

One-Shot multilingual Font Generation Via ViT

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Overview

- Font design poses unique challenges for languages like Chinese, Japanese, and Korean (CJK), which contains thousands of unique characters.
- Our goal is automatic generate fonts in **multi language**, even for **unseen font, unknown and made up characters**.
- We Introduces a Bi-encoder Vision Transformer (ViT) based model with Combined loss pretraining on MAE task. Our model not rely on **base font**.



Dataset & Task & Eval

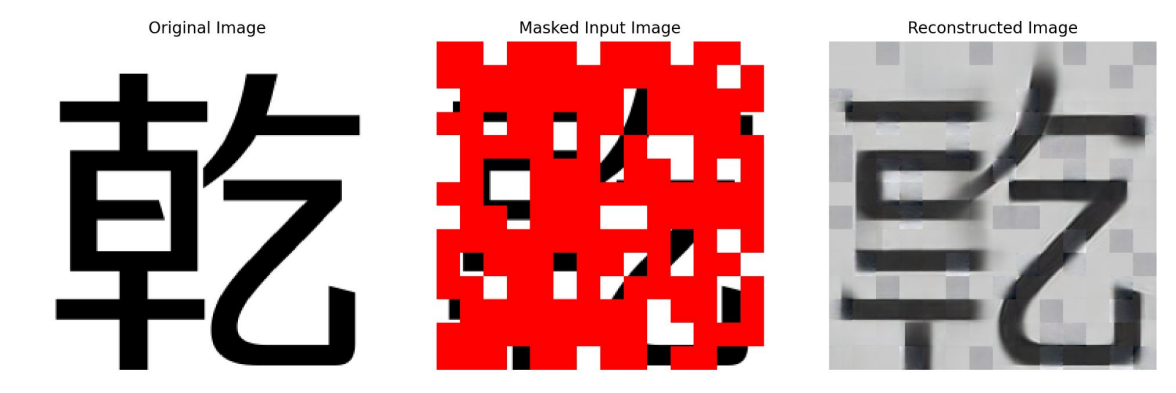


- 308 Fonts in CJK + EN
- 2.2M training samples
- Evaluation on pixel-level and perceptual metrics



Method

- **Pretrain** encoder & decoder on MAE task for spatial reasoning



- From 2 encoders, get:
 - content repr **C**
 - Style repr **S**
- **Cross-attention Q=C, K,V=S**:
 - content specific style repr **S'**
- **Concate S', C**, send to generator
- Get output

1. Train on Combined LOSS

$$\mathcal{L}_{total} = \alpha \mathcal{L}_{content} + \beta \mathcal{L}_{style} + \gamma \mathcal{L}_{MSE}$$

2. Refine on L1+MSE

+ Retriever module

1. Compute image embedding use *content encoder*
2. For each style, build *FAISS* Index for known chars
3. Search most suitable style expamlar during inference

RAG not contribute to eval matrices, but address specific failure cases and improve performance on hard examples

Conclusion

- Our model demonstrates the ability to transfer styles in different languages and even made-up characters.
- Our model achieves better result then DiffusionFont and delivers competitive performance with other approaches, all while offering **enhanced generalizability, usability, and scalability**.

Results

Unseen Settings					Metrics				
SS	SC	CS	CC		L1 Loss ↓	RMSE ↓	SSIM ↑	LPIPS ↓	FID ↓
✓	×	×	×	DG-Font	0.07841	0.2442	0.6853	0.1198	27.98
✓	×	×	×	CF-Font	0.07394	0.2354	0.7007	0.1182	26.51

- Ours also work well on unseen style, **unknow or even self-craft characters**

Unseen Settings					Metrics				
SS	SC	CS	CC		L1 Loss ↓	RMSE ↓	SSIM ↑	LPIPS ↓	FID ↓
✓	×	×	×		0.19858	0.56531	0.65361	0.20315	26.49332
✓	✓	×	×		0.19875	0.56551	0.65507	0.20319	26.37470
×	×	✓	×		0.19812	0.56434	0.65462	0.20121	26.61482
×	×	✓	✓		0.19930	0.56612	0.65337	0.20307	27.13604

