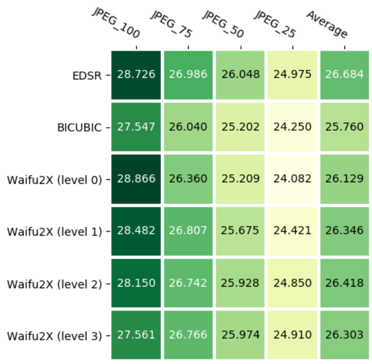
(E) SSIM results with JPEG noise

FIGURE B.1: PSNR and SSIM results on the shown image

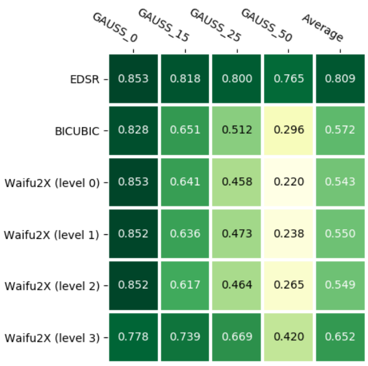
(A) High Resolution



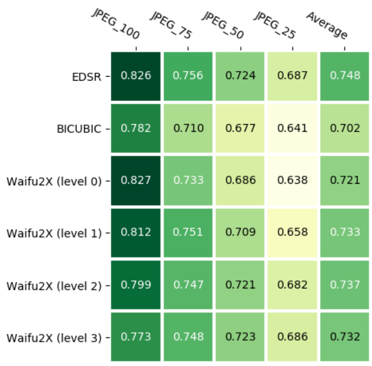
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



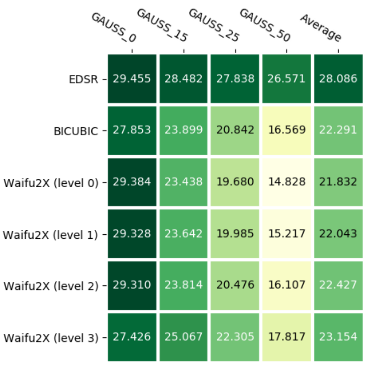
(D) SSIM results with gaussian noise



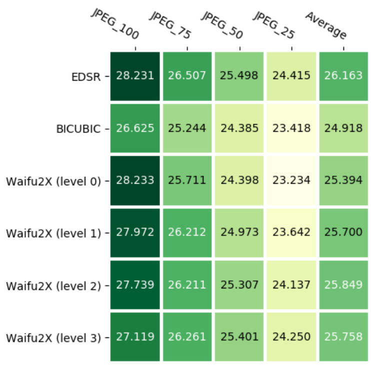
(E) SSIM results with JPEG noise

FIGURE B.2: PSNR and SSIM results on the shown image

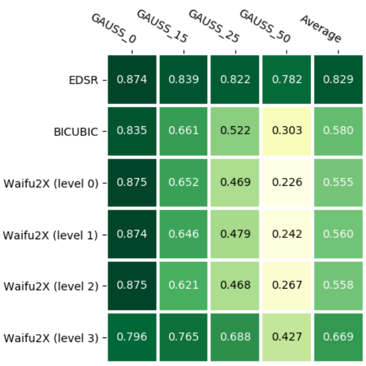
(A) High Resolution



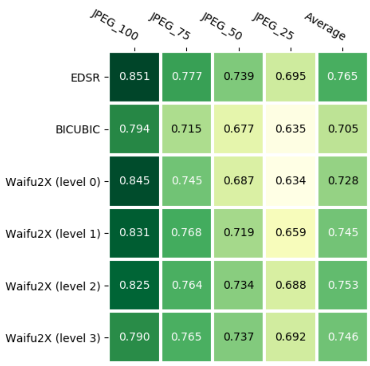
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



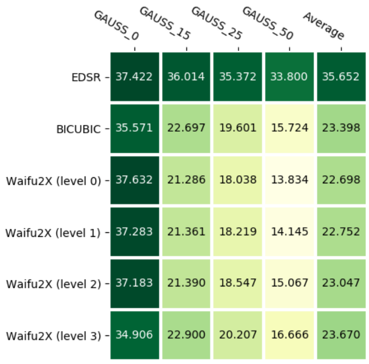
(D) SSIM results with gaussian noise



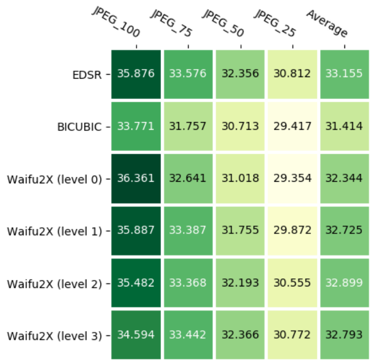
(E) SSIM results with JPEG noise

FIGURE B.3: PSNR and SSIM results on the shown image

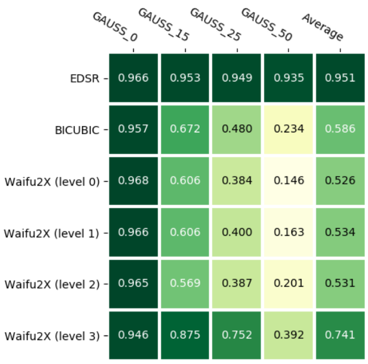
(A) High Resolution



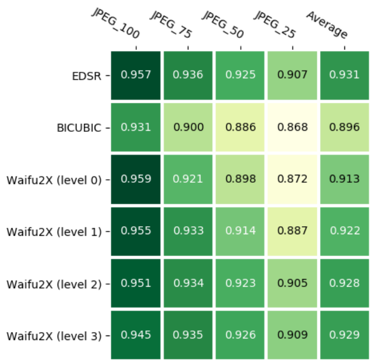
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



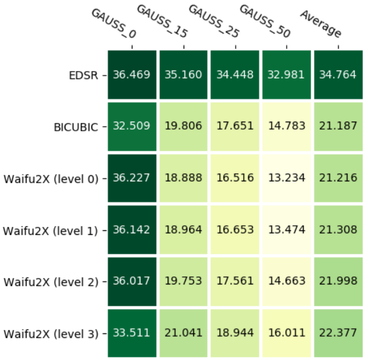
(D) SSIM results with gaussian noise



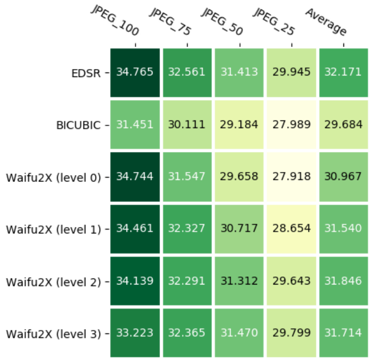
(E) SSIM results with JPEG noise

FIGURE B.4: PSNR and SSIM results on the shown image

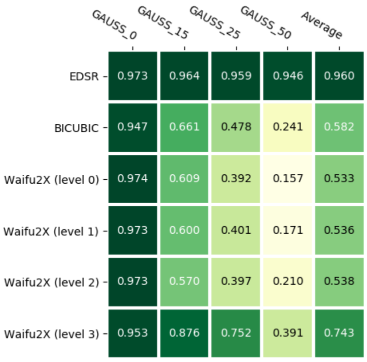
(A) High Resolution



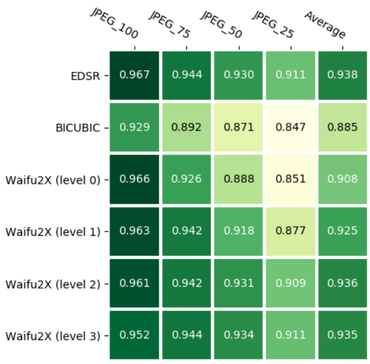
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise



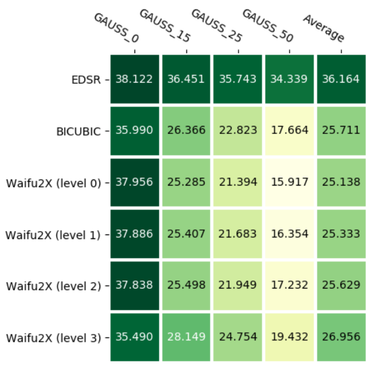
(D) SSIM results with gaussian noise



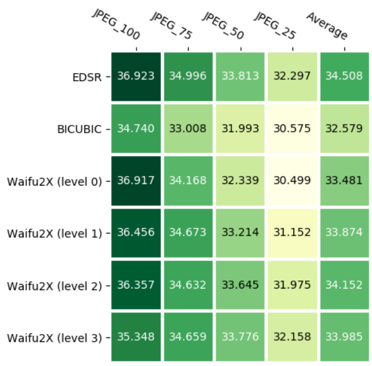
(E) SSIM results with JPEG noise

FIGURE B.5: PSNR and SSIM results on the shown image

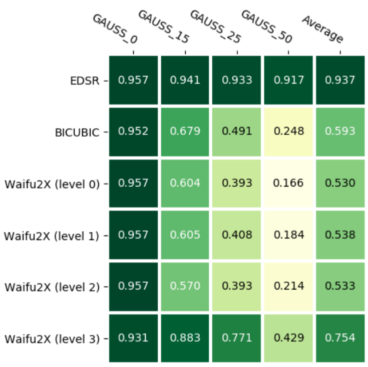
(A) High Resolution



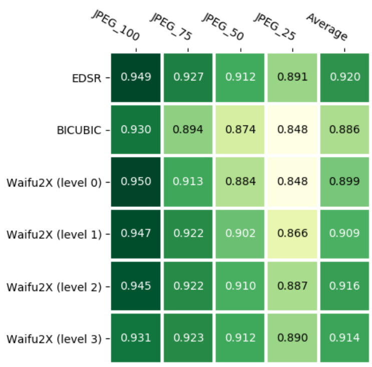
(B) PSNR results with gaussian noise



(C) PSNR results with JPEG noise

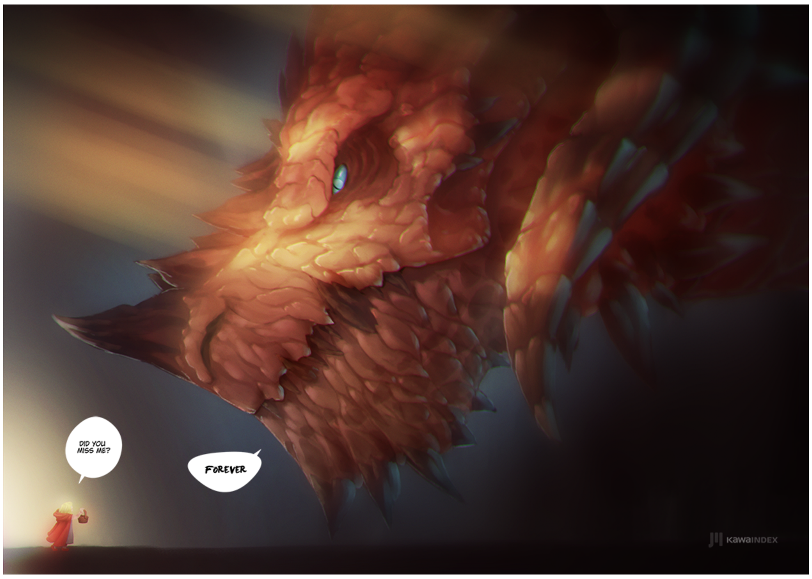


(D) SSIM results with gaussian noise

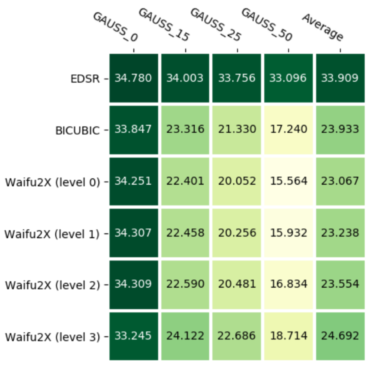


(E) SSIM results with JPEG noise

FIGURE B.6: PSNR and SSIM results on the shown image

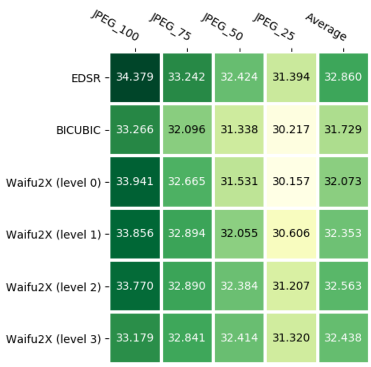


(A) High Resolution



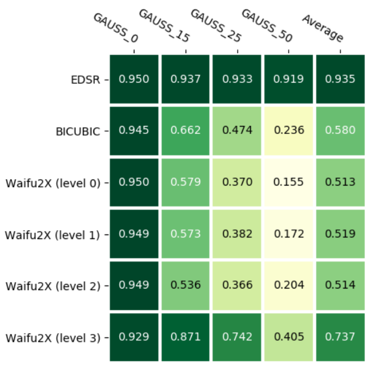
	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	34.780	34.003	33.756	33.096	33.909
BICUBIC	33.847	23.316	21.330	17.240	23.933
Waifu2X (level 0)	34.251	22.401	20.052	15.564	23.067
Waifu2X (level 1)	34.307	22.458	20.256	15.932	23.238
Waifu2X (level 2)	34.309	22.590	20.481	16.834	23.554
Waifu2X (level 3)	33.245	24.122	22.686	18.714	24.692

(B) PSNR results with gaussian noise



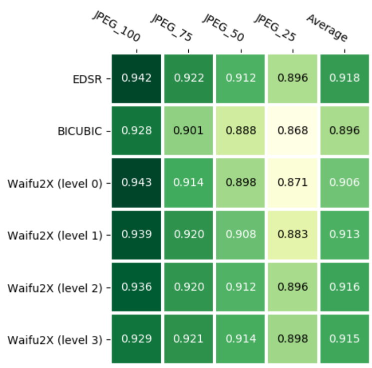
	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	34.379	33.242	32.424	31.394	32.860
BICUBIC	33.266	32.096	31.338	30.217	31.729
Waifu2X (level 0)	33.941	32.665	31.531	30.157	32.073
Waifu2X (level 1)	33.856	32.894	32.055	30.606	32.353
Waifu2X (level 2)	33.770	32.890	32.384	31.207	32.563
Waifu2X (level 3)	33.179	32.841	32.414	31.320	32.438

(C) PSNR results with JPEG noise



	GAUSS_0	GAUSS_15	GAUSS_25	GAUSS_50	Average
EDSR	0.950	0.937	0.933	0.919	0.935
BICUBIC	0.945	0.662	0.474	0.236	0.580
Waifu2X (level 0)	0.950	0.579	0.370	0.155	0.513
Waifu2X (level 1)	0.949	0.573	0.382	0.172	0.519
Waifu2X (level 2)	0.949	0.536	0.366	0.204	0.514
Waifu2X (level 3)	0.929	0.871	0.742	0.405	0.737

(D) SSIM results with gaussian noise



	JPEG_100	JPEG_75	JPEG_50	JPEG_25	Average
EDSR	0.942	0.922	0.912	0.896	0.918
BICUBIC	0.928	0.901	0.888	0.868	0.896
Waifu2X (level 0)	0.943	0.914	0.898	0.871	0.906
Waifu2X (level 1)	0.939	0.920	0.908	0.883	0.913
Waifu2X (level 2)	0.936	0.920	0.912	0.896	0.916
Waifu2X (level 3)	0.929	0.921	0.914	0.898	0.915

(E) SSIM results with JPEG noise

FIGURE B.7: PSNR and SSIM results on the shown image

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