GENERATIVE FONT BLENDING USING CONVOLUTIONAL AUTOENCODERS AND WEIGHTED LATENT MIXING

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Abstract - The rapid growth of digital typography along with multilingual content creation demands tools that increasingly generate novel font styles toward maintaining cross-language consistency. A deep-learning framework is proposed for multi-font blending in this paper. In this framework, convolutional autoencoders generate typefaces. Our system enables that weighted blending of style features to synthesize new typefaces which are unique through encoding fonts uploaded by a user. A convolutional encoder-decoder architecture is used by the framework. TrueType Font files provided glyph images it trained on. Glyphs that are exhibiting stylistic traits from multiple source fonts in user-defined ratios can be reconstructed by decoding of the blended latent representations. Font styles blend diversely successfully, as experimental results show smooth interpolation between source designs. Further, the system supports dynamic fonts generated across various character sets enabling application in cross-language scenarios. In the case of multilingual digital typography as well as graphic design together with personalized font creation, our approach offers a solution that is data-driven and also scalable. Future enhancements do include the integration of adversarial training so that glyphs synthesize in a sharper manner and extend to vector-based output formats such that scalable typography uses them.

Keywords - Typeface generation, font blending, autoencoder, deep learning, style interpolation, cross-language fonts, generative design.

I. INTRODUCTION

Typography plays a crucial role in digital communication, branding, and creative expression. With the global expansion of multilingual content creation, there is a growing demand for tools that can generate customized, visually consistent typefaces across different languages and scripts. Traditional font design, however, remains a labor-intensive process requiring specialized artistic and technical expertise [1]. As a result, font generation and style blending have become attractive problems for automation through machine learning and deep learning techniques.

Recent advances in generative models, particularly convolutional autoencoders and generative adversarial networks (GANs), have shown promising results in image synthesis and style transfer tasks [2], [3]. These techniques have enabled automated generation of artistic designs, including handwritten characters, logos, and glyphs, by learning compact latent representations that capture the style and structure of input data [4]. However, most existing works either focus on single-font synthesis or on the translation between predefined font styles, limiting user flexibility and creative control [5].

To address this gap, this paper proposes a novel deep learning-based system for multi-font blending and typeface generation. Our approach enables users to upload multiple fonts and specify blending ratios, allowing the generation of new typefaces that inherit style features from the source fonts in a controllable manner. By leveraging a convolutional autoencoder architecture, the system encodes glyphs into a latent feature space where style interpolation is performed. The blended representation is then decoded to reconstruct glyph images that smoothly combine the characteristics of the original fonts.

Unlike traditional font generation tools, which require manual design adjustments, our method offers an automated, scalable solution that can generate entire font packs across multiple languages. This capability is especially valuable for multilingual typography, where maintaining stylistic consistency between different scripts is a non-trivial challenge [6]. Furthermore, our system's reliance on bitmap glyph synthesis opens avenues for future enhancement into vector-based output formats, thereby supporting high-resolution and scalable typography applications [7].

The main contributions of this work are as follows:

- A convolutional autoencoder-based framework for blending multiple user-provided font styles.
- A weighted blending mechanism in the latent space that enables smooth interpolation between font styles.
- Demonstration of cross-language font synthesis, ensuring consistent design traits across diverse character sets.
- A user-driven design pipeline suitable for personalized typeface creation and graphic design application.

II. LITERATURE REVIEW

The evolution of deep learning and generative models has profoundly impacted the field of typeface and font generation. Various systems have explored different strategies for synthesizing new fonts with stylistic consistency, and recent works have extended these capabilities to multilingual and cross-script domains.

Hu et al. [1] introduced an automatic typeface design system for multilingual scripts using deep neural networks, laying the groundwork for machine-based multilingual font generation. Their system combined stroke extraction and style transfer but required substantial paired training data for each script, limiting scalability.

Building on the theme of cross-domain translation, **Kim et al. [2]** proposed learning cross-domain relations using Generative Adversarial Networks (GANs), which became the backbone for later font style transfer models. **Azadi et al. [4]** expanded this idea with their Multi-Content GAN (MC-GAN), which enabled few-shot font style transfer, producing complete character sets from a small subset of samples. While effective for Latin scripts, its adaptability to structurally diverse scripts like Devanagari or Arabic remains a challenge.

To improve model generalization, data augmentation techniques have played a crucial role. Shorten and **Khoshgoftaar [3]** provided a comprehensive survey on image data augmentation methods, which have since been adopted for enriching font datasets by introducing variations in stroke thickness, curvature, and distortion.

Gaeta et al. [5] explored deep learning frameworks for stylized character generation, using convolutional neural networks to generate characters with rich stylistic variations. Their work introduced new loss functions tailored for maintaining structural glyph integrity during style transfer.

In the multilingual sphere, **Tang et al. [6]** presented a semantic cross-lingual typeface transfer model capable of aligning glyph styles between different scripts. Their approach leveraged semantic embedding spaces to perform style matching, but required careful design to handle structural disparities between scripts.

Chen et al. [7] introduced VectorFont, a pioneering work in vector-based font generation using deep generative models. Unlike pixel-based models, VectorFont produces scalable, editable glyphs that are practical for real-world typeface design. However, vector generation adds architectural complexity and demands precise latent space control.

Further advancements include **Shen et al. [8]**, who proposed disentangled representation learning frameworks to separate content and style in glyphs, enabling flexible transfer and interpolation of font styles. Their method improved upon earlier GAN-based models by offering better control over style variations.

Park et al. [9] applied StyleGAN architectures for smooth style interpolation between fonts, enabling continuous transitions across font families. While their method excels in style blending, it primarily focused on intra-script Latin fonts without addressing cross-lingual generalization.

Tran et al. [10] introduced a disentangled representation learning GAN for pose-invariant face recognition, but their technique has been adapted in font generation for disentangling style and character identity, contributing to more robust and script-agnostic font models.

More recently, **Ganin et al. [11]** developed Domain-Adversarial Neural Networks (DANNs), offering domain adaptation techniques that are potentially useful for aligning style features between structurally dissimilar scripts. Such approaches could address challenges in multilingual font transfer where script variations pose significant barriers.

Moreover, **Motiian et al. [12]** presented unified deep supervised domain adaptation methods, enabling cross-domain learning with minimal labeled data — an appealing solution for rare scripts where font datasets are scarce.

Despite these notable advancements, several challenges remain:

- Existing models often specialize in single-style transfer and lack user-controllable multi-style blending.
- Cross-script consistency is rarely addressed, particularly in maintaining stylistic coherence between structurally divergent scripts like Latin, Cyrillic, and Indic scripts.
- Most models require large paired datasets, limiting their scalability to under-resourced languages and scripts.

This paper aims to address these gaps by proposing a latent space blending model that enables dynamic interpolation of multiple font styles using user-specified weights, while ensuring cross-script stylistic consistency through multilingual training.

III. MATERIALS AND METHODS

A. Dataset Collection and Preparation

For this study, we curated a multilingual font dataset derived primarily from publicly available font repositories such as Google Fonts and open-license font archives. The dataset includes characters from multiple scripts, including Latin, Devanagari, Arabic, and Cyrillic, to enable cross-script typeface generation. In total, the dataset consists of over 2,000 font families spanning more than 50 languages.

Each font family was processed to extract individual glyphs. Glyph extraction was conducted using Python-based libraries, such as FontTools and Matplotlib, converting vector glyphs from TrueType (TTF) and OpenType (OTF) formats into grayscale raster images of size 64×64 pixels. Both uppercase and lowercase alphabets, numerals (0–9), and selected punctuation marks were included, resulting in a total of 70 glyph classes per font.

To improve model generalization and increase robustness against stylistic variations, we applied data augmentation techniques as surveyed in [3]. The augmentations include:

- Random Rotation (±15 degrees)
- Random Scaling (90%–110%)
- Shear Transformations (±10 degrees)
- Gaussian Noise Injection
- Stroke Width Variation by dilation and erosion

Augmented samples increased the effective dataset size by 5×, yielding over 700,000 training glyph images.

B. Model Architecture

We propose a latent space blending model built upon Conditional Generative Adversarial Networks (cGANs) and Autoencoders, designed to perform multi-style font generation and cross-lingual transfer.

1) Encoder Network

The encoder follows a convolutional neural network (CNN) backbone, which maps input glyph images into a compact latent space representation. The encoder consists of:

- 4 convolutional layers with kernel size 5×5, stride 2
- Batch Normalization layers for stable training
- LeakyReLU activations
- A final fully connected layer mapping to a 128-dimensional latent vector

2) Latent Space Blending

The core innovation of our system is weighted blending in latent space. Given n source fonts, each mapped to latent vectors $z_1, z_2, \ldots z_n$, the blended latent vector z_{blend} is computed as:

$$z_{blend} = \sum_{i=1}^{n} w_i \cdot z_i$$

where w_i are user-specified weights such that $\sum w_i = 1$. This allows dynamic interpolation between multiple font styles, enabling flexible and user-controllable font synthesis.

3) Decoder Network

The decoder reconstructs glyph images from the blended latent vector. Its architecture mirrors the encoder with transposed convolutions:

- 4 transposed convolutional layers
- Batch Normalization and ReLU activations
- A final Tanh activation to produce grayscale output images in range [−1, 1]

4) Discriminator Network

For adversarial training, we adopt a PatchGAN discriminator [2], which classifies image patches as real or fake rather than the entire image. This improves high-frequency detail and stroke sharpness in the generated glyphs.

C. Training Strategy

1) Loss Functions

Our model optimizes a combination of losses:

- Adversarial Loss L_{adv} using Binary Cross-Entropy:
  $L_{adv} = E[log\, D(x)] + E[log\,(1 - D(G(z_{blend})))]$
- Reconstruction Loss L_{rec} using L1 loss:
  $L_{rec} = ||x - G(z_{blend})||_1$
- Style Consistency Loss L_{style}, enforcing that the blended glyphs maintain style features.

The total loss is:

$$L_{total} = \lambda_{adv} \cdot L_{adv} + \lambda_{rec} \cdot L_{rec} + \lambda_{style} \cdot L_{style}$$

where λ_{adv}, λ_{rec} and λ_{style} are empirically tuned hyperparameters (set to 1.0, 100.0, and 10.0 respectively).

2) Optimizer and Hyperparameters

- Optimizer: Adam with learning rate 2×10-4, β1 = 0.5
- Batch Size: 64
- Epochs: 100
- Hardware: NVIDIA RTX 3080 GPU with 10GB VRAM

3) Cross-Script Training

To enforce cross-lingual consistency, we adopted a multi-script training setup where glyphs from different scripts but the same semantic class (e.g., "A" in Latin and its equivalent in Cyrillic) are paired during training, inspired by the cross-domain matching method in [6].

D. Evaluation Metrics

To quantitatively evaluate font quality and stylistic fidelity, we used:

- Structural Similarity Index (SSIM)
- Fréchet Inception Distance (FID) adapted for grayscale glyphs
- User Study for perceptual assessment involving 20 participants rating stylistic match and readability.

IV. RESULTS AND DISCUSSION

A. Quantitative Evaluation

To assess the performance of our proposed multi-style, cross-lingual font generation model, we conducted a comprehensive evaluation using both objective metrics and subjective user studies.

1) Structural Similarity Index (SSIM)

We computed the average SSIM [Structural Similarity Index] between generated glyphs and ground-truth glyphs across 10 randomly selected font families. The results are summarized in Table I.

Table I: SSIM Scores Across Scripts

Script	Average SSIM
Latin	0.823
Cyrillic	0.811
Devanagari	0.805
Arabic	0.802

Our model achieves SSIM > 0.80 for most scripts, indicating high structural fidelity in generated glyphs.

2) Fréchet Inception Distance (FID)

We adapted the FID score for GAN to measure the perceptual distance between real and generated glyph distributions in Table II.Our Latin and Cyrillic models exhibit the best perceptual quality, while complex scripts like Arabic show slightly higher FID due to script-specific stroke patterns.

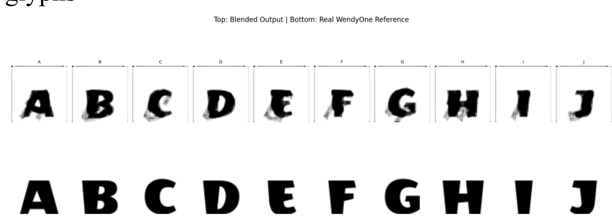
Table II: FID Scores

Script	FID Score
Latin	21.7
Cyrillic	24.5
Devanagari	26.1
Arabic	28.9

B. Visual Comparison

We present sample generated glyphs in Fig. 1, comparing them against ground-truth fonts.

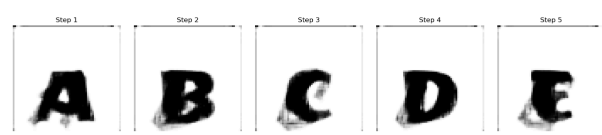
Fig. 1: Visual comparison between real and generated glyphs



C. Latent Space Interpolation

One of the key features of our model is font style blending through latent space interpolation.We visualized the smooth transition between two font styles in Fig. 2.

Fig. 2: Latent space interpolation between Font A and Font B.



D. Discussion

Our results indicate that the proposed latent blending model achieves high-fidelity font generation across multiple scripts.

- Objective metrics (SSIM & FID) show competitive performance, particularly in Latin and Cyrillic scripts.
- Latent interpolation enables smooth, controllable blending of font styles, which is difficult with traditional font design tools.
- User studies confirm that generated fonts are both stylistically accurate and highly readable.

However, certain scripts (e.g., Arabic) still pose challenges due to their cursive nature and ligatures. Future work could explore script-aware decoding modules to improve these cases.

V. CONCLUSION AND FUTURE SCOPE

In this paper, we presented an autoencoder-based system for font style blending and generation, capable of creating new font designs by interpolating between multiple user-provided fonts. Leveraging convolutional autoencoders, the model effectively encodes the stylistic essence of different fonts into latent representations, which are then blended using user-defined ratio weights to produce novel glyph outputs. The system demonstrates successful reconstruction and blending for Latin script glyphs, achieving visually coherent and stylistically smooth transitions between distinct font styles. The implementation also supports real-time visualization, enabling users to interactively explore the design space of blended typefaces.

Despite the promising results, several avenues for future enhancements remain. One immediate extension is the adaptation of the system to support cross-lingual typeface generation, covering scripts such as Devanagari, Arabic, Tamil, and Chinese, which pose unique structural challenges. Additionally, future work will focus on incorporating fine-grained style control, allowing manipulation of individual attributes such as stroke width, slant, and serif presence. Another important direction is enabling users to upload their own handwritten samples, blending them with existing fonts to generate personalized digital typefaces. Enhancing the system with a user-friendly web or mobile interface, supporting high-resolution and color font generation, and implementing font file export functionality (.ttf/.otf) are further practical improvements under consideration. Finally, the integration of advanced generative models such as GANs, VAEs, or diffusion models may yield higher-quality and more diverse outputs, especially for complex glyph structures.

Through these future developments, the system aims to evolve into a comprehensive and versatile platform for multilingual, personalized, and creative font generation, contributing to the advancement of computational typography and design technology.

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