ARTISTIC IMAGE PRODUCTION USING CONVOLUTION NEURAL NETWORKS

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PROBLEM STATEMENT

The problem statement of our project revolves around the production of images with the help of convolution neural networks. It involves artistic style transfer where one image can be represented in the style of other image using machine learning techniques.

Producing a high-quality art is the endeavour of the great artists. But we as humans, curious beings, seek to observe how the art looks if there is a change in the background scenery or the main content of the art itself - drawn or painted in different style- or even applied to our images. This work can’t be requested to the artists as every artist is good at certain kinds of art but not all. So, in here we use neural style art transfer to address the problem.

In simple words, if one wants to produce an image in the style of a specific artist, he can do it by using the algorithm that we propose. Transferring the style from one image onto another can be considered a problem of texture transfer. In texture transfer the goal is to synthesise a texture from a source image while constraining the texture synthesis in order to preserve the semantic content of a target image.

Although, there are some existing techniques which do this, they are not that efficient. They use only low-level image features of the target image to inform the texture transfer. Ideally, however, a style transfer algorithm should be able to extract the semantic image content from the target image and then inform a texture transfer procedure to render the semantic content of the target image in the style of the source image.

To separate style and content from natural images is a pretty difficult job. However, the recent advance of Deep Convolutional Neural Networks has produced powerful computer vision systems that learn to extract high-level semantic information from natural images. It was shown that Convolutional Neural Networks trained with sufficient labelled data on specific tasks such as object recognition learn to extract high-level image content in generic feature representations that generalise across datasets and even to other visual information processing tasks, including texture recognition and artistic style classification.

In this work we show how the generic feature representations learned by high-performing Convolutional Neural Networks can be used to independently process and manipulate the content and the style of natural images. Conceptually, in the proposed algorithm, constrains a texture synthesis method by feature representations from state-of-the-art Convolutional Neural Networks. Since the texture model is also based on deep image representations, the style transfer method elegantly reduces to an optimisation problem within a single neural network. New images are generated by performing a pre-image search to match feature representations of example images.

INTRODUCTION

MOTIVATION:

The motivation of our project involves around the point of producing various images in our desired style. The prisma application which is available in both the android play store and the apple store had inspired us to do a research in this field of artistic style transfer.

This field is less explored and has a great future prospect. To separate style and content from natural images is a pretty difficult job. However, the recent advance of Deep Convolutional Neural Networks has produced powerful computer vision systems that learn to extract high-level semantic information from natural images. It was shown that Convolutional Neural Networks trained with sufficient labeled data on specific tasks such as object recognition learn to extract high-level image content in generic feature representations that generalise across datasets and even to other visual information processing tasks, including texture recognition and artistic style classification.

SIGNIFICANCE:

The significance of our project is that there has been less progress in the field of artistic style transfer and the field of convolution neural networks including the VGG model. the recent advance of Deep Convolutional Neural Networks has produced powerful computer vision systems that learn to extract high-level semantic information from natural images.

Although, there are some existing techniques which do this, they are not that efficient. They use only low-level image features of the target image to inform the texture transfer. Ideally, however, a style transfer algorithm should be able to extract the semantic image content from the target image and then inform a texture transfer procedure to render the semantic content of the target image in the style of the source image.

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SCOPE AND APPLICATIONS:

As mentioned above, there is a lot of scope in the work we have undertaken. Although, there have been many attempts to change the style of images, majority of them haven't been that successful.

The applications of our project include:

1) In applications like pics art and prisma which are used to represent images in various styles.
2) Using the algorithm that we proposed, we can represent the content of the images in the style of a particular artist by grabbing the style from the pictures that he has already painted.

3) DeepDream:- It uses a convolutional neural network to find and enhance patterns in images via algorithmic pareidolia, thus creating a dream-like hallucinogenic appearance in the deliberately over-processed images.

4) This algorithm can be extended to videos where each frame can be taken out separately and the video can be changed into whatever style one wants.

5) It can be used to point out certain kind of objects with the same kind of material, etc using the image segmentation techniques.

LITERATURE SURVEY

1) In the paper titled " Image Style Transfer Using Convolutional Neural Networks " the author focuses on recreating an image(photograph) using the style of another image(painting) using the techniques of convolution neural networks and correlation. The content from the photogRaph is extracted using the CNN where the features are extracted in layers. The top layers are considered for styling. The style of the painting is then extracted by using correlation and both the content image and style image are merged. In this method, VGG 19 networks are used to stylise the image in 3 steps.

2) In the paper titled " PARTIAL STYL E TRANSFER USING WEAKLY SUPERVISED SEMANTIC SEGMENTATION " the style transfer can be done only on a particular object in the image. This is done using image segmentation. using the method which is mentioned in [1], the style of the whole background of the image is changed. The style of a particular object cannot be changed. Hence, in this paper, neural transfer is combined with semantic segmentation. style transfer of glossy materials like metal, plastic and glass is not possible.

3) In the paper titled " FASTER ART-CNN: AN EXTREMELY FAST STYLE TRANSFER NETWORK " deconvolution neural network used in order to achive a high speed style transfer k to apply a specific style to the provided content image. To make the problem computationally tractable, the content images in this work are restricted to the dataset of Labeled Faces in the Wild. In this method, VGG16 networks are used. The only significant drawback is its current inability to transfer some low frequency style elements to the content image.

4)In the paper titled" Flexible selecting of style to content ratio in Neural Style Transfer" the author focuses on adressing the restrictions which are present for the style transfer techniques and provide a system which allows any style image selection with a user defined style weight ratio in minimum time possible. The issue of relatively long running time has been resolved by restricting the choice in style images and the fixed weight ratio of content to style. VGG16 is used. The processing time is reduced by varying the content to style ratio.

5) In the paper titled "Image Style Transfer in Deep Learning Networks" the design idea of the classical model in the process of the development of style transfer is summarized by searching the relevant technology of style transfer extensively, and the improvement of these models is investigated and introduces the classical style migration model, on the basis of the research on the migration of style of the deep learning network for collecting and organizing, and put forward related to gathered during the investigation of the problem solution, finally some classical model in the image style to display and compare the results of migration.

6) The paper titled " A Literature Review of Neural Style Transfer " survey major techniques of doing neural style transfer on images, and then briefly examine one way of extending neural style transfer to videos. This paper mentions that there are some works which apply existing style transfer techniques to the individual frames of the videos, and the resulting video doesn't have any coherence. It also mentions about one paper where consecutive frames as input instead of single frame. The neural network takes previous stylized frame and the current video frame as input.

7) The paper titled " Fast Texture Transfer" uses coherent synthesis technique as the basis of the method. There is a source image and a target image and this coherent sysnthesis technique is used for the style transfer. It does many limitations. It uses only low-level image features of the target image to inform the texture transfer.

GAPS IDENTIFIED

The separation of image content from style is not necessarily a well-defined problem. This is mostly because it is not clear what exactly defines the style of an image. It might be the brush strokes in a painting, the colour map, certain dominant forms and shapes, but also the composition of a scene and the choice of the subject of the image and probably it is a mixture of all of them and many more.

Therefore, it is generally not clear if image content and style can be completely separated at all. New techniques can be developed in order to counter this issue.

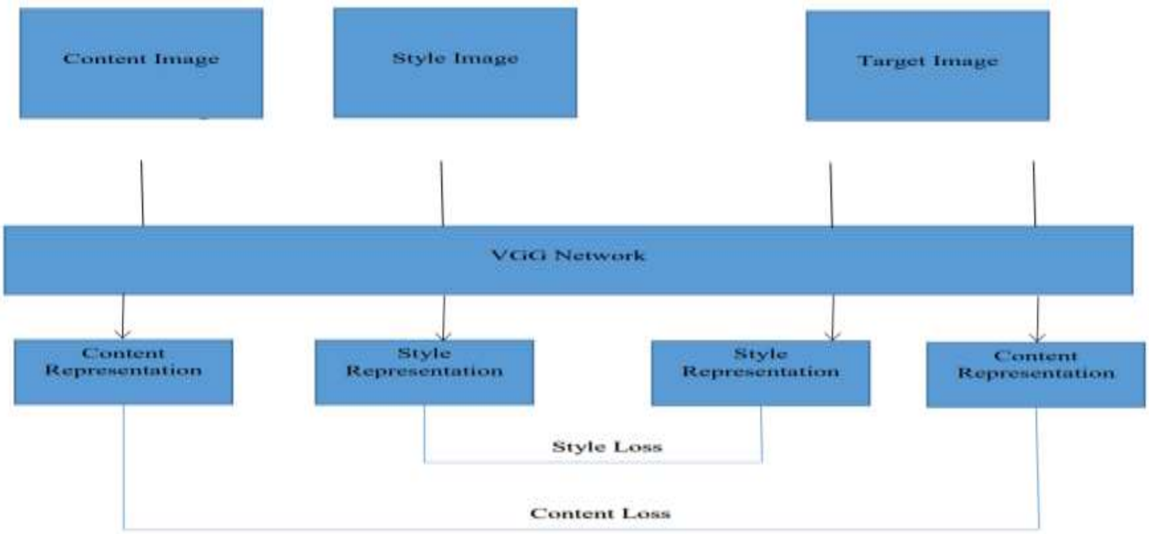
DRIVE TO THE PRESENT WORK

The motivation of our project involves around the point of producing various images in our desired style. The prisma application which is available in both the android play store and the apple store had inspired us to do a research in this field of artistic style transfer.

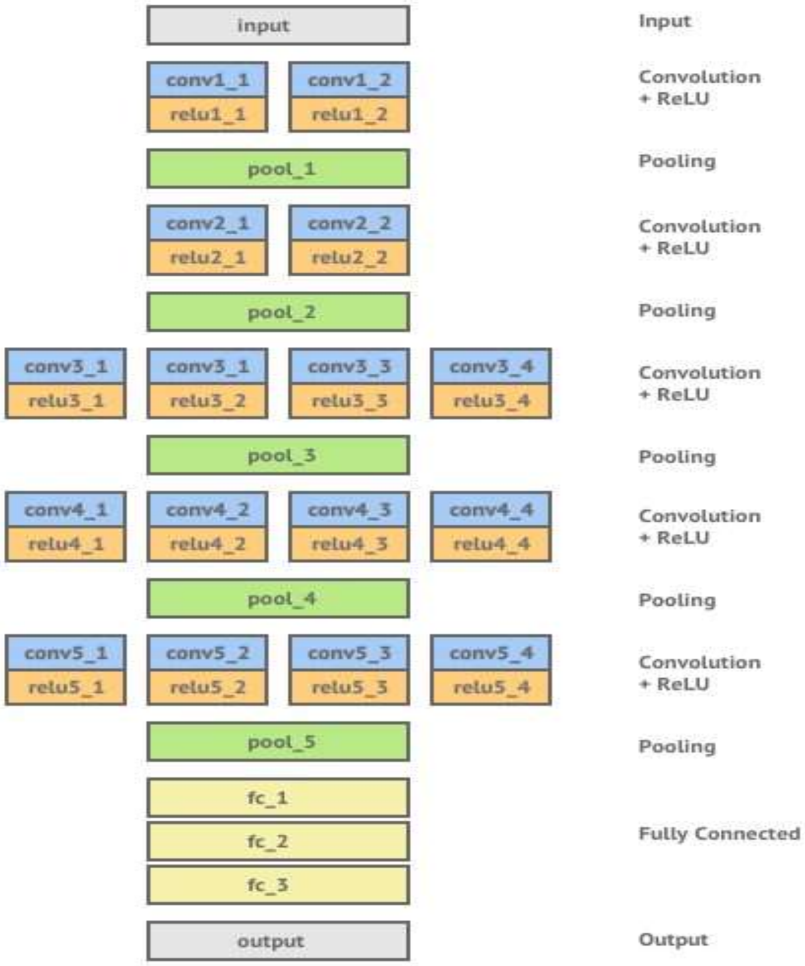
This field is less explored and has a great future prospect. To separate style and content from natural images is a pretty difficult job. However, the recent advance of Deep Convolutional Neural Networks has produced powerful computer vision systems that learn to extract high-level semantic information from natural images. It was shown that Convolutional Neural Networks trained with sufficient labeled data on specific tasks such as object recognition learn to extract high-level image content in generic feature representations that generalise across datasets and even to other visual information processing tasks, including texture recognition and artistic style classification.

IMPLEMENTATION

Architecture Diagram



VGG Network Diagram



Algorithm

1. Select a “style image” from which you want to extract the style.
2. Select a “content image” to which you want to apply the style.
3. Select an appropriate convolutional neural net model with pre-trained weights. Eg. AlexNet, VGG-16, VGG-19.

(We have selected VGG-19)

4. Compute “Gram Matrix” on all the layers to find the “style cost”.
5. Compute “content cost” by selecting few middle layers.

(Avoid layers at either extreme of the CNN model to prevent overfitting and underfitting)

6. Then, total cost = style cost + content cost.
7. Run an optimizing algorithm on the total cost for desired number of iterations.
8. The output image will be our newly produced artistic image from our “content” and “style” images.
9. In addition, you can also tune the weights of “content” and “style” images to vary the look of the output image.

RESULT ANALYSIS

1)

Content image

Style image

Output Image

2)

Content Image

Style Image

Output Image

Expected output

FUTURE WORK

There are lot of aspects where many changes can be made and has a big scope in the future.

Some of the future works which we can do is to adjust the extent of the ratio of style and content while applying the algorithm by using weights.

Other works can include the application of artistic style transfer on videos which has not been implemented effectively till date.

Reducing the time to run this algorithm can be another aspect which can be changed and improved.

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