Brain MRI Project Report

Jeremy Shelton, Yuanyuan Yang, Andy Liu, Daniel Wu

Abstract:

Brain tumors represent a critical oncological challenge, characterized by uncontrolled proliferation of brain cells, which can lead to severe health implications. As highlighted in the World Cancer Report, brain cancer constitutes approximately 2% of all cancer cases (Wild, 2014), underscoring the imperative need for effective detection methods. With most cases not having symptoms until later stages, diagnosis primarily from magnetic resonance images (MRIs), and with a low survival rate, there is a need for models that can assist with the early detection of the illness. This project aims to address this need by collecting and classifying MRI images of the brain, annotated as 0 (absence of tumor) or 1 (presence of tumor), utilizing a convolutional neural network (CNN). Given the prevalent challenge of data scarcity in medical imaging, we propose two innovative strategies to enrich our dataset: the employment of generative adversarial networks (GANs) for data augmentation, and the application of transfer learning from large, pre-trained models. These approaches are anticipated to enhance the model's ability to accurately classify brain tumors, provide more variance to prevent over fitting during training, and better generalization. These additions may contribute significantly to the early detection and treatment of this formidable condition.

1 Methods

1.1 Convolutional Neural Network (CNN)

For this project, we utilized a traditional convolutional neural network (CNN) to aid in classifying brain MRI scans into two categories: 1 for the presence of a tumor and 0 for no presence of a tumor. CNNs are particularly suited for image processing tasks due to the fact that they can capture intricate patterns and features in the data using convolutional filters.

Given the known constraints of our dataset (limited images in the dataset), we chose to implement our CNN as a benchmark to evaluate the effectiveness of our other methodologies (Transfer Learning and Data augmentation through Generative Adversarial Networks (GANs)) and establish a baseline for comparison.

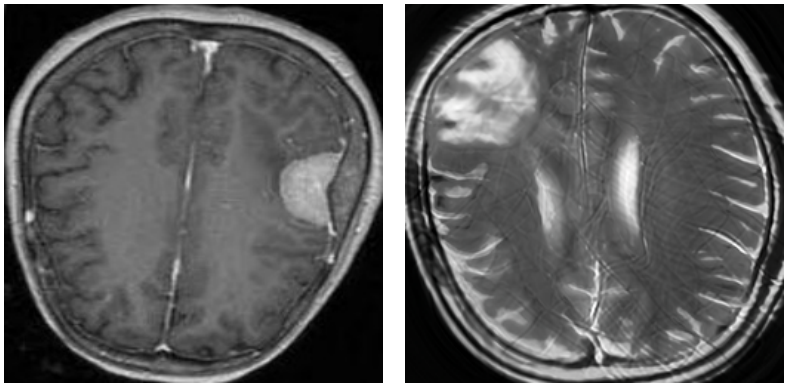
1.2 Transfer Learning

This project uses VGG16 (Simonyan, K., & Zisserman, A. 2015) as a starting point for transfer learning. VGG16 is a convolutional neural network that is widely applied to transfer learning for image classification tasks. It consists of 13 convolutional layers and 3 fully connected layers, totaling over 138 million parameters. The model achieves remarkable accuracy across a diverse dataset of over 14 million images spanning 1000 classes. Due to its training on this broad set of ImageNet images, VGG16 has already learned a rich hierarchy of image features. These features can be effectively transferred to new image classification tasks, including medical imaging.

In the context of medical images, such as brain tumor MRIs, the datasets available are often very limited. Given the small size of the dataset and the high dimensionality of the image data, there is a significant risk of over-fitting. Utilizing a pre-trained model like VGG16 can enhance performance and prevent over-fitting. This approach leverages the comprehensive learning from vast and varied images on ImageNet, making it highly effective for our specialized needs in medical image classification.

1.3 Generative Adversarial Network (GAN)

GANs played a pivotal role in this project and the experiments. The GANs we used were both published by NVIDIA – PGGAN (Progressive Growing of Generative Adversarial Network) and StyleGAN3 (Karras et al., 2017; Karras et al., 2021). StyleGan3 is the most recent publication by NVIDIA. It was published in 2021 as the most recent in a line of papers, each improving on each other starting from the PGGAN paper published in 2017.



(a) Real Tumor MRI. (b) StyleGan3 Tumor MRI.

Figure 1: Real and Generated MRI

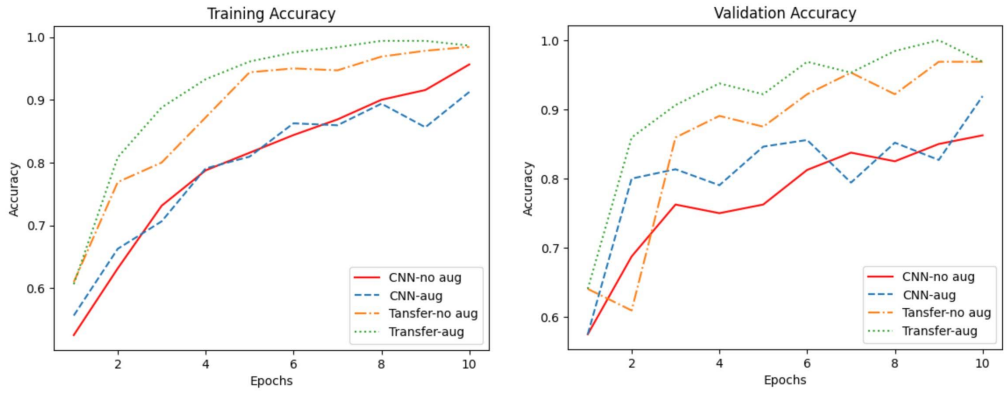
The PGGAN architecture was initially trained on a 4070ti for 12 hours. Though the model could converge, on a 4070ti, the model would take an estimated 300 days due to its having several million parameters. The PGGAN also has flaws that could lead to suboptimal results such as artifacts, and it is prone to over-fitting with less generalization capability. Thus, we switched to the NVIDIA's newer StyleGan3 architecture and a A100 graphics card, which will hopefully mitigate these issues. The model created from StyleGan3 had around 58 million parameters for each network for a total of 116 million parameters, one network for generating the brain MRI's with tumors and the other network for MRI's without tumors.

2 Experimental setup

Our data set consisted of 400 images, 80% being the training set and 20% being the validation set. The split is thus 320 training images and 80 validation images. A dataset with so few images was intentionally selected to test the efficacy of data augmentation with GAN-generated images and transfer learning, aiming to enhance generalization and prevent over-fitting.

Each training iteration was only ran for 10 epochs with a dropout rate of 0.5%. There was a ReLU activation between layers and a Sigmoid activation for the final output.

The benchmark convolutional neural network consisted of 3 convolutional layers and 1 fully connected layer with a sigmoid activation output.



(a) Training Accuracies (b) Validation Accuracies

Figure 2: Benchmark CNN and Transfer learning models accuracy: with and without data augmentation

Transfer learning with the VGG16 consisted of the base model followed by an additional fully connected layer with a sigmoid activation output.

Each StyleGan3 network was trained for 23 hours each on an A100. It was trained with only the original 420 training images. The validation images were never used during the training of the GANs. The hyper parameters for training the network on NVIDIA's official StyleGan3 repo are:

$discriminator - gamma = .2$, $batch = 16$, $cdg = stylegan3 - t$,
$mirror = True$, $cbase = 16384$, $snap = 10$

With the trained GAN networks, we generated a total of 101 tumor and 101 normal brain MRI images, which, when combined with the original training data set, totaled 522 images. The proportion of fakes in the total augmented training set was therefore 19.5%. The test data set remained unchanged at 80 images.

3 Results

As seen in Figure 2.
Transfer learning showed promising results with higher accuracy, on both training and validation, in comparison to the benchmark CNN with and without data augmentation.
Transfer learning, as shown by the results, converged quicker and even achieved an

accuracy of 99% with the augmented data set. The benchmark CNN without any data augmentation performed with an accuracy of 92% in the training set but only 83% in the validation set, which can be a sign of over-fitting.
When using the same benchmark CNN with the training set augmented with the fake images, it performed with an accuracy of 89% in the original training set. However, the validation set performed with an accuracy of 91%.

4 Discussion and Conclusion

The goal of this project was to determine whether transfer learning and data augmentation would help to generalize and prevent over-fitting of models that use small datasets. To achieve this goal, we first used the VGG16 base model to test the effect of transfer learning. We then implemented a custom-built benchmark CNN to test with the StyleGan3-generated images. Finally, we combined both methods, testing transfer learning with the StyleGan3-generated images in order to improve upon issues relating to generalization and over-fitting.
Transfer learning alone improved the accuracy of correct image classification (validation accuracy) in Figure 2. This result demonstrates that transfer learning is an effective technique to improve image classification in small datasets, an issue that faces fields such as neuro oncology in which most datasets are image-limited. In contrast, while the custom-built CNN slightly improved validation accuracy, it additionally helped to mitigate over-fitting. The mitigation of over-fitting is crucial as it enhances the model's ability to correctly classify data - new MRI images, in this case - it has never seen. Interestingly, the combination of these two techniques allowed the model to converge quicker, but it only demonstrated slight improvement to validation accuracy.
We think that possible reasons for the lack of a significant improvement on the combination of methods could be because of our VGG16 model's complexity and potential over-parameterization. In addition, our GAN-generated data, although visually similar to real MRI scans, may not replicate underlying statistical and medical properties of real images perfectly. Additionally the GAN-generated images may have been potentially over-fit from the training images in the data set, due to its small size. A combination of these factors may have been the reason behind the lack of improvement to our validation accuracy with the augmented data and transfer learning.
Both augmenting a data set with generated fake images to supplement smaller data sets and using transfer learning have showed promising results. The results have demonstrated that, on a small scale, there is potential for combating over-fitting and

better generalization.

Acknowledgements

Links to project repository, official StyleGan3 repository, and source dataset:
https://github.com/shelton-je/BrainTumorMRIClassification
https://github.com/NVlabs/stylegan3
https://www.kaggle.com/datasets/mhantor/mri-based-brain-tumor-images

Contributions:

Jeremy Shelton:
Sourced and trained both GANS. Generated fake training images. Wrote Abstract, Methods Subsection 1.3, Setup, Results and Discussion.

Andy Liu:
Created and trained the CNN Model. Wrote Methods subsection 1.1

Yuanyuan Yang:
Sourced and trained VGG16 transfer learning model. Wrote Methods subsection 1.2

Daniel Wu:
Misc. Programming, Wrote Discussion and potential faults, Proofreading

References

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