LOCALIZED IMAGE AUGMENTATION USING DEEP LEARNING

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ABSTRACT.
In this project, we propose a new approach for image style transfer that utilizes a subset of features from the style image rather than using the entire image as a reference. By taking into account the differences in objects present in the style image, our approach is able to generate a modified target image that is more tailored to the specific content of the target image. This approach has the potential to revolutionize the field of data augmentation by allowing for the generation of additional data from existing datasets, ultimately leading to improved performance of convolutional neural networks. This project demonstrates the generated images from the image style transfer technique on Brain MRI Images for Brain Tumor Detection.

1. INTRODUCTION

Data augmentation is an important technique in machine learning because it allows for the expansion of a dataset without the need for additional data collection. This is especially useful in cases where it is difficult or impractical to obtain a large amount of annotated data. By augmenting the existing data, we can improve the generalizability and performance of a model by exposing it to a wider range of variations and scenarios.

In the field of image style transfer, data augmentation can be particularly useful in improving the realism and diversity of the resulting images. Traditional image style transfer techniques often rely on the use of the entire style image as a reference, which can lead to a less tailored and potentially less realistic result. Our proposed approach addresses this issue by utilizing a subset of features from the style image to generate a modified target image that better preserves the content of the original image while incorporating the desired style. By allowing for the generation of additional data from existing datasets, this novel image style transfer technique has the potential to significantly improve the performance of convolutional neural networks through data augmentation.

We have used the ”brain MRI images for tumor detection” dataset to investigate the potential of image style transfer for inducing tumors into tumor-less MRI scans. Our goal was to determine whether this approach could be used to augment the dataset and potentially improve the performance of a tumor detection model. To extract the features from the style image, we utilized OpenCV, a powerful open-source computer vision library.

To accomplish this, we first selected a set of MRI scans from the dataset that contained tumors as our style images. Using OpenCV, we extracted the features of interest from these images. We then used these features as a reference to modify a set of tumor-less MRI scans, which served as our target images. By applying our proposed image style transfer technique, which utilizes a subset of features from the style image rather than the entire image, we were able to generate a series of modified target images that contained artificially induced tumors. These modified images were then used to augment the original dataset and were used to train and evaluate a tumor detection model. Through this process, we were able to demonstrate the effectiveness of our approach in augmenting the dataset and improving the performance of the tumor detection model.

1.1. Contributions.

We have made contribution to the fields of image style transfer and data augmentation. Firstly, we have proposed a novel approach for image style transfer that utilizes a subset of features from the style image rather than the entire image as a reference. This approach allows for a more tailored and realistic result, especially when the style image contains a variety of objects or features that may not be present in the target image. We have utilized OpenCV to extract the features of interest from the style images, further demonstrating the flexibility and potential applications of our proposed image style transfer technique.

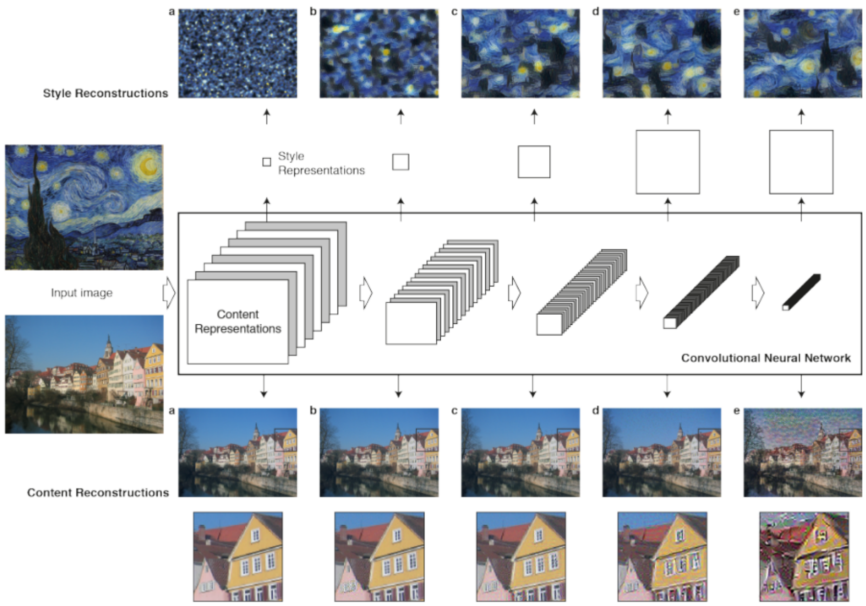


FIGURE 1. Artistic

2. BACKGROUND

Image style transfer is a technique in which the style of one image is transferred to another image, resulting in a new image that combines the content of the first image with the style of the second image. This can be used to create a wide variety of artistic effects, such as replicating the style of a famous painter or adding a specific theme or mood to a photo.

However, one of the main challenges in image style transfer is preserving the content of the original image while accurately applying the style. This can be difficult because the style and content of an image are often intertwined and altering one can have unintended effects on the other. Additionally, the complexity of the style transfer process can make it time-consuming and computationally intensive, which can be a problem for applications that require real-time processing or handling large numbers of images.

3. RELATED WORK

One of the earliest and most influential works in the field of image style transfer is the paper by Gatys et al., which introduced the use of CNNs for extracting style and content information from images. This work inspired a number of follow-up papers that explored various aspects of style transfer, including the use of different CNN architectures and optimization techniques.

Another important development in the field was the use of adversarial training, which involves training a neural network to generate images that are difficult for a discriminator network to distinguish from real images. This approach has been shown to produce high-quality style transfer results, although it can be computationally intensive.

Other techniques that have been explored in related work include the use of spatially-adaptive normalization layers to handle more complex styles, and multi-style transfer methods for transferring multiple styles to a single image. Additionally, there has been a focus on developing techniques for real-time style transfer and handling large numbers of images, such as the use of fast style transfer algorithms and distributed processing. Overall, the field of image style transfer has seen a great deal of progress and innovation, with many exciting advances still to come.

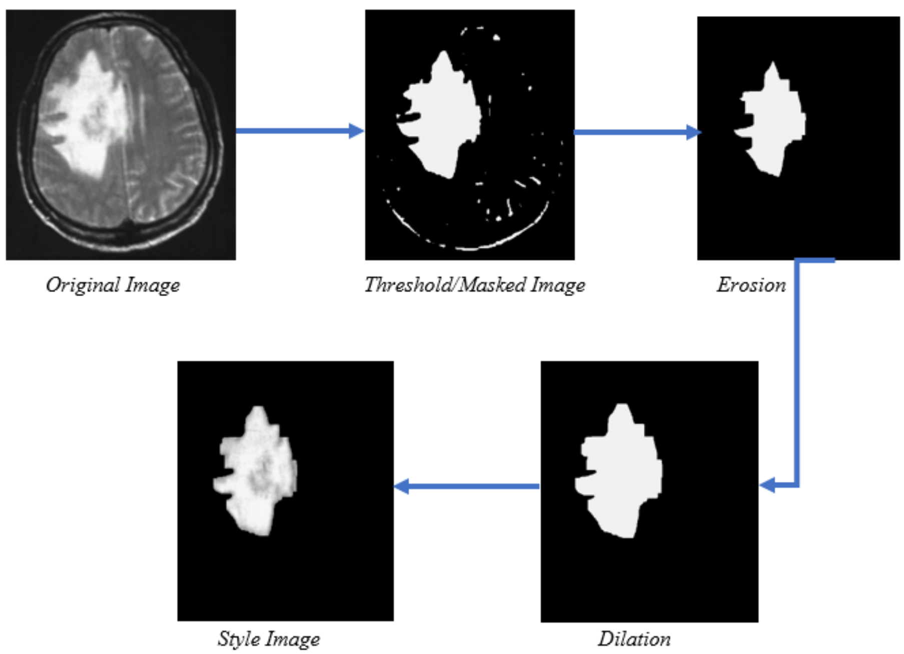
Compared to the STaDa (Style transfer as data augmentation) approach, our approach transfers style from specific location. Whereas the STaDa does it more genereally for the whole image.

4. Approach

Our approach involved using the Python library cv2, along with thresholding and erosion dilation techniques, to extract the tumor from an MRI image as a style image. The goal of this approach was to use the extracted tumor as a "style" to be transferred to other MRI images, in order to introduce tumors into tumor-less images for the purpose of tumor detection.

To extract the tumor as a style image, We first applied thresholding to the MRI image in order to segment the tumor from the surrounding tissue. Thresholding is a common technique in image processing that involves setting a threshold value to separate pixels into two or more classes based on their intensity values. In this case, we set the threshold value to a level that would separate the tumor pixels from the background pixels.

Once the tumor had been segmented from the background, We applied erosion and dilation to further refine the tumor boundary and remove any noise or artifacts. Erosion is a process that involves eroding away the boundaries of a binary image, while dilation is the opposite process that involves expanding the boundaries of a binary image. Then apllying this mask on the original tumour image we get the required style image.



After extracting the tumor as a style image, we then used the "A Neural Algorithm of Artistic Style" paper as a guide to introduce the tumor into tumor-less images. This paper presents a method for combining the content of one image with the style of another image using a convolutional neural network (CNN). The network is trained to extract the style and content information from the two input images, and then generate a new image that combines the content of the first image with the style of the second image.

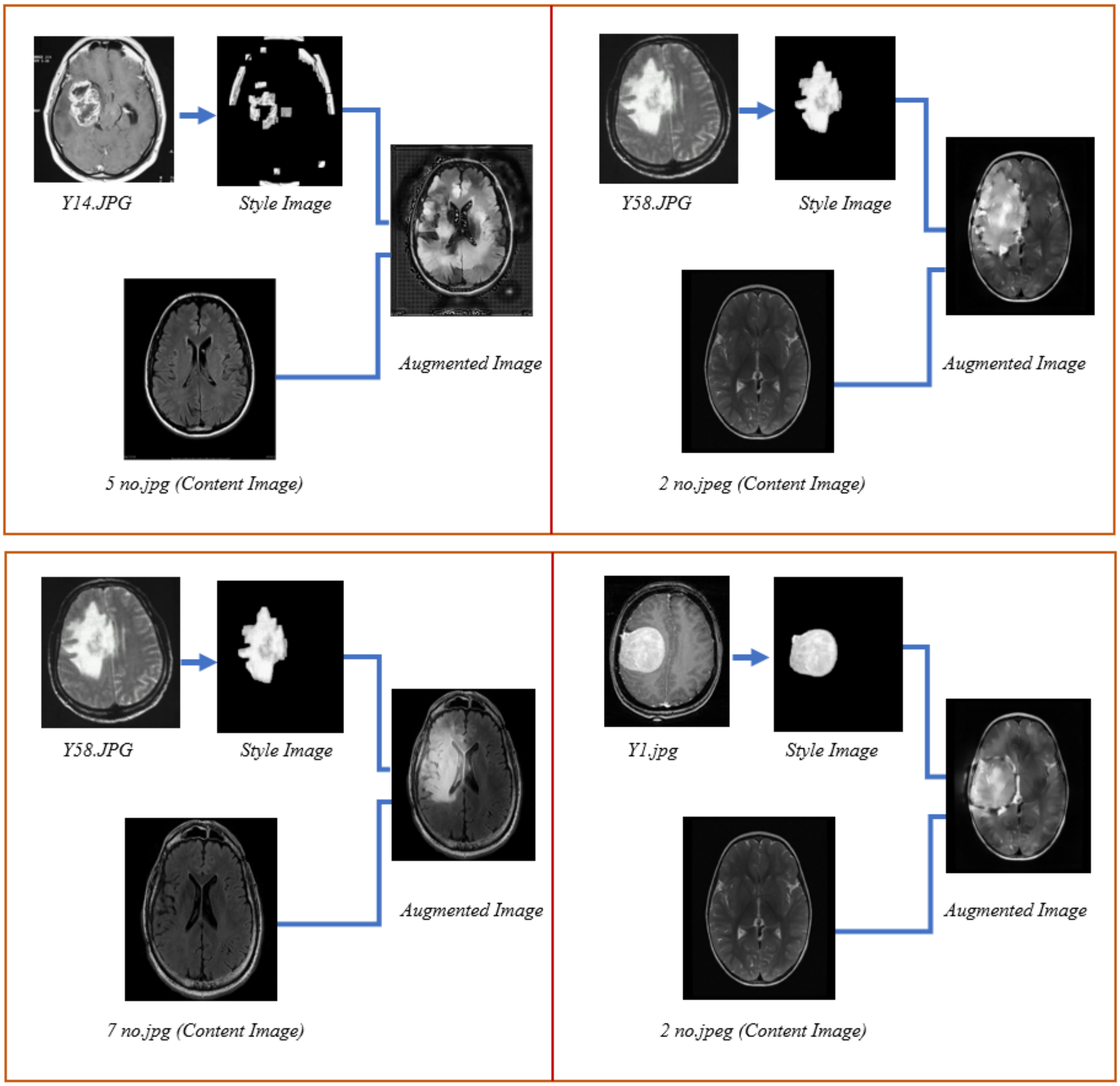
We used the extracted tumor as the style image and a tumor-less MRI image as the content image. We then trained a CNN using these images and used the trained network to generate a new image that combined the content of the tumor-less image with the style of the tumor. The resulting image would show the tumor as if it were present in the tumor-less image, providing a way to detect the presence of tumors that may not be visible in the original image.

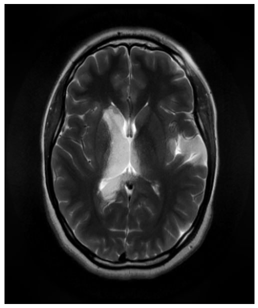
While this approach to image style transfer had the potential to be effective for tumor detection, there were several challenges that had to be overcome. One of the main challenges was preserving the content of the tumor-less image while accurately applying the style of the tumor. This was difficult because the style and content of an image are often intertwined, and altering one can have unintended effects on the other. This requires a lot of fine tuning for the style weight and content weight that tell us how much of the style or the content image is to be present in the resultant image.

5. Experimental Results

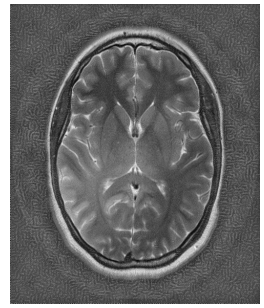
In this experiment, the VGG19 network was utilized as the basis for image style transfer. The dataset used consisted of brain MRI images obtained from Kaggle. Rather than using the entire image as the style image, a targeted approach was taken by extracting the tumorous area of the image through the use of binary thresholding in OpenCV. This mask was then further processed using morphological closing, erosion, and dilation operations. The resulting image served as the style image for the style transfer process. Hyperparameters such as the style weight, content weight, and number of weight updates were adjusted to generate new brain tumour images from tumourless brain images.

We have used a CNN learner which is created using the ResNet34 architecture and specified metrics for evaluation of the images. The learner is fine-tuned for a number of epochs and the learning rate is searched for to identify the optimal value. Some of the results where the augmented image predicted 'yes' using the ResNet34 architecture are





(A) Incorrectly classifies this image as no



(B) No tuning for this image

Sometimes the model may fail to correctly identify images that contain tumors. For example, an augmented image may be generated that the model does not classify as containing a tumor. Also a lot of noise is generated when the model is not properly tuned for a particular image.

6. Discussion

We obtained augmented images when running our model, which can be used to increase the size of our training and validation datasets. However, we found that certain factors can impact the effectiveness of the augmentation. For example, we observed that higher resolution images tend to result in better augmentation and more accurate predictions from our FastAI model. Additionally, we found that using style and content images with similar resolutions is important for producing successful augmentations. These considerations are important to consider when augmenting images for use in our project.

During the process of extracting a style image from a tumour image, manual tuning of certain parameters was required. These parameters, which are used in erosion and dilation of the image, help to determine which part of the tumour will be segmented and included in the style image. While the process of adjusting these parameters was relatively straightforward, it was necessary to make adjustments for each individual image in order to obtain a satisfactory style image.

Another hurdle we came into was tuning the style weight, content weight and number of weight updates. These parameters had to be carefully tuned for each image to get the style transfer that gives a good image of the brain with tumour.

If we had more time, we would have liked to work on improving the data itself by pre-processing it to have images of the same resolution. This could potentially reduce the discrepancies in augmentation from image to image. Additionally, we would have liked to explore using a tool like grid search cross-validation to automatically tune the hyperparameters, such as the style and content weights, in the model.//

References

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