

Neural Style Transfer For Fonts

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Abstract: - This paper concentrates on an approach to generate new fonts by using neural style transfer. Neural Style transfer is a deep learning method which transfers style from a style image to a content image. Our approach combines the content of the style image and the content image. We also demonstrate the effects of using different number of iterations. We show the results using different languages and provide an insight of style transfer in designing new fonts.

I. INTRODUCTION

Designing of new digital fonts is very tough and time consuming. There are many elements that are put in to design a font like height, width, line width etc. The designer has to first sketch and convert into digital form for the design of a new font. So a neural network to design new fonts is an important tool which would make it easy for the design and implementation

Style transfer is used in images and is an active field in the recent years. Many methods are used in style transfer. It uses convolutional neural networks to synthesize images using a content image and style image. Texture and local features of the style image are applied to the content image. One famous application which uses style transfer is the Prisma Mobile application. In our method keras, VGG, Imagenet etc are used for achieving style transfer. The purpose of this project is to propose a method of generating new fonts using style transfer. In this project pre existing fonts are used as content images and exploited to change. Different number of iterations are used and the outputs for each case are demonstrated.



Fig 1. Example of neural style transfer

Simple black and white images have been used for this case because of limited compute power. Fonts are in black and white images which requires less compute power while doing style transfer.

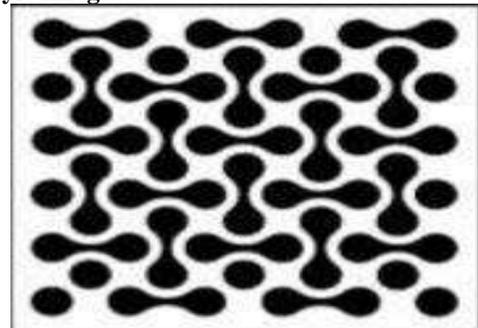
II. RELATED WORK

There are many ways to design new fonts but one approach is the neural style transfer. The idea proposed in this paper is by using convolutional neural networks.

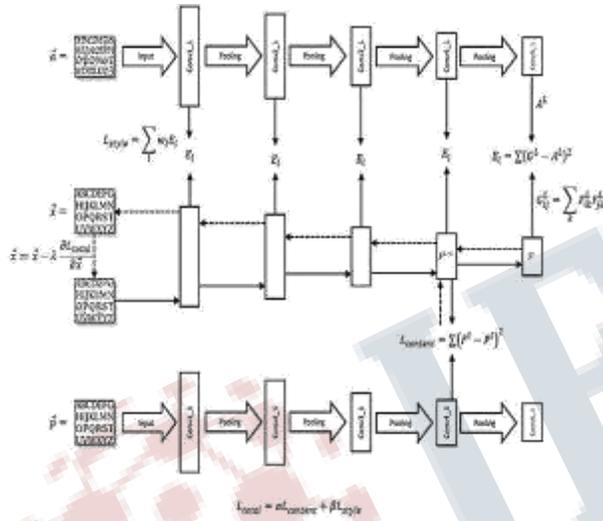
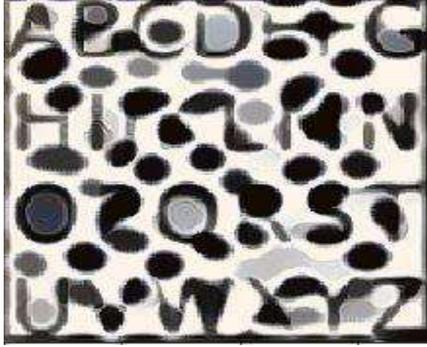
A. Content Image



B. Style Image



C. Final Image



III. NEURAL STYLE TRANSFER FOR FONTS

The basic principle of neural style transfer using a Convolutional Neural Network is to determine the contents of the content image and feature maps of style image to synthesize them using loss functions

A. Neural Style Transfer

To determine the content representation and feature maps of images, a CNN like Visual Geometry Group VGGnet is used .VGG is a pre trained network used for object detection . The pre trained networks are used for transfer learning to transfer features to other domains .In this paper all the results are proved using VGG16. First the content image p is passed to the neural network, on every layer the representation is calculated. The image x is initialized with content image p, runs through the network and content representation is calculated. loss on every layer is calculated as

$$L_{content}(\vec{p}, \vec{x}, \vec{l}) = \frac{1}{2} \sum_{i,j} (F_{ij}^l - P_{ij}^l)^2. \quad (1)$$

Style image is run through the CNN and its representation of style is calculated. With the use of style representation nad style features, Style loss at each layer is calculated.

$$E_l = \sum (G^L - A^L)^2. \quad (2)$$

The total style loss on each layer is calculated as,

$$L_{style}(\vec{a}, \vec{x}) = \sum_{l=0}^L w_l E_l. \quad (3)$$

B. Font Generation using Style Tranfer

To transfer the style of image to content image. Ltotal is minimized. The weighted factors for content and style are used and total loss is expressed.

$$L_{total} = \alpha L_{content} + \beta L_{style}. \quad (4)$$

IV. EXPERIMENTAL RESULTS

In this section we give a detail about the experiments and the results on various combinations of content and style images. We observe the effects of different number of iterations.

- With 10 iterations
- 5 iterations
- Style transfer with two different languages

A. 10 iterations

In this case the number of iterations for creating the gram matrix and to extract the contents used is only 10 .Keras ,tensorflow and VGG net have been used.



Fig 3. Content and style image

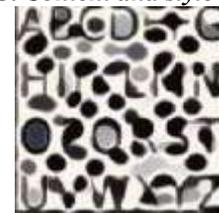


Fig 4. Final image with 10 iterations B. 5 iterations

In this case the number of iterations for creating the gram matrix and to extract the contents used is only 5. Keras ,tensorflow and VGG net have been used .



Fig 6. Content and style image



Fig 7. Final image with 5 iterations

C. Style transfer with different language

In this case the number of iterations for creating the gram matrix and to extract the contents used is only 5. Keras, tensorflow and VGG net have been used. here the style image used is of different language. the final image isn't so clear because of the iterations used



Fig 8. Style image is of different language

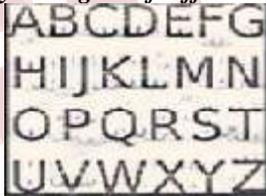


Fig 9. Final image

V. CONCLUSION

In this paper we have performed experiments and observed the performance of neural style transfer for generating new fonts. It has been proved that new fonts can be generated by using neural style transfer instead of using age old methods like sketching and converting it into digital media later. The change of iterations yielded different results providing various fonts. The use of different languages as style images was also demonstrated and yielded different results. But some results are not clear as they are distorted or not clear, however some alphabet are clear with style being transferred. This project is designed for creating new

fonts.

REFERENCES

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