Enhancement of Anime Imaging Enlargement using Modified Super-Resolution CNN

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Abstract—Anime is a storytelling medium similar to movies and books. Anime images are a kind of artworks, which are almost entirely drawn by hand. Hence, reproducing existing Anime with larger sizes and higher quality images is expensive. Therefore, we proposed a model based on convolutional neural networks to extract outstanding features of images, enlarge those images, and enhance the quality of Anime images. We trained the model with a training set of 160 images and a validation set of 20 images. We tested the trained model with a testing set of 20 images. The experimental results indicated that our model successfully enhanced the image quality with a larger image-size when compared with the common existing image enlargement and the original SRCNN method.

Index Terms—Anime, Image Enhancement, Image Enlargement, Image super-resolution, Convolutional Neural Networks

Fig. 1. Preview of input and output image in the experiment.

I. INTRODUCTION

Art images are a descriptive medium without using text to explain their meaning. Artists create each image or illustration always containing its value and meaning. One of these is Anime-style art images, which are storytelling mediums, like movies and books. Anime is a kind of artwork image, which is almost entirely drawn by hand. It combines graphic art, characterization, cinematography, and other forms of imaginative and individualistic techniques [1] along with Manga, a comic typically printed in black-and-white, displayed as a still image, and letters often placed in a format of picture sequences [2]. Both Anime and Manga are originated from Japan. In the past, it was impossible to re-create Anime as the same as the original one [3].

In the current digital era, a high resolution for storing and publishing art images is essential. Nevertheless, the former illustrations, currently published in the online media, may have a lower resolution. These images may look pixelated or blur. Applying existing image enhancement methods on lower resolution images may help fix this issue, but for enlarger images with details, the quality may not be good enough for online media.

Many of the technical purposes of using low-resolution images are for saving storage, decreasing upload or download speeds from the image sources, deterring illegitimate use of images, and using intentionally them as thumbnails [4]. Those purposes of using low-resolution images are not only getting insufficient details in the image itself but also decreasing their values. Fortunately, waifu2x [5], a free Anime-style art image enlargement and denoising website, and waifu2x program [6] for offline use, are available. Fig. 1 shows an example of the output enlarged image with high quality. It inspired us to investigate how to improve the quality of enlarged images.

By applying the deep learning model, called Super-Resolution Convolutional Neural Network (SRCNN), as the waifu2x used, the Anime image was enlarged and enhanced its output quality. As our preliminary experiments with waifu2x, the output image quality after enlargement was not adequate sometimes. We have assumptions that this phenomenon happened due to the SRCNN architecture that uses only one enhancement module.

As mentioned so far, we proposed a modified Super-Resolution CNN (m-SRCNN). This model can enhance the quality of art images and support image enlargement tasks. To achieve our goal (See details in Fig. 5), we provided pre-processing phase to enhance the quality of datasets for training a model; therefore, the model, trained by the high quality of datasets, usually resulted in a high quality output image. Furthermore, we provided four post-processing modules, called image-enhancement only, enlargement and enhancement, double enhancement, and double enlargement, for various purposes.

Finally, we tested our methods with Nico-illust dataset [7] and evaluated the performance by using the PSNR
and SSIM metrics. Results show that our models can outperform the conventional SRCNN and other baseline methods in most cases.

II. RELATED WORKS

A. Image Scaling and Interpolation

Image scaling is a geometric transformation. By performing this in image processing, images can be scaled up or down by an image scaling function. An important mechanism behind the image scaling function is an interpolation. Here, we used three common interpolation methods—Nearest Neighbor, Bilinear, and Bicubic [8] in our experiments. A nearest neighbor interpolation replaces every pixel with the nearest pixel in the output image. A bilinear method interpolates pixel values by estimating new pixel values in between two pixels. A bicubic method interpolates pixel values as the same as the bilinear method, but it uses third-degree polynomials instead [9]. By image scaling up, the pixel amount of the image is increasing, thus resulting in more details. On the other hand, the image scaling down causes the details of the image decreasing.

B. Super-Resolution (SR)

A super resolution (SR) is a process that transforms a low-resolution (LR) image into a high-resolution (HR) image. As reported in [10], SR can be categorized into four types—prediction models, edge-based methods, image statistical methods, and patch-based (or example-based) methods. Among them, the patch-based achieved the best performance. Inside this method, the Nearest Neighbor algorithm was used in the low-resolution space for reconstruction. Recently, the researchers have proposed a new method that applied deep learning like CNN instead of the Nearest Neighbor approach, and it can achieve better performance in the image enlargement [11]. As reasons mentioned previously, we have chosen the SR algorithm implemented on Convolutional Neural Network for our image enlargement method.

C. SRCNN

SRCNN is short for a Super-Resolution Convolutional Neural Network. SRCNN is a CNN model built to enhance image quality by learning the end-to-end mapping between bicubic interpolation of LR and HR images. The overall structure consists of three parts: (i) patch extraction and representation, which extracts patches from the input represents as a high-dimensional feature vector; (ii) non-linear mapping, which maps the HR feature, and (iii) reconstruction, which builds up features to form the final output image [10]. This designed structure is based on sparse coding, which aims in finding a sparse representation of input data in a form of a linear combination of basic elements [12].

III. METHODOLOGY

As we know, basic image upscaling algorithms, such as Nearest Neighbor, Bilinear, and Bicubic, do not achieve in enhancing the quality of enlarged images. An alternative way is using a neural network for image super-resolution, since it can learn to fill details, based on the information collecting from a large set of images. Therefore, here, we proposed a modified super-resolution CNN (m-SRCNN) as shown in Fig. 2 and the followings describe its functional operations and settings.

![Fig. 2. A simplified diagram of our modified super-resolution CNN.](image)

A. Data Collection

In the first step, we collected Anime art-style images from Nico-illust [7], a community illustration from Niconico Seiga and Niconico Shunga, for training, validating, and testing sets. The collected images, which are a JPG format, are split into 160 images for a training set, 20 images for validation, and 20 images for a testing set. Fig. 3 shows part of the collected images.

![Fig. 3. A part of collected images from Nico-illust dataset.](image)

B. Image Preprocessing

All collected images were sharpened and denoised to improve their image quality and then they were split into LR and HR. Here, we provided two sets of LR images. The first set were downscaled by a bilinear interpolation with 0.5x, and then they were upsampled by a bilinear interpolation with 2x. Likewise, the second set of LR images was processed in the same way of the first set, but using a bicubic interpolation. On the other hand, HR images were original images. All LR and HR images were cropped with the size of 32-by-32 pixels and then were converted to YCbCr color space. Since SR algorithms are only applied on the Y channel, while the Cb and Cr channels are upsampled by bicubic interpolation [10]. Lastly, images were stored in h5 file format.

C. Model Training

At this stage, we set up hardware and software for training a model as follows. The hardware specifications were Intel Core i5-11400F CPU, 1 unit of Nvidia GeForce
TABLE I
A configuration of the original SRCNN

| Layers                | Filters | Kernel Size | Activation | Bias |
|-----------------------|---------|-------------|------------|------|
| Convolution           | 128     | 9*9         | LeakyReLU  | True |
| Convolution           | 64      | 3*3         | LeakyReLU  | True |
| Convolution Transpose  | 32      | 3*3         | LeakyReLU  | True |
| Convolution Transpose  | 32      | 3*3         | LeakyReLU  | True |
| Convolution Transpose  | 3       | 1*1         | Sigmoid    | True |

TABLE II
A configuration of our m-SRCNN

| Layers                | Filters | Kernel Size | Activation | Bias |
|-----------------------|---------|-------------|------------|------|
| Convolution           | 64      | 5*5         | LeakyReLU  | True |
| Convolution           | 64      | 5*5         | LeakyReLU  | True |
| Convolution Transpose  | 32      | 3*3         | LeakyReLU  | True |
| Convolution Transpose  | 32      | 3*3         | LeakyReLU  | True |
| Convolution Transpose  | 3       | 1*1         | Sigmoid    | True |

Layers of the original SRCNN were from [10] and those of m-SRCNN were from [13], as visualized in Fig. 4. The m-SRCNN model was modified and customized by adding the convolution transpose layer and removing the upscaling layer from the deep learning model, when compared to the original SRCNN. In model learning, parameters were set as follows: 50 epochs, 0.003 of the learning rate for m-SRCNN, 32 of batch size.

D. Post Processing

At the last stage, output images, from a deep learning model, can be customized by post-processing, especially the image denoising process, developed by using Python 3 OpenCV fastNIMeans [14] and Bilateral filter [15]. Also, image enhancement-only, Double Enhancement, and Double Enhancement functions [16] are added for image quality improvement. Note that these functions are optional, depending on tasks and user satisfactions. Users may choose to apply these methods or maintain the original output.

IV. EXPERIMENTS

A. Data Preparation and Baseline Selection

We used Nico-illust dataset [7] for our experiments. We set the original images with their original size as reference (or ground truth). The input images (or test images) were downsampled by a bilinear interpolation to three different sizes of 0.50x, 0.33x, and 0.25x. For performance comparison, our baselines are Nearest Neighbor, Bilinear, Bicubic, SRCNN with the up-bilinear model, and SRCNN with the up-bicubic model. Three sizes for image enlargement in testing are 2x, 3x, and 4x upscalings.

B. Evaluation Metrics

In model training, we use Mean Squared Error (MSE), defined in (1), as a loss function, and use Peak Signal to Noise Ratio (PSNR) [17], denoted in (2), and Structural Similarity Index Measure (SSIM) [18], expressed in (3), as experimental assessment metrics.

$$\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$  

(1)

$$\text{PSNR} = 20 \cdot \log_{10} \left( \frac{255}{\sqrt{MSE}} \right)$$  

(2)

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$  

(3)

where $x$ and $y$ are two compared images, $\mu$ indicates the average intensity value of all pixels, and $\sigma$ denotes the contrast value, calculated by a standard deviation of all pixels.

C. Experimental Framework and Settings

Fig. 5 shows a diagram of all processes of cooperation of m-SRCNN. The followings briefly a flow of the experimental diagram. The training and validation image sets were preprocessed as described in III-A and III-B. Then all processed images were converted to h5 file format as mentioned in III-B. The trained model, proposed in III-C, was stored in h5 format and used for testing. Fig. 6 shows an example of model training in terms of a MSE graph. All model checkpoints also made and stored as h5 format if there were problems occurred during a model training. A testing set of the prepared dataset were bilinear-downscaled as the same as IV-A to use as an input image in model testing. Next, pre-upsampling image was enlarged by the bicubic method, and then converted from RGB to YCbCr color space for a model prediction. Lastly, the newly saved enhanced image was stored and kept for model evaluation.

D. Results

In the first experiment, as can be seen in Table III, at 2x upscaling, our m-SRCNN in both models, up-bilinear and up-bicubic, outperform all test baselines and the original SRCNN, especially m-SRCNN with up-bilinear model. Nonetheless, at 3x upscaling, the original SRCNN with up-bicubic model is slightly better than our method, m-SRCNN with up-bicubic. When regarding in overall performance of all test methods, the average PSNR and
SSIM are much reduced. As expected, when compared with 3x upscaling, the overall performance of all test methods with 4x upscaling is slightly decreased.

In the second experiment, our baseline is an online application, waifu2x. As can be seen in Table IV, our m-SRCNN with up-bilinear model outperforms the waifu2x in all upscaling factors and in all cases. Fig. 7 shows visual test results.

In real-world use, users can input their images into a program without downscaling them. Hence, we must test it without a reference. The visual test results show in Figs. 8, 9, and 10, when the test images were enlarged with 2x upscaling.
TABLE III
AVERAGE PSNR AND SSIM IN COMPARISON OF DIFFERENT ENLARGEMENT METHODS AND DIFFERENT UPSCALING FACTORS.

| Nearest Neighbor | Bilinear | Bicubic | SRCNN (Up-Bilinear) | SRCNN (Up-Bicubic) | Modified SRCNN (Up-Bilinear) (Proposed) | Modified SRCNN (Up-Bicubic) (Proposed) |
|------------------|----------|---------|---------------------|---------------------|----------------------------------------|----------------------------------------|
|                  | PSNR     | SSIM    | PSNR                | SSIM                | PSNR                                  | SSIM                                  |
| 2x               | 27.4984  | 0.8979  | 27.7958             | 0.8996              | 29.1088                               | 0.9029                                |
|                  | 29.1088  | 0.9172  | 31.0977             | 0.9317              | 29.3876                               | 0.9184                                |
| 3x               | 22.7810  | 0.8037  | 24.5525             | 0.8308              | 24.4020                               | 0.8267                                |
|                  | 24.4020  | 0.8235  | 23.6992             | 0.8255              | 24.6550                               | 0.8328                                |
| 4x               | 22.3578  | 0.7744  | 23.8173             | 0.7926              | 23.9540                               | 0.7995                                |
|                  | 23.9540  | 0.7995  | 23.7808             | 0.8006              | 23.8359                               | 0.7941                                |

Green is the best result for the bilinear model, while Blue is the best result for the bicubic model.

TABLE IV
AVERAGE PSNR AND SSIM IN COMPARISON OF M-SRCNN WITH UP-BILINEAR, WAIFU2X (RGB), AND WAIFU2X (CUNET) MODELS IN THREE DIFFERENT UPSCALING FACTORS.

| Upscaling Factor | Modified SRCNN (Up-Bilinear) (Proposed) | waifu2x-caffe (RGB Model) | waifu2x-caffe (CUnet Model) |
|------------------|----------------------------------------|--------------------------|----------------------------|
|                  | PSNR                                  | SSIM                     | PSNR                       | SSIM|
| 2x               | 31.0013                               | 0.9337                   | 29.1175                    | 0.9032|
| 3x               | 23.6713                               | 0.8268                   | 22.7281                    | 0.7942|
| 4x               | 23.5286                               | 0.7960                   | 22.2065                    | 0.7689|

Fig. 8. An example of original, output, and denoised images of an unseen illustration “Dijel” using m-SRCNN with up-bilinear model.

Fig. 9. Results of four post-processing modules, including image-enhancement only, enlargement and enhancement, double enhancement, and double enlargement, when an unseen illustration “Link Cosplay” was tested by m-SRCNN with up-bilinear model.

Fig. 10. An example of enlarged unseen illustration “Miyagami-San” using m-SRCNN with default settings.

By comparing m-SRCNN with up-bilinear model and waifu2x, we found that our model performs better than the baseline, because of adding a step of image preprocessing (image sharpening and denoising) also with the different upsampling methods in the model training. Furthermore, all images were pre-upsampling [19] before the model enhancement.

V. CONCLUSION

This paper has proposed a modified SRCNN (m-SRCNN) with up-bilinear and up-bicubic models. The previous approach, like waifu2x using SRCNN model, for image enlargement suffered from a lack of ability to enhance the quality of enlarged images effectively. Hence, the m-SRCNN was designed to fulfill this gap. Responding to this, in our design, the key components, that can be viewed as the main contributions of this paper, are listed
below: 1

- A denoised and sharpened dataset was added for model training.
- Image enhancement-only function was created.
- Double enhancement and double enlargement functions were developed.
- User customization for image scaling, image denoising, double enhancement, and double enlargement was provided.

As shown in experimental results, our m-SRCNN can outperform the original SRCNN and waifu2x in most cases.

In future work, we aim to investigate another issue to allow us to inspect the diversity of the Anime-style art images. Furthermore, we desire to upgrade our work to achieve a faster and more accurate model.

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1Source code available: https://github.com/TanakitInt/SRCNN-anime