RetroGAN: Translating Unpaired Video Game Images Using CycleGANs

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Abstract

Video games from the retro era have a signature style due to the 8-bit and 16-bit technology at the time. Limitations on resolution, color, bandwidth, and processing power all created constraints that limited the vision and scope of what video game creators could implement. Using a CycleGAN architecture to allow unpaired translation, we can learn from screenshot data of two separate video game generations (8-bit and 16-bit) and translate images from one generation to the other. Our results show that we can take images from the Nintendo Entertainment System (NES) and Super Nintendo (SNES) and translate screenshots from both consoles into the style of the other. Experiments demonstrate that the CycleGAN architecture can learn many constraints of each system in order to perform relatively accurate translations between generations.

1. Introduction/Background/Motivation

In the 1980s, 8-bit consoles were king. These were characterized by limited color palettes and relatively simple 2D graphics. In the 1990s, 16-bit consoles took over and offered increased power, color palettes and the ability to display more complex graphics.

Despite huge advances in technology, retro-games from the 8- and 16-bit eras remain popular, as evidenced by the number of remakes, emulators, modern "Indie" games using pixel art and even specialist magazines dedicating to retro gaming.

Our experiment is based on the observation that the primary difference between 8- and 16-bit games (as exemplified by the NES and SNES, respectively) was in the fidelity of the graphics. Additionally, many of the graphical remasters today view the 16-bit era as the gold standard in pixel-based artwork, given that the graphical capabilities of the SNES still allowed artists to express themselves far more than the limited NES.

Our primary objective is to train two systems, one that can take in an 8-bit NES graphic and "up-convert" it to a realistic 16-bit version and another system that can take in a 16-bit SNES graphic and "down-convert" it to a realistic 8-bit version.

Another area of interest is in software emulators that are often used to breathe life into older games. For example, the Nintendo Switch provides a paid emulation service that allows players to access a library of older games. In some cases, the emulators provide graphical filters that allow the appearance of the game to be altered (e.g. a CRT filter, or a resolution up-scaling filter). However, currently the only way to improve the graphical color depth of a game is for artists to redraw all of the game's graphics.

If successful, this can allow the graphical content of a particular video game console to be translated into the style of another. Pixel artists are in very high demand and creating high quality pixel art is one of the largest financial strains that can be put on games, and is very time consuming/labor intensive. Pixel artists are often so hard to find that studios will save money by switching to 3D modeling as there are more artists and tools to assist them. This could allow for pixel artists to become more efficient, taking images from a previous game or console generation and translating it to the current project's generation. For instance, if one wished to modernize an 8-bit game, retroGAN enables someone to take the images from the original game and create new baseline screenshots for the sequel. Pixel artists would only need to tweak the translation instead of starting from scratch. There is also the interesting possibility of creating a real-time filter that could do this conversion "on-the-fly" as the game is being played. This conversion process is not constrained to translation between NES and SNES, and could be done on other consoles and generations given suitable datasets.

Datasets for NES/SNES images did not exist in a suitable form, so we created our own from various screenshot databases on the internet. We implemented our own preprocessing, which included unsupervised color clustering to remove image artifacts, clamping colors to more closely adhere to the console's original color palette, resizing and cropping as appropriate, and other noise reduction techniques. This provided us with a reasonably large set of images that were organized into quality bands based on how much preprocessing was required. This process is detailed in the appendix to this paper.

2. Approach

We attempted to implement translation between video game images from different generations. The primary problem was a lack of paired image data (an image from each generation) since each console generation consists almost solely of different games (with a small number of remakes). We thought CycleGAN had the potential to be a solution as it doesn't require paired data due to the cyclic process for training. That is, a NES image can be converted to a SNES fake by one leg of the cycle, and then the SNES fake can be converted back to a NES "fake fake" by the reverse leg. Then the round-trip images (the NES original and its doubly-converted "fake fake") can be compared for differences. In an ideal system, the real image and the "fake fake" image would be virtually identical. Both directions of the conversion process (NES→SNES and SNES→NES) can be cross-checked in this fashion.

We initially started by taking the driver code[1] for the original CycleGAN paper [2], implemented in Python with PyTorch. We then removed all of the code not directly related to the CycleGAN model and added our own datasets, pre-processing, augmentation, hyper-parameter tuning code, and metrics. Our code can be viewed at https://github.com/team-triforce/retroGAN.

Given the almost miraculous results in the literature that have been achieved using CycleGANs with unpaired datasets (and admittedly vast computing resources way beyond our reach), we were reasonably confident that we could use similar techniques to perform a non-trivial conversion between 8-bit and 16-bit screenshots of games. We expected the 16→8-bit conversion to be much simpler than the 8→16-bit conversion, but we were hopeful that we might be able to achieve at least some worthwhile results in the latter case.

While the CycleGAN architecture has been used to solve many problems, our dataset is unique and to our knowledge, no other work has properly explored unpaired image-to-image translation in this domain.

The main problem we expected was a lack of clean data. While there are plenty of screenshots of games available across the Internet, we could not find any pre-sorted collections of clean images. As such, we ended up writing several custom web scrapers and image processing tools to collect and homogenize screenshots from several game catalog websites.

Additionally, we had concerns if CycleGAN would be able capture the "pixel-perfect" constraints and requirements for the conversion process. Previously, CycleGANs have been typically used for experiments that have not required such exact results; for example, the well-known Horse to Zebra results were not conditioned on the exact shades of white and black of the zebra stripes.

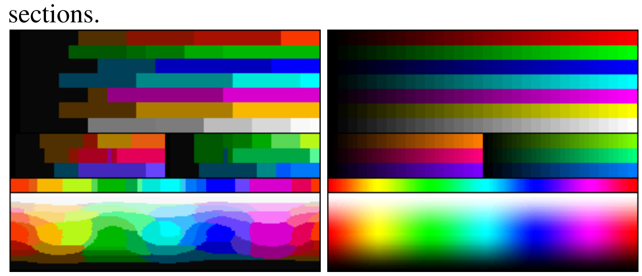
Conversely, in our situation, there are several palette restrictions that apply to the NES and SNES consoles. While the main difference between these consoles is their available color palettes, the NES also has several other graphical restrictions that place some difficultly in quantifying restrictions on the number of colors in a particular areas of the screen. The SNES also has similar restrictions, although nowhere near as severe. This was anticipated to be very difficult to generalize without magnitudes more data then we had available to us (approximately 100,000 images of varying quality between the two consoles). We didn't see great results in our first attempt, however after performing the additional pre-processing, we started seeing interesting results with convincing translations very early on.

2.1. NES / SNES Palette Considerations

The NES palette comprises 56 fixed colors[2], whereas the SNES is more flexible with a full 15-bit RGB palette (with 5 bits for each of the red, green and blue channels)[3], as shown in Figures 1a and 1b respectively.

As previously mentioned, there are some additional restrictions to how these colors can be used, but we do not cover them here; they are of more concern to emulator writers, and it was hoped that – given enough data – the CycleGAN would be able to figure these out for itself.

As such, for an effective conversion, the GAN must learn to conform to each palette. In the case of SNES→NES, this could be as simple as a naive nearest color reduction from the 15-bit SNES palette to the fixed NES palette. Similarly, for the NES→SNES conversion, the GAN could simply ensure that the chosen colors fit the 15-bit RGB restriction. However, we hoped for (and observed) more complex behaviors than this, implying that the GAN was able to somewhat successfully extract more of the stylistic differences between NES and SNES graphics. This will be discussed in later sections.



(a) NES 56 Color Palette

(b) SNES 15-bit Palette

Figure 1: Color palettes for NES and SNES

2.2. Generative Models and CycleGANs

For our main architecture, we chose CycleGAN for the many positives it brings. First, being a Generative Model, it brings us the ability to generate new models via sampling from our implicit density estimation. On top of that, we

[1] https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix, Commit Id 00d5574908eb66fe0127b32d7b030001453f21d0

[2] https://en.wikipedia.org/wiki/List_of_video_game_console_palettes

[3] https://en.wikipedia.org/wiki/List_of_monochrome_and_RGB_color_formats

also were drawn by the advantages of specifically Generative Adversarial Networks(GANs)[1]. GANs provide several benefits over other generative models, including not needing labeled data as GANs are unsupervised. They are also flexible on the types of data they ingest. Most importantly, since they sample from their density instead of doing any kind of averaging, GANs result in the sharpest images over other generative models. This is a very important property as retro graphics involve small, sharp pixel placement which makes this a vital quality for this dataset.

Finally, we chose CycleGAN[2], as it provides the ability to translate between two datasets without the need for paired images. Instead of the usual GAN architecture of a single generator and discriminator, the CycleGAN architecture uses mappings: G and F with the goal of having G learn a mapping from domain $X \rightarrow Y$ such that $G(X)$ is indistinguishable from the distribution Y using adversarial loss. However, due to the low constraints of unpaired data, a second, inverse mapping $F : Y \rightarrow X$ is created to induce a cycle consistency loss to push $F(G(X)) \approx X$, as shown:

$$G : X \rightarrow Y, F : Y \rightarrow X : F(G(X)) \approx X$$

These mappings are combined with two *cycle consistency losses* that can capture the intuition that translating from one domain to another and back again should result to something similar to the original input.

Additionally, an *identity loss* is used to provide color/hue stability. This is defined as $F(X) \approx X$ and $G(Y) \approx Y$. The *identity loss* is combined with the *cycle consistency loss* proportionally as determined by a bias hyperparameter.

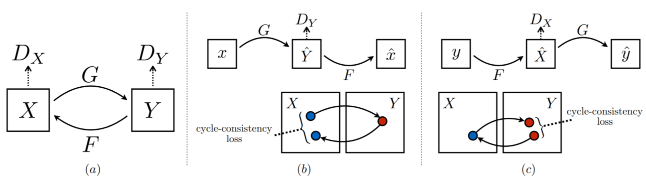


Figure 2: CycleGAN Architecture

3. Experiments and Results

The CycleGAN framework allowed for significant configurability of hyperparameters, and we took full advantage of the flexibility provided. As such, for our first pass success measure, we selected for the hyperparameters that showed the smallest amount of loss for at least *one* direction of the cycle. This gave us a shortlist of candidates to examine that we evaluated manually to determine which to investigate further. One interesting (but not entirely unexpected) observation we found was that the cycle performance was not even; a set of hyperparameters that performed well for the NES→SNES conversion would not necessarily perform well for the SNES→NES conversion, and vice versa.

For each promising candidate set, we then ran a customized metric to evaluate the final images for their adherence to the hardware restrictions of each console. We produced several iterations of this metric, before finally settling on Algorithm 1. This was applied as a post-training evaluation metric and was not a learned parameter.

This metric scores an image based on how closely the pixels match the target console palette modulated by the percentage of image pixels that match the target palette exactly. This modulation was necessary to compensate for the fact that the SNES palette has many more entries, and consequently, it was easier for the algorithm to score highly as any selected color was never too far away from a valid palette entry in RGB space. A perfect metric of either system would require accounting for hundreds of variables(pixel limit, per-pixel color palette limits, transparency limitations, max sprites per screen, etc), however this would be a task outside the scope of this paper and would heavily depend on domain knowledge, so we chose a metric that focuses on color palette, as it's a much more tractable task and is a metric that could be adapted to consoles other than just the NES/SNES.

In practice, we found that using the stricter NES metric produced more meaningful results; that is, for the SNES→NES conversion, we found that measuring the increase in value for this metric between the real SNES and fake NES image was a strong indicator of success. Conversely, for the NES→SNES conversion, the decrease in value of this metric was a good (although looser) indicator of success.

Using the hyperparameter search driver, each of the three authors ran a random hyperparameter search using the time available; once this was complete we first compared our results by the metric described above, selecting a shortlist of best candidates. We considered each direction of the cycle separately for the reasons mentioned previously. For each candidate, we performed a visual inspection of the output and reached a consensus on which of these had generated the best overall results. The final candidate from each cycle direction was then used to generate the images and graphs in the following sections.

3.1. SNES→NES Results

As expected, the SNES→NES conversion proved to be the most effective cycle leg. For a training group size of 2500 images from the best quality band, the averaged NES metric was 0.9848, indicating that across all of the training images, roughly 98% of the pixels conformed to the NES palette.

We selected several of the most aesthetically pleasing conversion images, and re-ran the NES metric on both the real and fake images, as shown in table 1. These results show that, while there was definite improvement, and hence learning, the network was unable to score the same metric as the training set. For a dataset size of 2500 (with a 90/10 train/test split), the averaged SNES metric was 0.6382, indicating that across all of the training images, roughly 64% of the pixels conformed to the NES palette. The specific dataset size was chosen due to training time constraints, and the resulting training graph is shown in figure 3.

Source SNES Image	Real	Fake
ActRaiser	0.0449	0.5190
Super Ghouls 'n Ghosts	0.0171	0.3330

Table 1: SNES→NES Results (NES Metric)

These results were generated using the hyperparameters shown in table 2. Note that only hyperparameters different than the defaults specified in the CycleGAN code are shown.

Hyperparameter	**Value**
Batch size	4
GAN Mode	lsgan
netG	unet_128
Pre-process	pixel double and crop
Epochs	50
Decay Epochs	10

Table 2: SNES→NES Hyperparameters

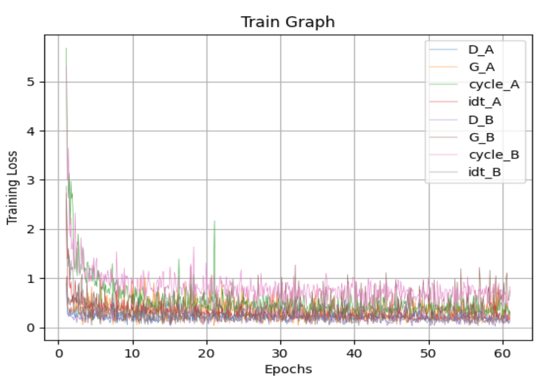


Figure 3: Training Graph with best SNES→NES results

The generator network used a U-Net 128 architecture internally, and the discriminator network used the default basic architecture. Figure 4 shows the general structure of a U-Net architecture[4]. The generator had 41.829×10^6 trainable parameters and the discriminator had 2.766×10^6. The "least squares" loss function was used by the discriminator (as determined by the *lsgan* hyperparameter choice for GAN Mode.

[4] Adapted from https://github.com/matthias-wright/cifar10-resnet

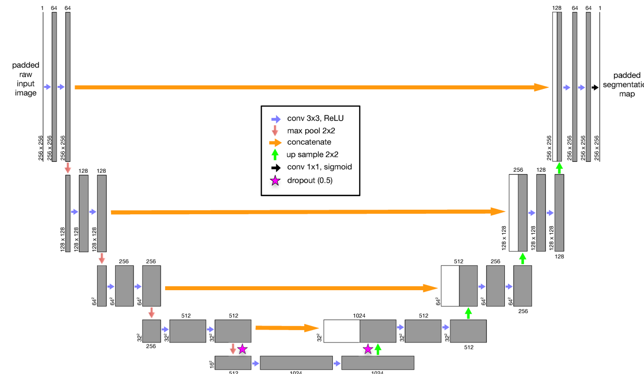
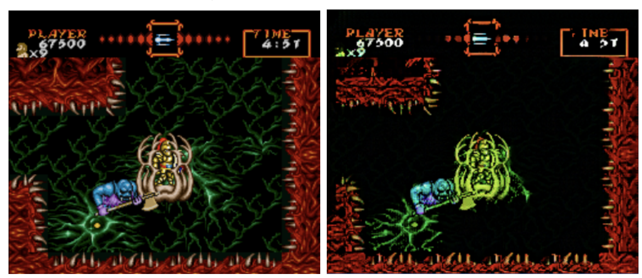


Figure 4: Example U-NET Architecture

(a) Real SNES Screenshot
(b) Fake NES screenshot

Figure 5: ActRaiser: SNES→NES



(a) Real SNES Screenshot
(b) Fake NES screenshot

Figure 6: Super Ghouls 'n Ghosts: SNES→NES

Despite the lower metric score, a visual examination of the results in figures 5a and 5b show that the fake image is clearly closer to the target aesthetic, and the conversion process appears to be more involved than a simple palette conversion. In particular, figure 6b seems to show that different conversion criteria have been applied to different areas of the image. If one compares the lower left brighter green area in figure 6a with the similar intensity green area just right of center, it appears that the lower left area is rendered brighter in 6b than the right of center area, even though the same areas in the source image are of similar intensity.

Overall these results are promising, although they are far from perfect. Since we are using an imperfect metric, the fact that we chose our final network based on the performance of that metric is inducing some level of bias towards color. As we stated before, to truly represent a NES game requires accounting for many additional constraints beyond color. However, since this is not a tractable metric we can create and our metric is centered only on color, it's reasonable that the network is prone to overfitting color at the cost of other features not reliant on color palette.

There is evidence that the network is learning beyond color though, as 5a shows that the NES conversion removed the foggy backdrop of the original image. This is very important, as drawing a foggy background in this example was mostly likely done using transparency on the SNES, which is something that the NES can't replicate as it didn't have enough spare memory to allow for it. This is evidence that the model was able to account beyond replicating the color palette and started understanding from NES data that effects like transparency aren't possible.

3.2. NES→SNES Results

For the NES→SNES conversion we performed an almost identical analysis. We selected several of the most aesthetically pleasing conversion images, and re-ran the stricter NES metric on both the real and fake images, as shown in table 3.

Source NES Image	Real	Fake
Crisis Force	1.0	0.0155
Ninja Kid	1.0	0.0157

Table 3: NES→SNES Results (NES Metric)

These results were generated using the hyperparameters shown in table 4. Note that only hyperparameters different than the defaults specified in the CycleGAN code are shown, and the resulting training graph is shown in figure 7.

Hyperparameter	**Value**
Batch size	4
GAN Mode	lsgan
netG	resnet_9
Pre-process	pixel double and crop

Table 4: NES→SNES Hyperparameters

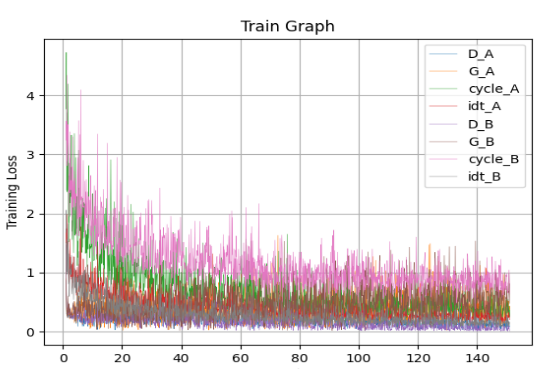


Figure 7: Training Graph with best NES→SNES results.

The generator network used a 9-block ResNet architecture internally, and the discriminator network used the default basic architecture. Figure 8 shows the general structure of a ResNet architecture[5]. The generator had 11.383×10^6 trainable parameters and the discriminator had 2.766×10^6. The "least squares" loss function was used by the discriminator (as determined by the *lsgan* hyperparameter selection for GAN Mode.

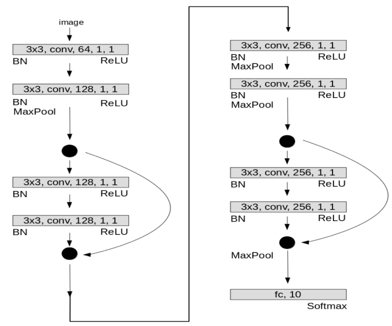
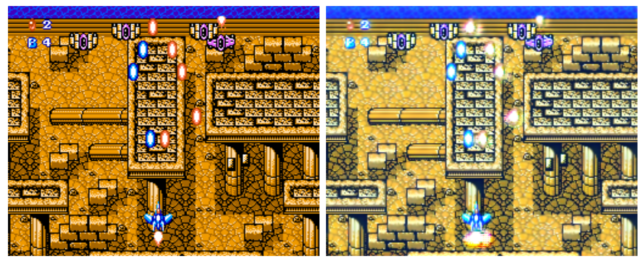
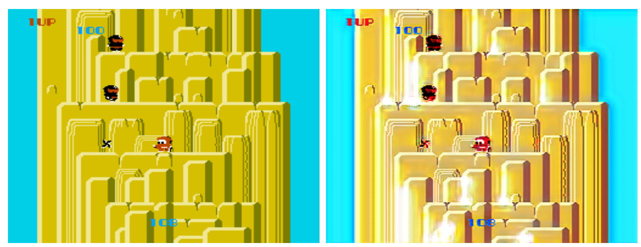


Figure 8: Example ResNet Architecture



(a) Real NES Screenshot (b) Fake SNES screenshot

Figure 9: Crisis Force: NES→SNES



(a) Real NES Screenshot (b) Fake SNES screenshot

Figure 10: Ninja Kid: NES→SNES

Although it is apparent that this leg of the conversion was not as successful as the reverse leg, it is still interesting that the results show that some selective conversion has taken place. Notably, figures 9 and 10 show that background areas tended to be lightened and blurred, bright spots tended to be blown out and made brighter, while areas of darker colors – particular those with black pixel outlines – tended to be left relatively untouched, implying that the network did at least extract some relevant feature information.

For two reasons we concluded that we underfit the model. First, the fake training images continued to improve as the training went on. At no point did the generated image's quality plateau. Second, we used smaller training sizes due to time constraints. Given more time we may have been able to use our entire dataset and fully train the model.

4. Conclusion And Future Work

Our results show that despite the complications, some promising results emerged from our experiments. As expected, the results for the SNES→NES conversion were better than the NES→SNES due to the comparative simplicity

[5]Adapted from https://github.com/matthias-wright/cifar10-resnet

of a down-conversion (where information loss isn't necessarily a problem) versus up-conversion, where information has to be synthesized from learned experience.

In essence, the former conversion is almost trivially easy for the CycleGAN compared to the latter.

With further experimentation and architecture tweaks, we believe that we would have been more successful with the NES→SNES conversion.

Examples of possible future work could include video-based training, using pixel-perfect screen captures from console emulation software. The use of video would hopefully help the CycleGAN perform stable modifications as the game progressed. If successful, this could be used to perform real-time up-conversion of games played in an emulator.

Additional follow-up work could include improvements to the scoring metrics to take into account the additional hardware restrictions, as well as the incorporation of the metrics into the respective loss functions.

Future work could also focus on expanding the consoles that the framework supports. For example, mapping from 16-bit to 32-bit or even mapping larger jumps from 16-bit to 64-bit. There would be added complexity to this, which may result in needing larger training sets or alternate loss functions.

Alternate loss functions in particular are an interesting area for further research. The CycleGAN architecture was built for the general problem on mapping images from one domain to another. However, for the specific problem of mapping images from one console generation to another, loss functions could be more precise. Others could research using the loss function to additionally model the console's graphical constraints, learning the exact color palette of each console generation.

In the short term, given more time, we would have liked to have explored the possibility of enforcing some of the palette constraints (particularly for the SNES→NES conversion) by modifying the output layer of the GAN so that, for example, each pixel in the output image was represented by a one-hot encoded palette entry. This would have resulted in an output layer of size $56 \times 256 \times 256 \approx 3.67 \times 10^6$ parameters, and would have ensured palette adherence, but may well have been significantly harder to train. This implementation would not have been feasible for the SNES, because it would have required approximately 2.147×10^9 parameters in the output layer.

Another area that we were unable to investigate due to time constraints was the idea of sequentially training the network with successive datasets; starting from a small and clean set and increasing in noise and size. This has been shown in the literature to help improve learning and generalization in some cases.

5. Appendixes

5.1. Dataset Preparation

Due to the lack of any readily available datasets for SNES and NES image, we had to create our own. This task was made more difficult due to the number of sources that do not have clean images (for example, badly scaled, artifact-laden and/or watermarked images). Ultimately, a web scraper was written that allowed us to extract screenshots from four separate websites: https://mobygames.com, https://www.video-games-museum.com, https://superfamicom.org and https://archive.org.

Each of these sites had a wide variety of images that required varying degrees of preprocessing. As such, the program performed cropping and rescaling as necessary, taking care to preserve pixel detail as much as possible. Next, any images for each console that had more colors than allowed were run through an auto-clustering algorithm to reduce the number of colors below the allowable threshold for that console. Finally, each image was then classified into one of three "quality bands" depending on the amount of pre-processing required and the fidelity of the final image. The best quality band was reserved for images that required no pre-processing or none other than cropping. The next quality band contained images that required only cropping, color-correction and/or scaling by a factor of exactly $2\times$, and the final quality band contained images that required scaling of $2.5\times$ after cropping. Any images that did not fit into these three categories were discarded.

After processing, the best quality band contained roughly $20,000$ images per console, with an overall total of $50,000+$ images per console across all three bands. Note that for the experiments in this paper, we used 2500 from the best quality band due to training time constraints.

5.2. Dataset Loading

In order to make effective use of the dataset, we had to write a custom PyTorch loader in order to take advantage of the quality bands. This was integrated into the CycleGAN loader to allow seamless handling of the images within the constraints of the existing code.

Additionally, this allowed us to implement additional on-the-fly image processing, and custom transforms such as pixel-doubling and color-clamping. Color clamping was used to ensure that an input image used the correct console palette by forcing the pixels of the image to conform the closest color in the appropriate console palette. Pixel doubling was a special case of the inbuilt zoom augmentation of CycleGAN that used nearest-neighbor scaling by a factor of $2\times$ rather than the default bicubic, non-integer scaling. This was necessary to preserve the pixel and color integrity of the original image.

$console\_palette \leftarrow$ target console color palette normalized RGB values
$max\_rgb \leftarrow$ corners of RGB space for $(i, j, k) \in i = \{0, 1\}, j = \{0, 1\}, k = \{0, 1\}$
$m_bias \leftarrow 1/$number of colors in target console color palette
$total\_score \leftarrow 0$
$num_images \leftarrow$number of candidate images

for each candidate image **do**
  $img\_rgb \leftarrow$ per pixel normalized RGB values
  $min\_dists \leftarrow$ min distances between img_rgb and $console\_palette$
  $max\_dists \leftarrow$ min distances between img_rgb and max_rgb values.
  $match\_pct \leftarrow \sum_{i=1..n}[1 \text{ if } (min\_dists_i < 1) \text{ else } 0]/n$
  $bias\_factor \leftarrow max(0, min(1, m\_bias + (1 - m\_bias) \times match\_pct)$
  $img\_score \leftarrow (\sum_{i=1..n}(max\_dists) - \sum_{i=1..n}(min\_dists))/\sum_{i=1..n}(max\_dists)$
  $total\_score \leftarrow total\_score + img\_score \times bias\_factor$
end for
return $total\_score/num\_images$

Algorithm 1: Metric for evaluating conversion quality

References

[1] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks, 2014. 3

[2] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. *CoRR*, abs/1703.10593, 2017. 2, 3