1 Introduction

Generating new fonts is a time-consuming and labor-intensive, especially in a language with a huge amount of characters like Chinese. Various deep learning models have demonstrated the ability to efficiently generate new fonts with a few reference characters of that style. This project aims to develop a few-shot cross-lingual font generator based on AGIS-Net and improve the performance metrics mentioned in Section 3. Our approaches include redesigning the encoder and the loss function. We will validate our method on multiple languages and datasets mentioned in Section 4.

2 Literature review

2.1 Generative Adversarial Network

Generative Adversarial Network is a framework for estimating generative models via the adversarial net, first proposed by Goodfellow et al. in 2014 [11], featuring two neural networks (generator and discriminator) competing against each other for a zero-sum game to achieve an optimized solution. Since its introduction, there are several focuses that aim to improve the performance of the generative models. Mirza et al. introduced conditional GAN that allows the addition of conditions on both the generator and discriminator in GANs [30]. Radford et al. introduced an unsupervised representational learning method for deep convolutional GANs [35]. Salimans et al. proposed an improved training technique for semi-supervised GANs to generate images that humans find more realistic [38]. Chen et al. proposed InfoGAN that maximizes the mutual information between a small subset of latent variables and the observations and learns disentangled information unsupervised [6]. Odena et al. introduced a method that employs label conditioning in image synthesis to produce photorealistic generated images with GANs [31].

Isola et al. proposed $Pix2Pix$, an image-to-image translation network based on GANs [16]. Zhu et al. refined the image-to-image translation problem by introducing a multimodal variant BicycleGAN and modeling a distribution of possible outputs in conditional GAN setting [50]. Miao et al. proposed a method to encourage the generator to explore minor modes with a regularization method to solve the mode collapse problem for conditional GANs [28]. To solve the problem that paired data are hard to obtain, Lee et al. proposed a method for using unpaired data with disentangled representations.
and Zhu et al. proposed Cycle-consistent GANs to use learn a mapping such that the distribution of translated images is indistinguishable from the target image distribution using an adversarial loss.

As the application of image generation is usually in situations where abundant training data is not available, more recent approaches have been focused on few-shot learning based image generation tasks. Clouâtre and Demers proposed FIGR that mediates the lack of training data with a GAN meta-trained by Reptile. Liu et al. proposed FUNIT, an unsupervised few-shot image-to-image translation framework. However, these methods have a problem that the generated images have trouble retaining the structure or orientation of the original. Saito et al. proposed COCO-FUNIT that computes the style embedding of the example images conditioned on the input image.

2.2 Font generation

Font generation is a well-studied field. Campbell and Kautz introduced the manifold of alphabetic font and learned new fonts by using existing font for interpolation. Yang et al. introduced a Generative Adversarial Network (GAN)-based approach in text style transfer. Hayashi et al. proposed a GAN-based method to generate new fonts from seen fonts while maintaining consistency among the generated fonts and diversity from seen fonts. More recently, studies in font generation have been focused on non-alphabetic languages such as Chinese, as the number of classes of characters is huge compared to alphabetic languages, thus a font generator provides feasibility in applications. Tian proposed a conditional adversarial network for Chinese font generation with one-hot encoding for font styles, but its application is limited to seen font styles. Zhang et al. proposed a method of separating style and content in font generation. Gao et al. proposed a GAN that encodes content and few samples of style and decodes to the new style based on shape and texture, and used a local discriminator in addition to the shape and texture discriminator. Chen et al. introduced a few-shot Chinese font generation method with deep meta-learning that utilizes the characteristics of existing fonts to avoid overfitting. Jiang et al. proposed a one-shot Chinese character generation framework.

One common approach to font generation is decomposing characters into smaller components and studying their localized features. This approach often results in better performance on characters with complex structures, such as Chinese characters which can be decomposed into approximately 500 radicals or 40 strokes.

DM-Font introduced the component-wise extractor and stored component features in dual memory. However, the model was only tested on simple language (Korean and Thai) with fixed component size and failed on language with complex glyphs such as Chinese characters. LF-Font tackled the problem by proposing low-rank factorization modules to generate component and style factors. RD-GAN and CC-Font both applied radical decomposition and succeeded in predicting characters of unseen components, but the former failed in the cross-lingual system. Calli-GAN encoded the component sequence using recurrent neural network and does not require component labels, but it failed on cross-lingual prediction or unseen styles and components. To generalize the model to a cross-lingual system, MX-Font applied component-conditioned methods and interpreted the component assignment problem as a graph matching problem. More recently, CG-GAN introduced the component-aware module with a simple generator that succeeded in cross-lingual generation, and it can be further extended to scene text editing.

Decomposing handwritten characters is another challenging problem. Specifically, personalized Chinese font needs to generate at least 3,000 most commonly used characters but only with few training characters. Previous works leverage CycleGAN to automatically generate calligraphy work with aesthetic values. However, this method suffers the mode collapse issue. Designing an efficient and accurate decomposing strategy is quite crucial in order to compensate for information loss. Zeng et al. introduced one-bit stroke encoding and a stroke-encoding reconstruction loss imposed on the discriminator to preserve the key mode information of a Chinese character. The stroke encoding successfully alleviates the issue in CycleGAN with improved preservation of strokes and diversity of generated character.
2.3 Style Transfer

Style transfer is the process of adapting the style of an image to another source image to produce a new image with the adapted style while preserving the content of the source image. Gatys et al. first introduced a convolutional neural network based method of image artistic style transfer [9]. Johnson et al. furthered this approach by utilizing feed-forward network for image translation and introduced a perpetual loss for training [18]. Huang and Belongie proposed a method that allows arbitrary style transfer in real time by adaptive instance normalization [14]. Li et al. added a pair of feature transforms, whitening and coloring embedded in the image reconstruction network to improve the capability of generalizing to unseen styles and improve generation quality [23]. Kotovenko et al. proposed a method to reduce the amount of content removed from the source image by introducing a content transformation block between the encoder and the decoder [21]. Tuygen et al. introduced a method to generate multiple images with a single image-style pair by utilizing deep correlational multimodel style transfer [41]. The methods in image style transfer has also been explored in the style transfer applications in other forms of signals. Huang et al. proposed a method for video style transfer based on feed-forward network for image style transfer [13]. Verma and Smith adapted the work by Gatys et al. for audio style transfer [42].

2.4 Similarity score

Many of the generative models for images tend to produce blurry images with low bound approximation or restriction on the distribution [10]. A popular loss like mean square error is not ideal for image quality assessment [43]. Structural similarity Index (SSIM) is a perceptual measure shown to be perfect for different generative models and autoencoders. Using SSIM as the loss metric can improve the perceptual quality of the generated images [43]. Furthermore, Koch et al. explored a remarkable approach to make use of a unique structure, Siamese Neural Network, to calculate the similarity score between inputs which can be used to train a powerful feature extractor based on metric learning [19].

3 Baseline model

We adopt the architecture of AGIS-Net [46] to be our baseline model as shown in Figure 1 and evaluate its performance using Fréchet Inception Distance (FID), Structural Similarity Index Measure (SSIM), and Pixel-level Accuracy (pix-acc).

3.1 Problem Formulation

Our goal is to generate a stylized glyph image with the provided content and a few sample images of the specified style. We need two sets of input: the content reference image \( x_C \) and the style reference input \( X_s \). The content reference image \( x_C \) is a binary image in standard font with minimal style information. Given that the stylized examples are usually limited, we use \( n \) to denote the size of the few-shot style reference set \( R_s \), and we randomly sample \( m \leq n \) images from the reference set as style reference input \( X_s \subseteq R_s \).

3.2 Baseline Selection

Before AGIS-Net, previous approaches either focuses on shape synthesis or were designed for texture transfer. Campbell and Kautz [3] built a font manifold for Latin glyphs’ outlines. However, it can fail when the complexity of glyphs greatly increases. Zeng et al. [47] attempted to utilize strokes from Chinese glyphs and learn to produce corresponding strokes for others but in the same style. However, it is not suitable for other scenarios like synthesizing Latin glyphs. Therefore, the most relevant work for this task is MC-GAN [32] which is the first architecture that solved learning styles of both texture and shape. Moreover, it is capable to do glyph shape synthesis and texture transfer as well. However, it is limited to 26 Latin capital letters as input, and it performs badly in generating other writing systems like Chinese characters. Thus, it’s definitely not the best choice as the baseline model for our task. AGIS-Net [46] can effectively solve the above-mentioned problems. Compared to MC-GAN [32], it has a wider application scenario. In other words, it can not only handle Latin glyphs but also Chinese and any other writing systems. Other competitors like BicycleGAN [49] which is a leading general-purpose image-to-image translation model and TETGAN [45] which is the state-of-the-art
where AGIS-Net consists of a generator and three discriminators, as shown in Fig. 1. The generator has two parallel working branches of encoders and decoders, where the encoders are responsible for extracting the content and style features independently, and the texture decoder generates the synthesized image collaboratively with the shape decoder. The output synthesized image is then fed into the shape and texture discriminators as negative samples during training, and the real glyph images are cut patched, and blurred to introduce more fake samples for the local discriminator. The local discriminator helps generate more realistic images with reduced noise and alleviates the problem of unbalanced positive and negative glyph images in the few-shot setting.

**3.3 Model Description**

AGIS-Net consists of a generator and three discriminators, as shown in Fig. [1](#). The generator has two parallel working branches of encoders and decoders, where the encoders are responsible for extracting the content and style features independently, and the texture decoder generates the synthesized image collaboratively with the shape decoder. The output synthesized image is then fed into the shape and texture discriminators as negative samples during training, and the real glyph images are cut patched, and blurred to introduce more fake samples for the local discriminator. The local discriminator helps generate more realistic images with reduced noise and alleviates the problem of unbalanced positive and negative glyph images in the few-shot setting.

**Generator:** Fig. [2](#) shows the architecture of the generator. A binary image with minimal style information is inputted to the content encoder, and a set of stylized images are randomly sampled from the few-shot reference set as the input to the style encoder. The content and style features are extracted from several down-sampling convolution layers and skipped connected to the input of corresponding decoder layers as shown in [3](#). The shape decoder concatenates the output from the previous layer and the extracted content and style features from the corresponding encoder layer to generate the shape image \( y_{gray} \). The texture decoder further combines the texture information with the shape information through concatenation, and the synthesized image \( y \) is produced by feeding the concatenated shape image \( y_{gray} \) and texture information to a convolution layer.

**Objective Function:** The objective function consists of four different loss functions: the adversarial loss, the \( L_1 \) loss, the contextual loss, and the local texture refinement loss

\[
L(G, D_{sha}, D_{tex}, D_{local}) = L_{adv} + L_1 + L_{CX} + L_{local},
\]

where \( G \) is our generator, \( D_{sha}, D_{tex}, \) and \( D_{local} \) represent the shape, texture, and local discriminator respectively. We train our model by optimizing

\[
\min_G \max_{D_{sha}, D_{tex}, D_{local}} L(G, D_{sha}, D_{tex}, D_{local}).
\]

- **Adversarial Loss:** We train the generator \( G \) and two discriminators \( D_{sha} \) and \( D_{tex} \) based on the following adversarial loss. \( y_{gray} \) is the gray-scale image generated from the shape decoder, \( y \) is the synthesized image, \( t_s \) is the ground truth image, and \( t_{gray} \) is the gray-scaled ground truth image used to train the shape discriminator. \( \lambda_{adv,sha} \) and \( \lambda_{adv,tex} \) are the weights set to 1.0 according to [46].

\[
L(D_{sha}) = \mathbb{E}_{t_{gray}} [\log(1 - D_{sha}(t_{gray}))] + \mathbb{E}_{y_{gray}} [\log(1 - D_{sha}(y_{gray}))]
\]

\[
L(D_{tex}) = \mathbb{E}_{t_{tex}} [\log(1 - D_{tex}(y_{gray}))] + \mathbb{E}_{y} [\log(1 - D_{tex}(y))]
\]

\[
L_{adv} = \lambda_{adv,sha}\mathbb{E}_{y_{gray}} [\log(1 - D_{sha}(y_{gray}))] + \lambda_{adv,tex}\mathbb{E}_{y} [\log(1 - D_{tex}(y))].
\]

- **\( L_1 \) Loss:** \( L_1 \) Loss helps stabilize the training. We simply combine the \( L_1 \) loss of the gray-scale image and the texture image with weights \( \lambda_{L_1gray} = 50.0 \) and \( \lambda_{L_1tex} = 100.0 \). These weights are set to zero for the unseen data.

\[
L_1 = \lambda_{L_1gray}\mathbb{E}_{y_{gray}}\mathbb{E}_{\tilde{y}_{gray}}\|y_{gray} - \tilde{y}_{gray}\|_1 + \lambda_{L_1tex}\mathbb{E}_{y,\tilde{y}}\|y - \tilde{y}\|_1.
\]

where \( \tilde{y} \) and \( \tilde{y}_{gray} \) are ground truth images of \( y \) and the gray-scale version of the ground truth, and we will reuse them in the following loss functions.

- **Contextual Loss:** Contextual loss measures the similarity between feature map collections of the images, and it focuses on high-level style features. The similarity \( CX \) between \( x_i \), the \( i \)-th feature map of image \( X \), and \( y_j \), the \( j \)-th feature map of image \( Y \) is defined as the normalized exponential of the shifted normalized cosine distances

\[
CX_{ij} = \frac{w_{ij}}{\sum_k w_{ik}}, \hat{d}_{ij} = \frac{d_{ij}}{\min_k d_{ik} + \epsilon}, w_{ij} = \exp \left( \frac{1 - \hat{d}_{ij}}{h} \right),
\]
Figure 1: AGIS-Net Architecture. The upper part is the generator consisting of two parallel-working encoders and decoders, and the lower three are discriminators.

\[
CX(X, Y) = \frac{1}{N} \sum_j \max_i CX_{ij},
\]
where \(d_{ij}\) is the cosine distance between \(x_i\) and \(y_j\), \(h\) and \(\epsilon\) are hyper-parameters set to 0.5 and 1e - 5 according to [29].

We use pre-trained VGG19 to extract features. \(\phi^l\) denotes the extracted features from the \(l\)-th layer of VGG19, and \(L\) is the total number of layers. In our experiment, we use \(\lambda_{CX_{gray}} = 15.0\) and \(\lambda_{CX_{tex}} = 25.0\) for the weights. The contextual loss is formulated as

\[
L_{CX} = \lambda_{CX_{gray}} \left( -\frac{1}{L} \sum_l \log(CX(\phi^l(y_{gray}), \phi^l(\hat{y}_{gray}))) \right) + \lambda_{CX_{tex}} \left( -\frac{1}{L} \sum_l \log(CX(\phi^l(y), \phi^l(\hat{y}))) \right).
\]

**Local Textual Refinement Loss:** The local discriminator \(D_{local}\) takes the cut patched real images \(p_{real}\) as positive samples, the blurred real images \(p_{blur}\) and our synthesized patches \(p_y\) as negative samples. We set the weights \(\lambda_{local} = 1.0\) based on [46].

\[
L(D_{local}) = \mathbb{E}_{p_{real}}[\log(D_{local}(p_{real}))] + \mathbb{E}_{p_{blur}}[\log(1 - D_{local}(p_{blur}))] + \mathbb{E}_{p_y}[\log(1 - D_{local}(p_y))],
\]

\[
L_{local} = \lambda_{local}\mathbb{E}_{p_y}[\log(1 - D_{local}(p_y))].
\]

### 3.4 Evaluation Metric

To evaluate the model performance, we adopt three commonly-used metrics in image generation tasks: Fréchet Inception Distance (FID), Structural Similarity Index (SSIM), and Pixel-level Accuracy (pix-acc).

**Fréchet Inception Distance (FID)**

FID compares the probability distributions of feature vectors. FID between the fake image distribution \(x\) and the ground truth image distribution \(y\) is computed as

\[
FID = \|\mu_x - \mu_y\|^2 + \text{Tr}(C_x + C_y - 2 \times \sqrt{C_x \cdot C_y}),
\]
where \(\mu_x\) and \(C_x\) are the mean and covariance matrix of the feature vectors distribution \(x\). We use the module "pytorch-fid" to generate our FID scores.
Figure 2: AGIS-Net Generator

Figure 3: AGIS-Net Generator Submodule
Table 1: Evaluation Metrics of AGIS-Net and our baseline model

| Evaluation Metrics | AGIS-Net | Baseline |
|--------------------|----------|----------|
| FID                | 74.567   | 91.4947  |
| SSIM               | 0.7389   | 0.6722   |
| pix-acc            | 0.6241   | 0.3917   |

Figure 4: MSE of test dataset

Structural Similarity Index (SSIM)

SSIM measures the structural similarity between the synthesized image $x$ and the ground truth image $y$ by

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

where $\mu_x$ and $\mu_y$ are the pixel sample mean of $x$ and $y$; $\sigma_x$, $\sigma_y$, and $\sigma_{xy}$ are the variance of $x$, $y$, and the covariance of $x$ and $y$; $c_1$ and $c_2$ are constants to avoid instability when the denominator is small.

In our evaluation, we adopt “skimage.metrics” package to evaluate the SSIM score.

Pixel-level Accuracy (pix-acc)

$$PA = \frac{\sum_{j=1}^{h} n_{jj}}{\sum_{j=1}^{k} t_j},$$

where $n_{jj}$ denotes the number of correctly classified pixels in class $j$, and $t_j$ is the number of pixels labelled as class $j$. We use gray-scale image for the evaluation, and thus the class is binary. Pixel-level accuracy is then averaged to evaluate the overall quality of the synthesized image.

4 Dataset

Gao et al. proposed a large-scale dataset using professional-designed fonts in different shape and texture styles[46]. We’ll use it to validate if our method is effective and extendable at the first stage. CASIA also provides standard datasets for handwritten Chinese character recognition[24]. The data has been annotated at character level, so it’s preferable to be tested on for evaluating performance metrics. For English glyph images, we use the dataset proposed by Azadi et al. [1]. Moreover, regarding plain context inputs we will take up the average font style as common as possible for Chinese characters and Code New Roman as MC-GAN [32] for English letters.

5 Baseline Implementation Completeness

From the $L_1$ losses computed during fine-tuning shown in Figure 7, we observed that our baseline model got almost the same performance as stated in the original paper[46]. We also compare the performance of the baseline model with AGIS-Net (setting $m=7$, $n=2$) using the evaluation metrics
Figure 5: pixel-level accuracy of test dataset

Figure 6: SSIM of test dataset

Figure 7: L1 Loss in Fine-Tuning Stage
used in their paper which are FID, SSIM, and pixel-level accuracy. Higher values of SSIM and pix-acc are better, whereas for FID, the lower the better. We didn’t measure the inception score of our results since it cannot directly reflect the quality of our synthesized glyph images. As shown in Table 1, we achieved roughly the same performance in terms of SSIM. Regarding FID, the results are close, but for pix-acc we still need to improve our baseline model to match the ideal performance. An example of a set of generated font is show in Figure 8.

6 Proposed Extensions

To extend our model, we consider integrating some transformer-based vision models into our model to enhance the effectiveness of feature extraction. To be more specific, we plan to replace the encoder with BEiT [2] and Swin Transformer [26]. BEiT follows BERT developed in the natural language processing area. The experimental results show that its architecture achieves competitive results on image classification and semantic segmentation as provided in their findings [2]. Swin Transformer can be served as a general-purpose backbone for computer vision tasks. The qualities of Swin Transformer make it compatible with various vision tasks as stated in [26]. Furthermore, the hierarchical design and the shifted window approach may also be beneficial for our generator. By doing experiments and an ablation study on these two different architectures, we hope to figure out whether they are suitable for our task. Moreover, AGIS-Net leverages pre-trained VGG19 to extract font embeddings. Taking the overall model size into consideration, we may need to find other efficient alternative models since VGG19 seems too large compared to the part of the generative network in our model. ConvNeXt[27] and EfficientNet [39] seem to be good choices to get started on with not much loss of accuracy and a great reduction in the model size.

References

[1] Samaneh Azadi, Matthew Fisher, Vladimir Kim, Zhaowen Wang, Eli Shechtman, and Trevor Darrell. Multi-content gan for few-shot font style transfer, 2017.
[2] Hangbo Bao, Li Dong, Songhao Piao, and Furu Wei. Beit: Bert pre-training of image transformers, 2021.
[3] Neill D. F. Campbell and Jan Kautz. Learning a manifold of fonts. ACM Trans. Graph., 33(4), jul 2014.
[4] Junbum Cha, Sanghyuk Chun, Gayoung Lee, Bado Lee, Seonghyeon Kim, and Hwalsuk Lee. Few-shot compositional font generation with dual memory, 2020.
[5] Bo Chang, Qiong Zhang, Shenyi Pan, and Lili Meng. Generating handwritten chinese characters using CycleGAN. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE, mar 2018.
[6] Xi Chen, Yan Duan, Rein Houwhoof, John Schulman, Ilya Sutskever, and Pieter Abbeel. Infogan: Interpretable representation learning by information maximizing generative adversarial nets, 2016.
[7] Xu Chen, Lei Wu, Minggang He, Lei Meng, and Xiangyu Meng. Milfont: Few-shot chinese font generation via deep meta-learning. In Proceedings of the 2021 International Conference on Multimedia Retrieval, ICMR ’21, page 37–45, New York, NY, USA, 2021. Association for Computing Machinery.
[8] Louis Clouatre and Marc Demers. Figr: Few-shot image generation with reptile, 2019.
[9] Leon A Gatys, Alexander S Ecker, and Matthias Bethge. Image style transfer using convolutional neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2414–2423, 2016.
[10] Benyamin Ghojogh, Fakhri Karray, and Mark Crowley. Theoretical insights into the use of structural similarity index in generative models and inferential autoencoders. In Lecture Notes in Computer Science, pages 112–117. Springer International Publishing, 2020.
[11] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K.Q. Weinberger, editors, Advances in Neural Information Processing Systems, volume 27. Curran Associates, Inc., 2014.

[12] Hideaki Hayashi, Kohtarou Abe, and Seiichi Uchida. Glyphgan: Style-consistent font generation based on generative adversarial networks. CoRR, abs/1905.12502, 2019.

[13] Haozhi Huang, Hao Wang, Wenhan Luo, Lin Ma, Wenhao Jiang, Xiaolong Zhu, Zhifeng Li, and Wei Liu. Real-time neural style transfer for videos. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 783–791, 2017.

[14] Xun Huang and Serge Belongie. Arbitrary style transfer in real-time with adaptive instance normalization. In Proceedings of the IEEE international conference on computer vision, pages 1501–1510, 2017.

[15] Yaoxiong Huang, Mengchao He, Lianwen Jin, and Yongpan Wang. Rd-gan: Few/zero-shot chinese character style transfer via radical decomposition and rendering. In Andrea Vedaldi, Horst Bischof, Thomas Brox, and Jan-Michael Frahm, editors, Computer Vision – ECCV 2020, pages 156–172, Cham, 2020. Springer International Publishing.

[16] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A. Efros. Image-to-image translation with conditional adversarial networks, 2016.

[17] Haochuan Jiang, Guanyu Yang, Kaizhu Huang, and Rui Zhang. W-net: One-shot arbitrary-style chinese character generation with deep neural networks. In Long Cheng, Andrew Chi Sing Leung, and Seiichi Ozawa, editors, Neural Information Processing, pages 483–493, Cham, 2018. Springer International Publishing.

[18] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In European conference on computer vision, pages 694–711. Springer, 2016.

[19] Gregory Koch, Richard Zemel, and Ruslan Salakhutdinov. Siamese neural networks for one-shot image recognition. 2015.

[20] Yuxin Kong, Canjie Luo, WeiHong Ma, Qiuyan Zhu, Shenggao Zhu, Nicholas Yuan, and Lianwen Jin. Look closer to supervise better: One-shot font generation via component-based discriminator, 2022.

[21] Dmytro Kotovenko, Artsiom Sanakoyeu, Pingchuan Ma, Sabine Lang, and Bjorn Ommer. A content transformation block for image style transfer. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10032–10041, 2019.

[22] Hyojin Park, YoungJoon Yoo, and Nojun Kwak. Mc-gan: Multi-conditional generative adversarial network for image synthesis, 2018.

[23] Jangkyoung Park, Ammar Ul Hassan, and Jaeyoung Choi. Ccfont: Component-based chinese font generation model using generative adversarial networks (gans). Applied Sciences, 12(16), 2022.
[34] Song Park, Sanghyuk Chun, Junbum Cha, Bado Lee, and Hyunjung Shim. Few-shot font generation with localized style representations and factorization, 2020.

[35] Song Park, Sanghyuk Chun, Junbum Cha, Bado Lee, and Hyunjung Shim. Multiple heads are better than one: Few-shot font generation with multiple localized experts, 2021.

[36] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks, 2015.

[37] Kuniaki Saito, Kate Saenko, and Ming-Yu Liu. Coco-funit: Few-shot unsupervised image translation with a content conditioned style encoder, 2020.

[38] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training gans, 2016.

[39] Mingxing Tan and Quoc V. Le. Efficientnet: Rethinking model scaling for convolutional neural networks. 2019.

[40] Prateek Verma and Julius O Smith. Neural style transfer for audio spectograms. arXiv preprint arXiv:1801.01589, 2018.

[41] Zhou Wang and Alan C. Bovik. Mean squared error: Love it or leave it? a new look at signal fidelity measures. IEEE Signal Processing Magazine, 26(1):98–117, 2009.

[42] Shuai Yang, Jiaying Liu, Wenjing Wang, and Zongming Guo. Tet-gan: Text effects transfer via stylization and destylization. In AAAI Conference on Artificial Intelligence, 2019.

[43] Yexun Zhang, Ya Zhang, and Wenbin Cai. Separating style and content for generalized style transfer. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 8447–8455, 2018.

[44] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. Toward multimodal image-to-image translation, 2017.

[45] Jinshan Zeng, Qi Chen, Yunxin Liu, Mingwen Wang, and Yuan Yao. Strokegan: Reducing mode collapse in chinese font generation via stroke encoding. 2020.

[46] Yexun Zhang, Ya Zhang, and Wenbin Cai. Separating style and content for generalized style transfer. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 8447–8455, 2018.