

## Department of Computer Science and Engineering

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# FONT SET BLENDER AND GENERATOR

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# Problem Statement and Motivation

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- ❑ Designing fonts for multiple languages is time-consuming and requires manual effort from expert designers.
- ❑ Existing tools lack the capability to easily blend styles or generate customized, multilingual fonts.
- ❑ Users have no simple way to create personalized fonts, such as mixing their handwriting with existing styles.
- ❑ There is a need for an automated, user-friendly system to generate and customize fonts across scripts.

# Problem Statement and Motivation

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- ❑ Rising demand for creative, personalized, and multilingual typography in digital platforms.
- ❑ Designers and users seek efficient tools to explore new font styles without technical barriers.
- ❑ Advances in deep learning offer potential to automate and simplify the font creation process.
- ❑ This project aims to empower users to blend fonts, create unique styles, and extend designs across languages.

## Existing System

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- ❑ Font creation today relies heavily on manual design using tools like Adobe Illustrator, FontForge.
- ❑ Multilingual fonts are designed separately for each script, leading to inconsistent styles.
- ❑ Some AI models exist (e.g., MC-GAN [4], Semantic Typeface Transfer [6]):
  - ❑ Focused on single-script transfer (like Latin only).
  - ❑ Require large datasets and are not user-driven.
- ❑ No existing tool allows easy font blending and personalization using user input.

# Objectives

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- ☐ To develop an AI-powered system for font generation and blending.
- ☐ Enable users to mix multiple font styles to create unique designs.
- ☐ Provide an option to include user handwriting in the generated font.
- ☐ Make the system user-friendly and efficient, requiring no design expertise.

# Abstract

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- ❑ This project presents an AI-driven Font Generation and Blending System that enables users to create unique, cross-lingual fonts.
- ❑ Using a **deep autoencoder model**, the system learns to represent and reconstruct font glyphs.
- ❑ Users can **blend multiple font styles** by **adjusting mixing ratios** and even incorporate their own handwriting samples.
- ❑ The generated fonts can be previewed and downloaded, empowering both designers and non-designers to create customized typefaces effortlessly.

# Proposed System

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- ❑ Uses a Convolutional Autoencoder trained on diverse fonts to learn compressed representations.
- ❑ Font Blending Module:
  - ❑ Takes user-selected fonts and blends their encoded features based on chosen ratios.
  - ❑ Decodes the blended encoding to generate new glyphs.
- ❑ Supports User Handwriting Upload:
  - ❑ Users can upload handwritten samples for personalized font generation.
- ❑ Enables Cross-Lingual Style Transfer:
  - ❑ The blended style can be applied to other scripts (e.g., Tamil, Hindi, Japanese).
- ❑ Outputs a preview and downloadable font pack for immediate use.

# System Architecture

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- ❑ Font Input: User selects multiple fonts (TTF files) or uploads handwriting samples.
- ❑ Preprocessing Module:
  - ❑ Extracts and renders glyph images from fonts.
  - ❑ Normalizes and resizes them (e.g., 64x64 pixels).
- ❑ Encoder (Feature Extraction): A convolutional encoder compresses glyph images into compact style embeddings.



# System Architecture

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- ❑ Blending Module:
  - ❑ Takes multiple font embeddings and blends them using user-defined ratios.
  - ❑ Supports dynamic style mixing (e.g., 40% Font A + 60% Font B).
- ❑ Decoder (Glyph Generation): The blended encoding is decoded to reconstruct the glyph images with new styles.
- ❑ Output: Users can preview generated fonts and download them as font packs.

# List of Modules

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- ☐ Font Preprocessing Module
- ☐ Encoder
- ☐ Blending Module
- ☐ Decoder
- ☐ Preview and Download

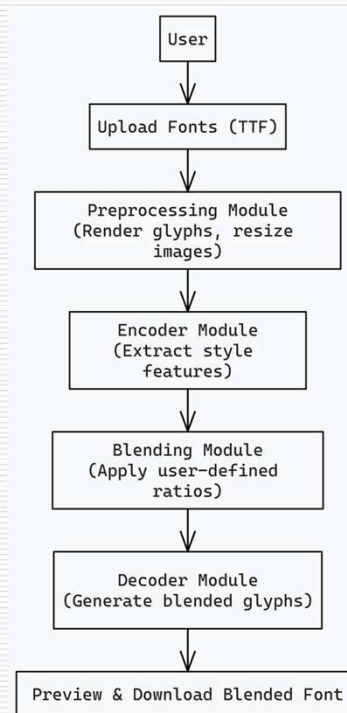
# Functional Description for each modules with DFD and Activity Diagram

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- ❑ Font Preprocessing Module - Renders glyphs from TTF/OTF files and standardizes image sizes.
- ❑ Encoder - Extracts compact style features from font glyphs (CNN-based).
- ❑ Blending Module - Mixes multiple style features based on user-specified ratios.
- ❑ Decoder - Reconstructs new glyph images from blended features.
- ❑ Preview & Download – Displays generated font samples and provides a download option.

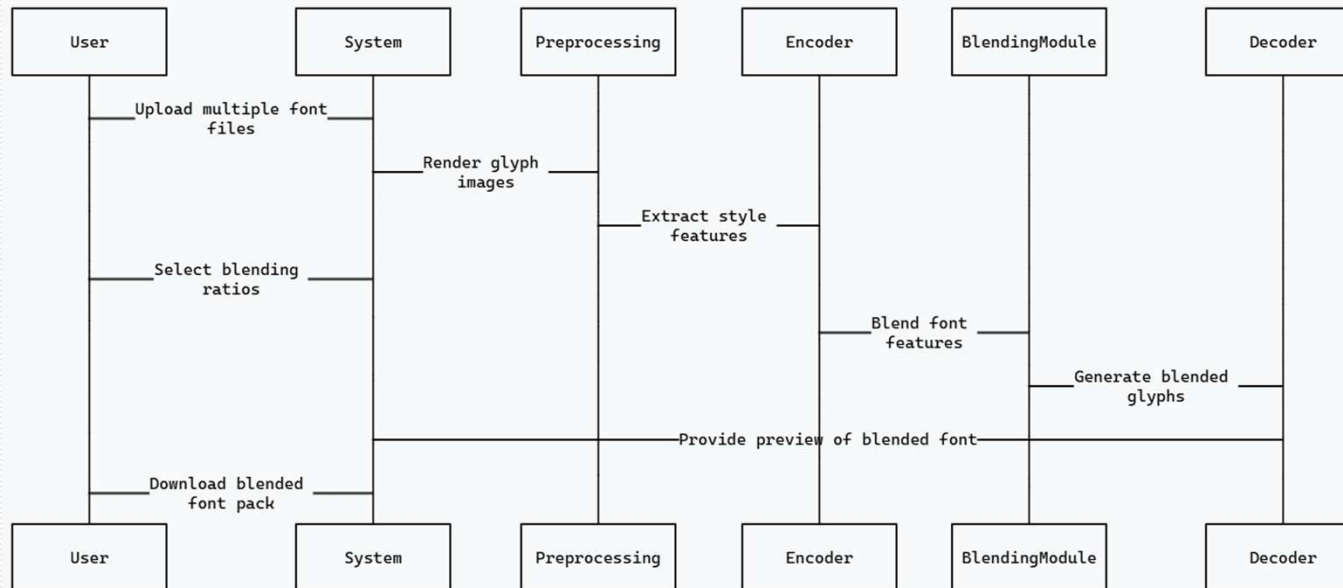
# Functional Description for each modules with DFD and Activity Diagram

## □ Data Flow Diagram



# Functional Description for each modules with DFD and Activity Diagram

## □ Activity Diagram



# Implementation & Results of Module

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- ❑ Tech Stack : Python, TensorFlow/Keras, NumPy, PIL, Matplotlib
- ❑ Model Used : Convolutional Autoencoder trained on glyph images
- ❑ Blending Mechanism : Encoded glyphs from multiple fonts are combined using weighted averages (ratios set by user)
- ❑ Frontend : Uses Matplotlib for preview; outputs images and downloadable blended font pack
- ❑ Modules :
  - ❑ Glyph Renderer (TTF to image)
  - ❑ Encoder & Decoder (Autoencoder-based)
  - ❑ Font Blender (Weighted encoding blending)
  - ❑ Output Generator (Blended glyph previews)

# Implementation & Results of Module

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## □ Blending Logic

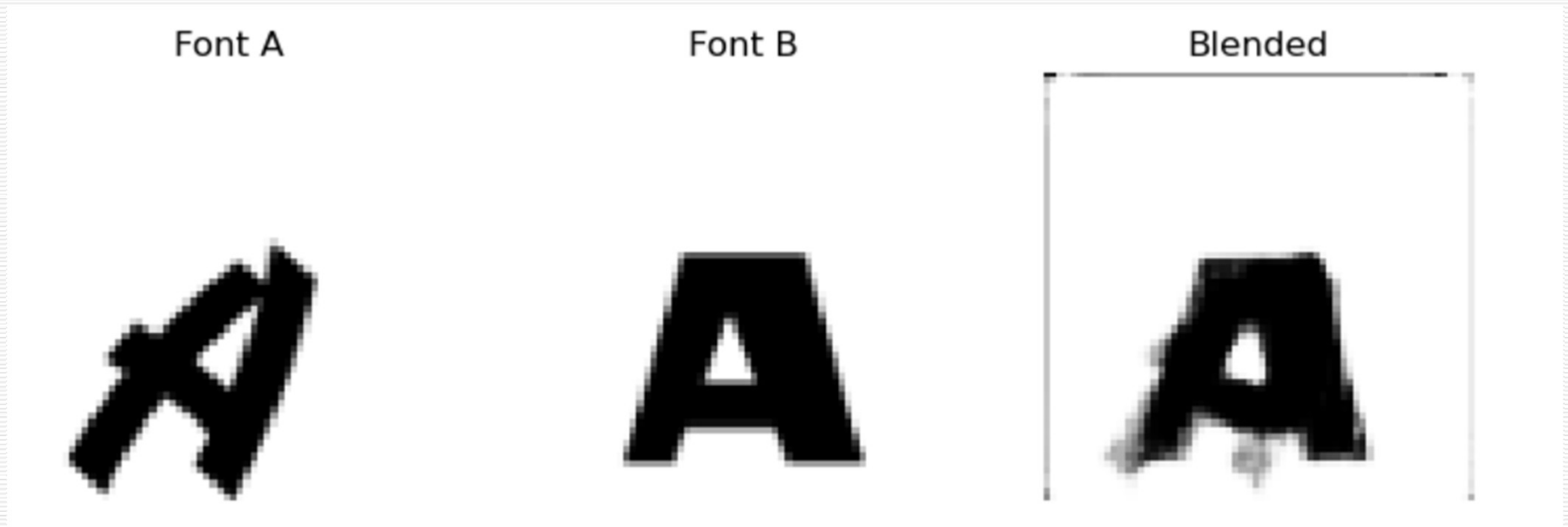
```
# Blend encodings
blended_encoding = np.zeros_like(encoded_fonts[0])
for encoded, ratio in zip(encoded_fonts, ratios):
    blended_encoding += encoded * ratio

# Decode to generate blended glyphs
reconstructed_fonts = decoder.predict(blended_encoding)
```

# Implementation & Results of Module

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## □ Generated Blended Fonts

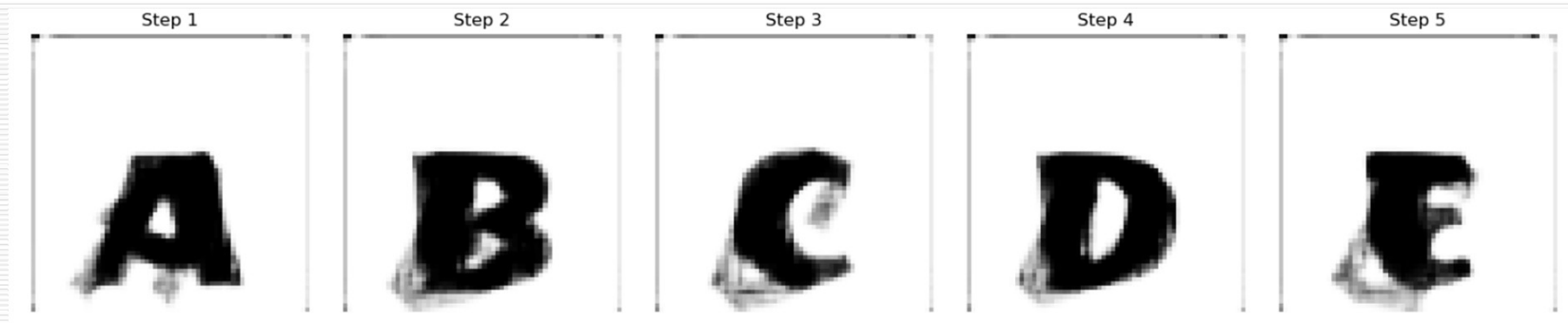




# Implementation & Results of Module

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## □ Interpolation Samples

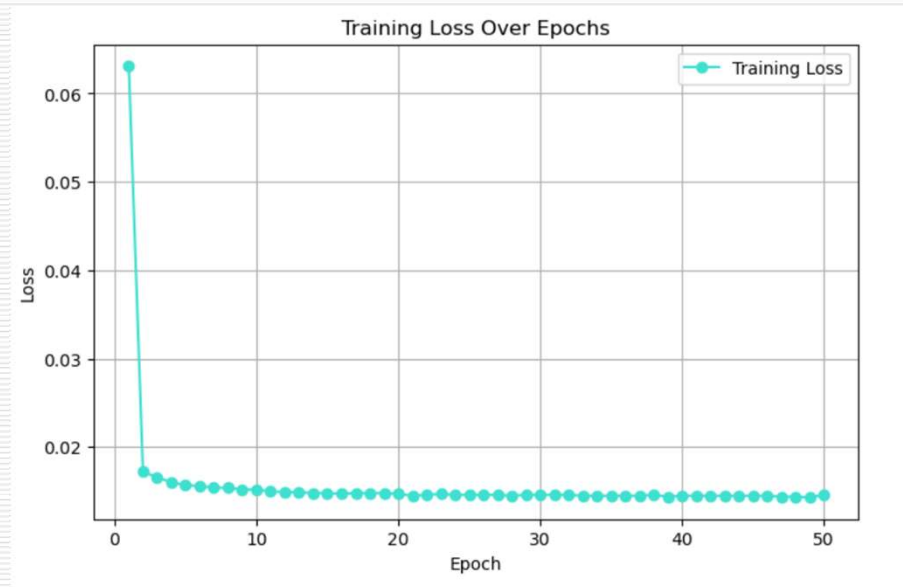


# Implementation & Results of Module

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## □ Quality Metrics

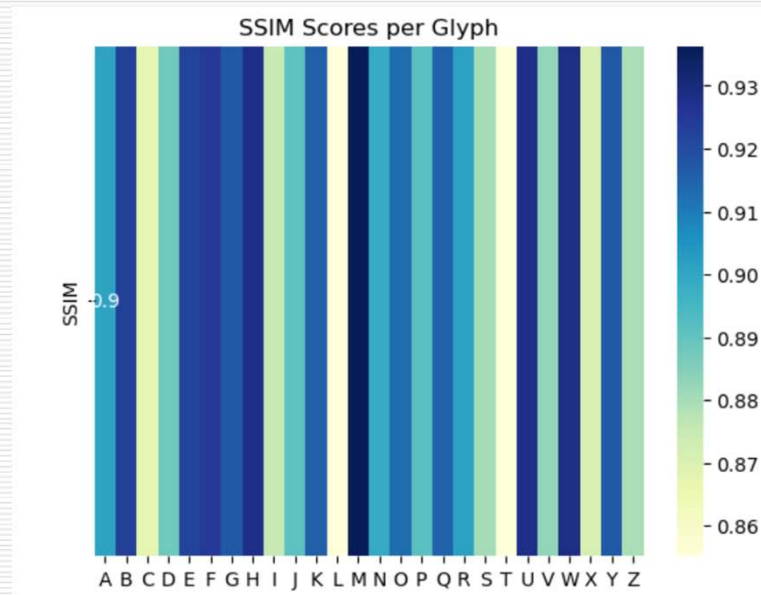
### □ Reconstruction loss during training



# Implementation & Results of Module

## □ Quality Metrics

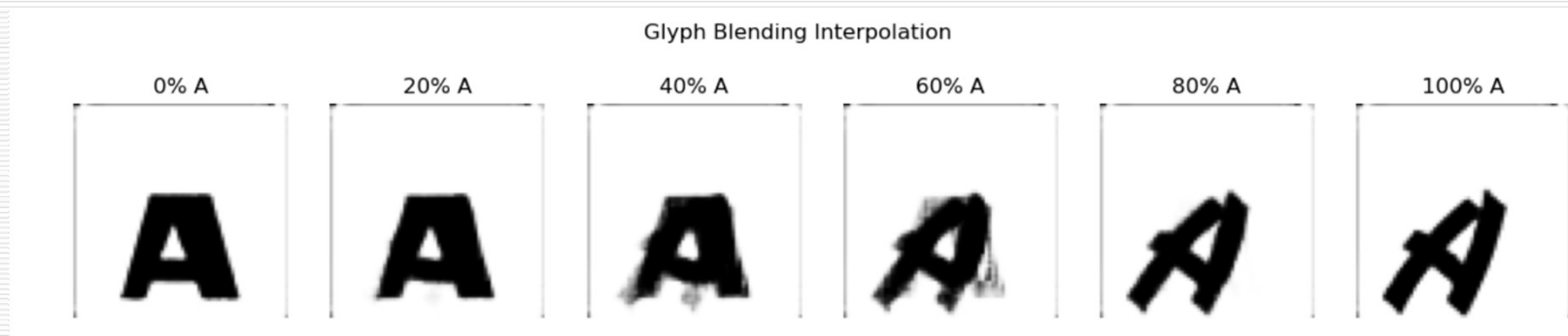
### □ SSIM scores per glyph



# Implementation & Results of Module

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## □ Ratio Control



## Conclusion & Future Work

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- ❑ Successfully implemented a font blending system using deep learning-based convolutional autoencoders.
- ❑ Allows users to upload multiple fonts and blend them using adjustable weight ratios.
- ❑ Generated new blended fonts that inherit features from the selected source fonts.
- ❑ Achieved good visual quality and structural similarity using SSIM scores for evaluation.
- ❑ Demonstrated an automated, flexible method for creative font generation without manual design work.

## Conclusion & Future Work

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- ❑ Multilingual Support - Extend the system to handle scripts like Devanagari, Arabic and Chinese for global font blending.
- ❑ User-Controlled Attribute Blending - Let users adjust specific features like thickness, roundness, or serif presence during blending.
- ❑ On-Device Deployment - Optimize for mobile and desktop applications to enable offline font generation.
- ❑ Interactive Preview Interface - Build a real-time system where users can adjust blending and preview results instantly.
- ❑ Dataset Expansion - Add more fonts and scripts to improve system generalization and versatility.

# References

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- [1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, et al., "Generative Adversarial Nets," *Advances in Neural Information Processing Systems*, vol. 27, pp. 2672–2680, 2014.
- [2] J. Johnson, A. Alahi, and L. Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution," *European Conference on Computer Vision*, pp. 694–711, 2016.
- [3] T. Karras, S. Laine, and T. Aila, "A Style-Based Generator Architecture for Generative Adversarial Networks," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4401–4410, 2019.
- [4] A. Radford, L. Metz, and S. Chintala, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks," *arXiv preprint arXiv:1511.06434*, 2015.
- [5] H. Lian and C. Meng, "Neural Font Style Transfer with Content Preservation," *IEEE Transactions on Image Processing*, vol. 30, pp. 2706–2718, 2021.

# References

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- [6] Y. Azadi, M. Fisher, V. G. Kim, et al., "Multi-Content GAN for Few-Shot Font Style Transfer," IEEE Conference on Computer Vision and Pattern Recognition, pp. 7564–7573, 2018.
- [7] Y. Kang, K. R. M. Gupta, and J. Lee, "Font2Font: A Dual Learning Framework for Font Style Transfer," Pattern Recognition, vol. 125, 108533, 2022.
- [8] Y. Li, L. Liang, H. Qin, et al., "Few-Shot Font Generation with Dual Memory," ACM Transactions on Graphics, vol. 40, no. 6, pp. 1–13, 2021.
- [9] Y. Yang, J. Liu, and X. Sun, "Controllable Font Generation via Complex Decomposition," IEEE Access, vol. 8, pp. 155930–155940, 2020.
- [10] Z. Chen, C. Chen, J. Xu, and M. Sun, "AI-Aided Typeface Design: A Review," IEEE Transactions on Visualization and Computer Graphics, vol. 29, no. 1, pp. 458–475, 2023.



# Paper Publication Status

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☐ Not Published



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