One Shot GAN for Medical Image Generation

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Problem Statement

Training a Generative Adversarial Network (GAN) Model on single Brain Magnetic Resonance (MR) Images to generate similar images with the aim of Data Augmentation, henceforth enhancing datasets for Brain Tumour classification models

Train a Classification Model for brain tumour using CNNs on our augmented dataset.

Brain MRI Images Dataset

- www.kaggle.com/datasets/mhantor/mri-based-brain-tumor-images

The Dataset consists of 400 magnetic resonance (MR) images each of which falling into either the Normal or Tumor category having the following distribution:

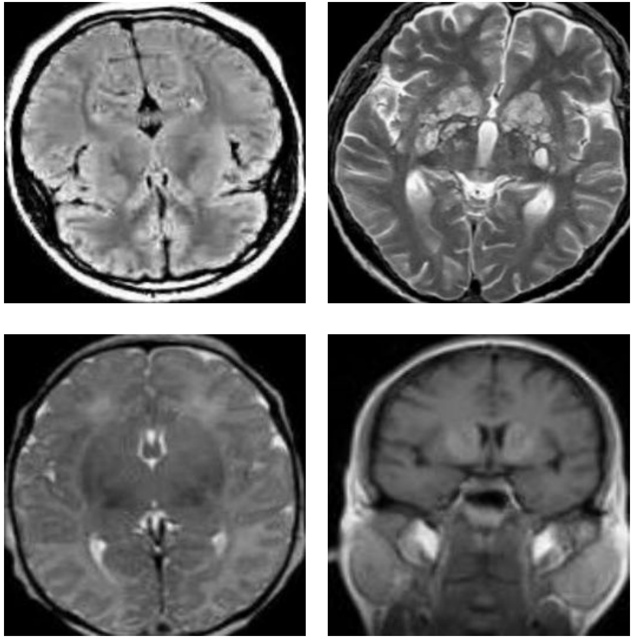
- Normal (170 MRI)
- Tumor (230 MRI)

The training dataset and our validation dataset is hence of the following composition:

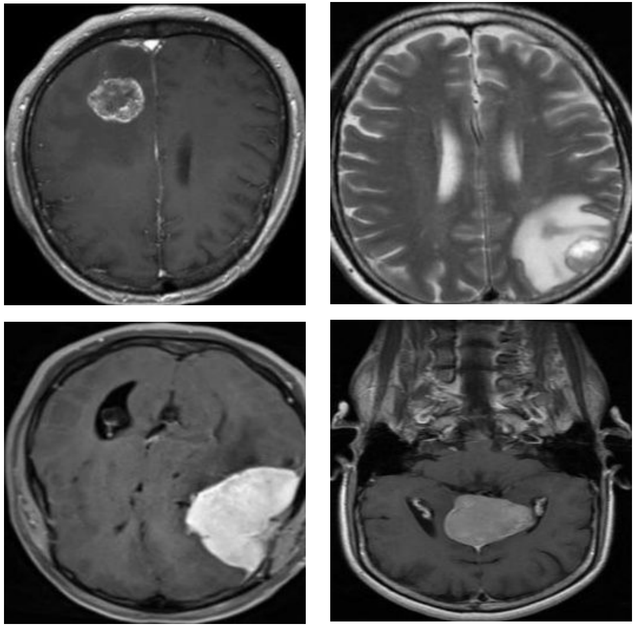
- Training set (Normal 119 and Tumor 161): 70% of the dataset
- Validation set (Normal 51 and Tumor 69): Remaining 30% of the dataset

Brain MRI Images Dataset

MRI of normal brain



MRI of brain having tumor



BrainGAN paper

- A framework for generating and classifying brain MRI images using GAN architectures and deep learning models
- Aims to increase the limited brain MRI dataset using GANs to improve the accuracy of tumor classification models
- The two approaches used:
  - Using Vanilla GAN and DCGAN to generate additional brain MRI images to expand the dataset.
  - Automatically validating the generated images using CNN, MobileNetV2, and ResNet152V2 models. The models are trained on the generated images and tested on real brain MRI images to assess the quality of the generated images.

One Shot GAN paper novelties

- A generative adversarial network that can learn to generate samples from a single image or video
- Uses a two-branch discriminator to judge the content and layout of images separately, which helps prevent overfitting and provides better guidance to the generator
- Diversity regularization is used to encourage the generator to produce diverse outputs
- Achieves higher quality and diversity compared to previous single-image GAN models, and can successfully learn from both single images and videos.

Our modification to the Architecture

- The original paper of BrainGAN uses DCGAN and Vanilla GAN.
- We adopted One Shot GAN to modify the quality of augmentation over here.
- Further we train different instance of the GAN for generating tumour images and non tumour images.
- Used pretrained resnet for classification

So what exactly is a GAN? (Architecture)

The Generator: A generator network takes a random normal distribution (z), and outputs a generated sample that’s close to the original distribution.

The Discriminator: A discriminator tries to evaluate the output generated by the generator with the original sample, and outputs a value between 0 and 1.

One Shot GAN: A GAN which can generate new images significantly different from original image preserving the context. The modified Discriminator includes **content** for aggregating spatial information, **layout** for aggregating information from different channels(global scene layout). Also the low level feature extractor to get the

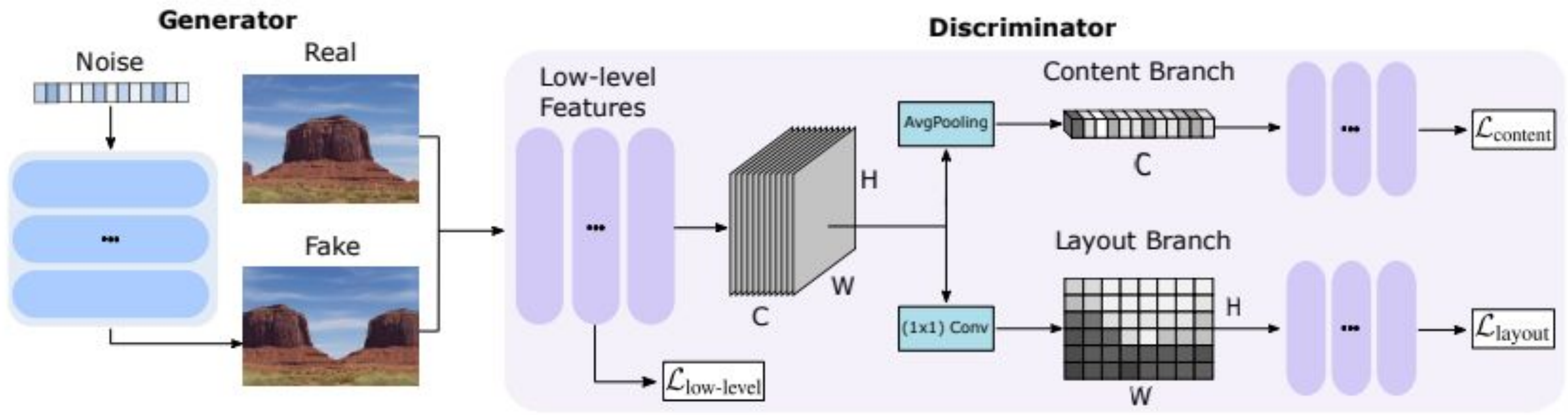
So what exactly is a GAN? (Architecture)

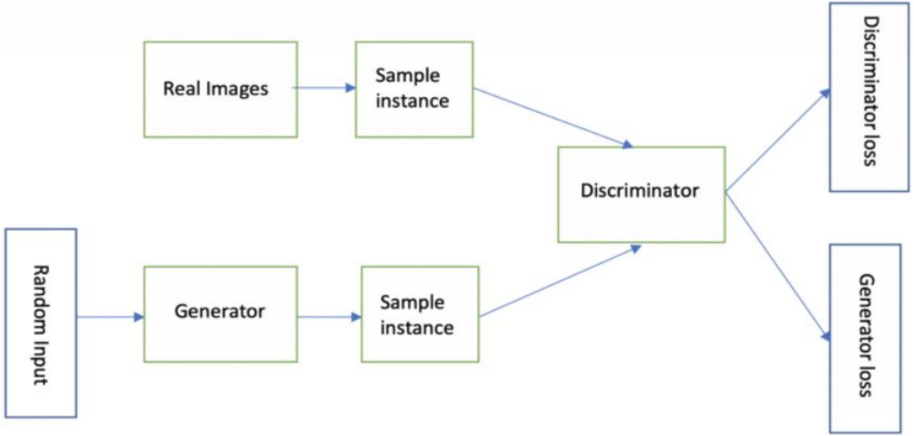
A random normal distribution is fed into the generator. The generator then outputs a random distribution, since it doesn’t have a reference point.

Meanwhile, an actual sample, or ground truth, is fed into the discriminator. The discriminator learns the distribution of the actual sample. When the generated sample from the generator is fed into the discriminator, it evaluates the distribution.

If the distribution of the generated sample is close to the original sample, then the discriminator outputs a value close to ‘1’ = real. If both the distribution doesn’t match or they aren’t even close to each other, then the discriminator outputs a value close to ‘0’ = fake.

One Shot GAN (Architecture)





We have used some blocks of Deconvolution layers in generator. In discriminator we used different blocks of convolutional layers for content and layout branches.
We have used Adam Optimizer, with batch size of 4 and learning rate 0.0002.

GAN Loss Function (Architecture)

The modified minimax Loss function

$$\min_G \max_D \mathcal{L}_{adv}(G, D) - \lambda \mathcal{L}_{DR}(G),$$

,λ was set to 0.15 (acts like regularization constant)

$$\mathcal{L}_{DR}(G) = \mathbb{E}_{z_1,z_2}[\frac{1}{L}\sum_{l=1}^{L} \|G^l(z_1) - G^l(z_2)\|)],$$

Diversity Regularization: the generator should produce images that are different from each other and substantially different from the original sample.

$$\mathcal{L}_{adv}(G, D) = \mathcal{L}_{D_{content}} + \mathcal{L}_{D_{layout}} + 2\mathcal{L}_{D_{low\text{-}level}},$$

Each L is binary cross entropy:

$$logD(x) + log(1 - D(G(z)))$$

Adversarial Loss: The 3 discriminators decision is based on low-level details of images, like textures, and high-scale properties, such as content and layout. The double weight of low level encourages the generation of low level details with coherent layout content.

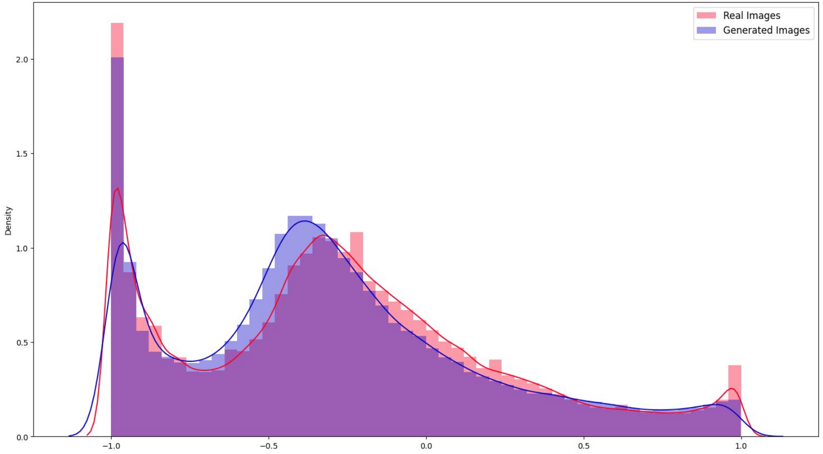
Preprocessing and Pre-train information

- Resized image to (128,128,1)
- Trained for 10 epochs
- 3750 steps per epoch
- Batch size is 4

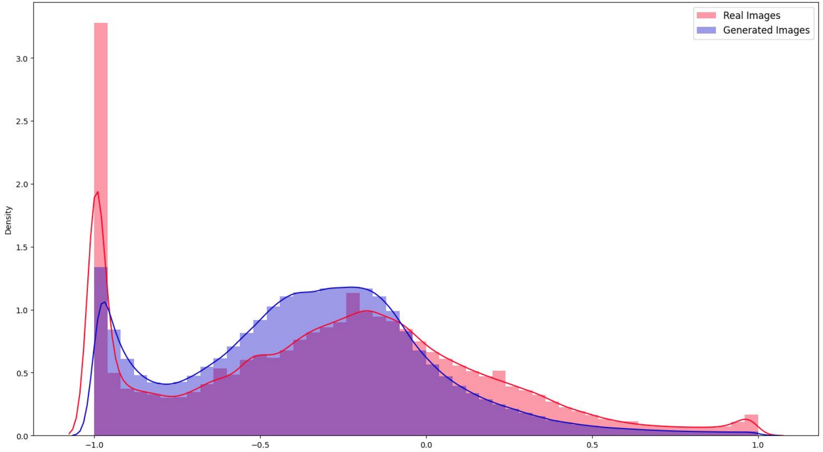
- Each GAN is trained on 70% of stratified split of the dataset
- Similarly for classification and we test on remaining 30% dataset.

Results & Observations

The distribution below plots the distribution of pixels in real images and generated images.



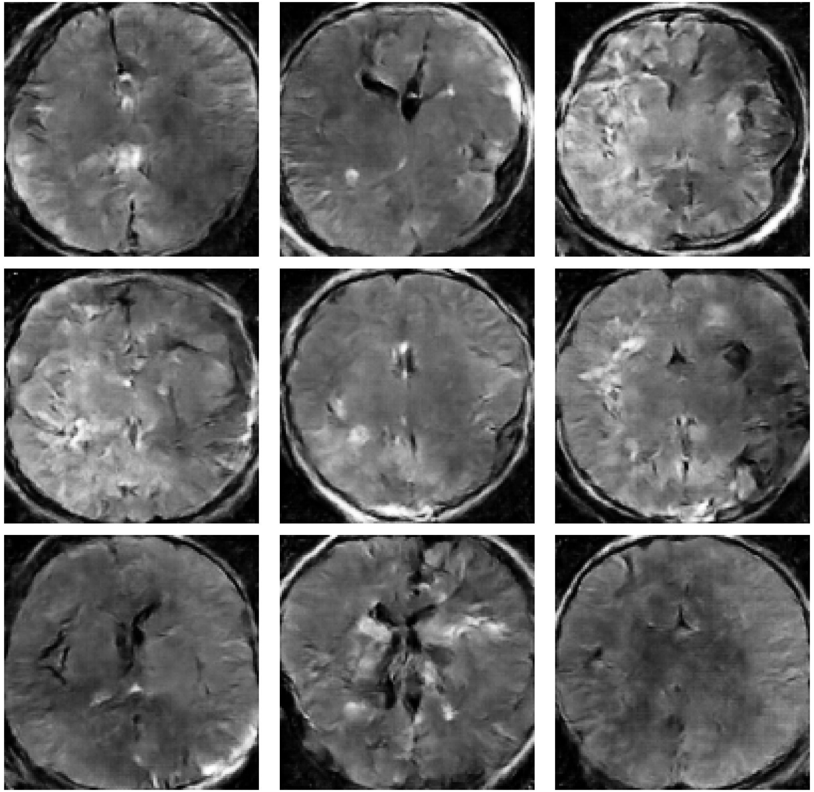
For tumour images



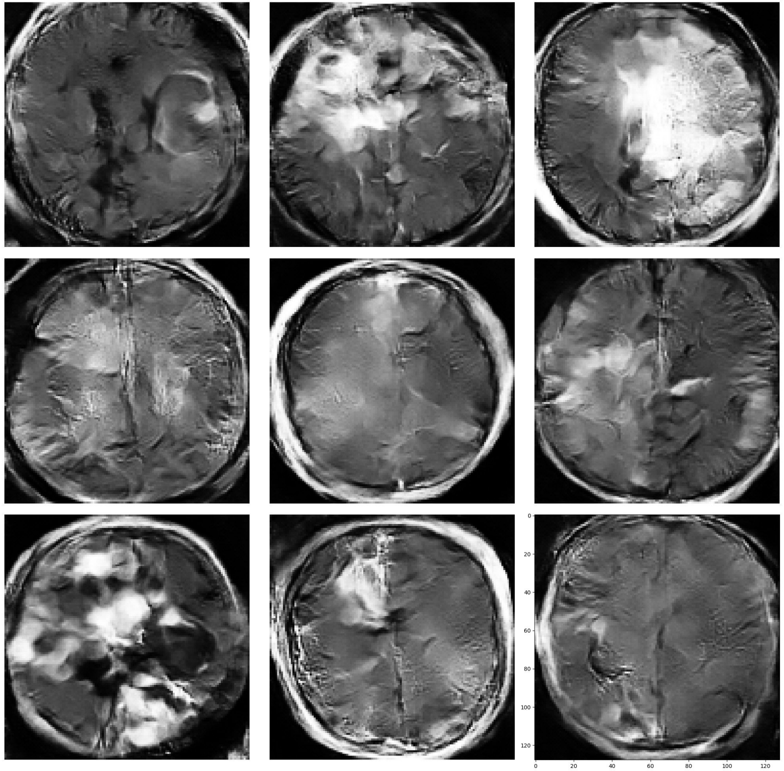
For normal images

Results & Observations

Generated Normal images



Generated Tumour images



Data Augmentation

- We initially had 170 Normal images and 230 Tumour images in our dataset
- Out of this, we have 119 Normal and 161 Tumour images in our training set for GAN.
- Using the GAN model, we generate a total of 700 Normal and 700 Tumour images
- We train a classification model on these 1400 images and then test on the 51 Normal and 69 Tumour images left in our validation set

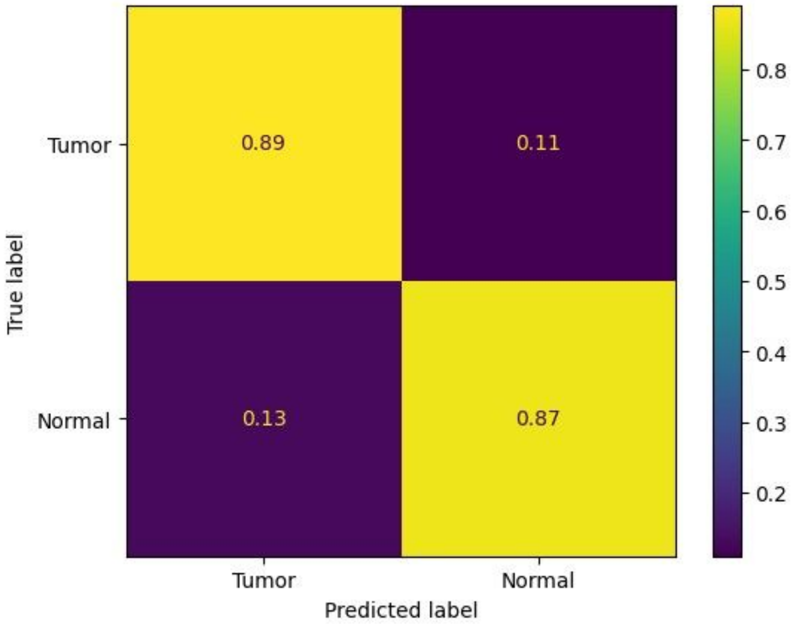
Classification Head

- The original paper tried 3 different architectures for the classification task: Custom CNN, MobileNetV2, ResNet152V2.
- ResNet152V2 gave the best results out of all the 3 models
- We directly use pretrained ResNet152V2 model for our classification

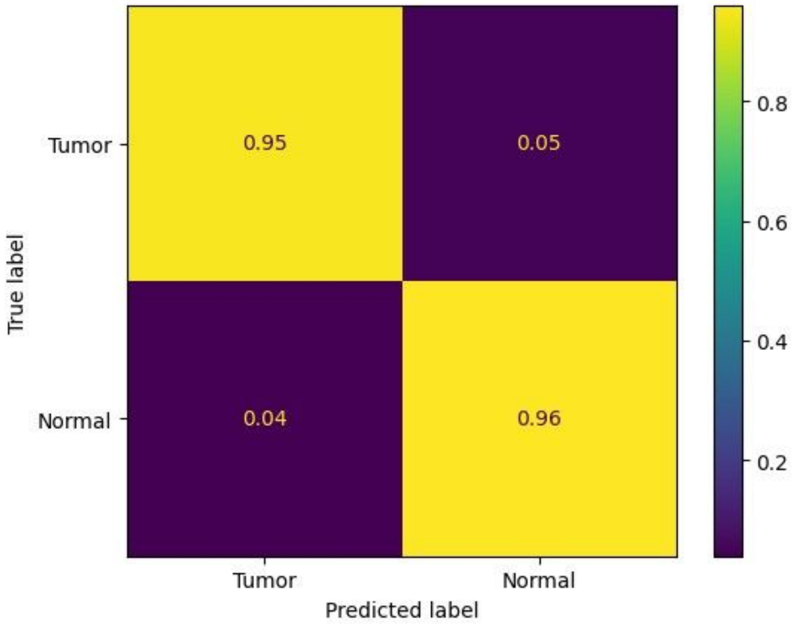
Table 4. The pre-trained ResNet152V2 model architecture.

Layer (Type)	Output Shape	Parameters
resnet152v2 (Model)	(None, 4, 4, 2048)	54,331,648
reshape_2 (Reshape)	(None, 4, 4, 2048)	0
flatten_2 (Flatten)	(None, 100352)	0
dense_3 (Dense)	(None, 256)	25,690,368
dropout_2 (Dropout)	(None, 256)	0
dense_4 (Dense)	(None, 1)	257

Results



Without data augmentation



With data augmentation

Conclusion & Future Work

- GAN is a really useful model for data augmentation in tasks where training data size is small
- There is a significant improvement in accuracy and other metrics after augmenting our dataset
- One shot GAN can have other applications like Xrays, CT and other domains where data collection remains challenging.
- Experiments can be performed with other MRI datasets also.

References

- V. Sushko, J. Gall and A. Khoreva, "One-Shot GAN: Learning to Generate Samples from Single Images and Videos," 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Nashville, TN, USA, 2021.
- Hussein, Dina & Ibrahim, Dina & Hamid, Halima & Fa, Atheer & Ali, Mohammad. (2022). BrainGAN Brain MRI Image Generation and Classification Framework Using GAN Architectures and CNN Models. Sensors. 22. 4297. 10.3390/s22114297.
- Code:
  - generating-brain-mri-images-with-dc-gan.ipynb - Colaboratory (google.com)
  - Copy of generating-brain-mri-images-with-dc-gan.ipynb - Colaboratory (google.com)
- Dataset: https://www.kaggle.com/datasets/mhantor/mri-based-brain-tumor-images

Thank You