

Summary

As deep learning models are getting more and more complex, they require large amounts of data to perform accurately. In medical image analysis, generative models play a crucial role as the available data is limited due to challenges related to data privacy, lack of data diversity, or uneven data distributions. In this work, we present a method to generate brain tumor MRI images using generative adversarial networks. We have utilized StyleGAN2 with ADA methodology to generate high-quality brain MRI with tumors while using a significantly smaller amount of training data when compared to the existing approaches. We use three pre-trained models for transfer learning. Results demonstrate that the proposed method can learn the distributions of brain tumors. Furthermore, the model can generate high-quality synthetic brain MRI with a tumor that can limit the small sample size issues. The code is available at: <https://github.com/rizwanqureshi123/Brain-Tumor-Synthetic-Data>.

Datasets and Implementation

Data: 154 brain MRI samples and contains 3064 T1-weighted images
Source: N. Chakrabarty, "Brain tumor dataset" on Kaggle
We resize all training images to 512×512 resolution.

We used Google Colab Pro platform for the training model as it allows access to faster GPUs which helps in speeding up the training. The model was trained on a Tesla P100 GPU with 25 GB RAM.

We utilized pre-trained models trained on FFHQ dataset [10], BreCaHaD dataset [14], AFHQ [15].

FFHQ512 [10] pre-trained model is trained on Flickr-Faces high-quality images (FFHQ) dataset. The FFHQ is an image dataset containing high-quality images of human faces.

BreCaHaD [14] pre-trained model is trained on a dataset consisting of 162 breast cancer histopathology images that are distributed into 1944 partially overlapping crops of 512×512.

Animal FacesHQ [16] (AFHQ) pre-trained model is trained on a dataset of 15,000 high-quality animal face images at 512×512 resolution in three domains of cat, dog, and wildlife, with 5000 images per domain. AFHQ sets a more challenging image-to-image translation problem by having three domains and diverse images of various breeds. We used weights from the AFHQ (Cat) and AFHQ (Wild) pre-trained models.

The Learning Process

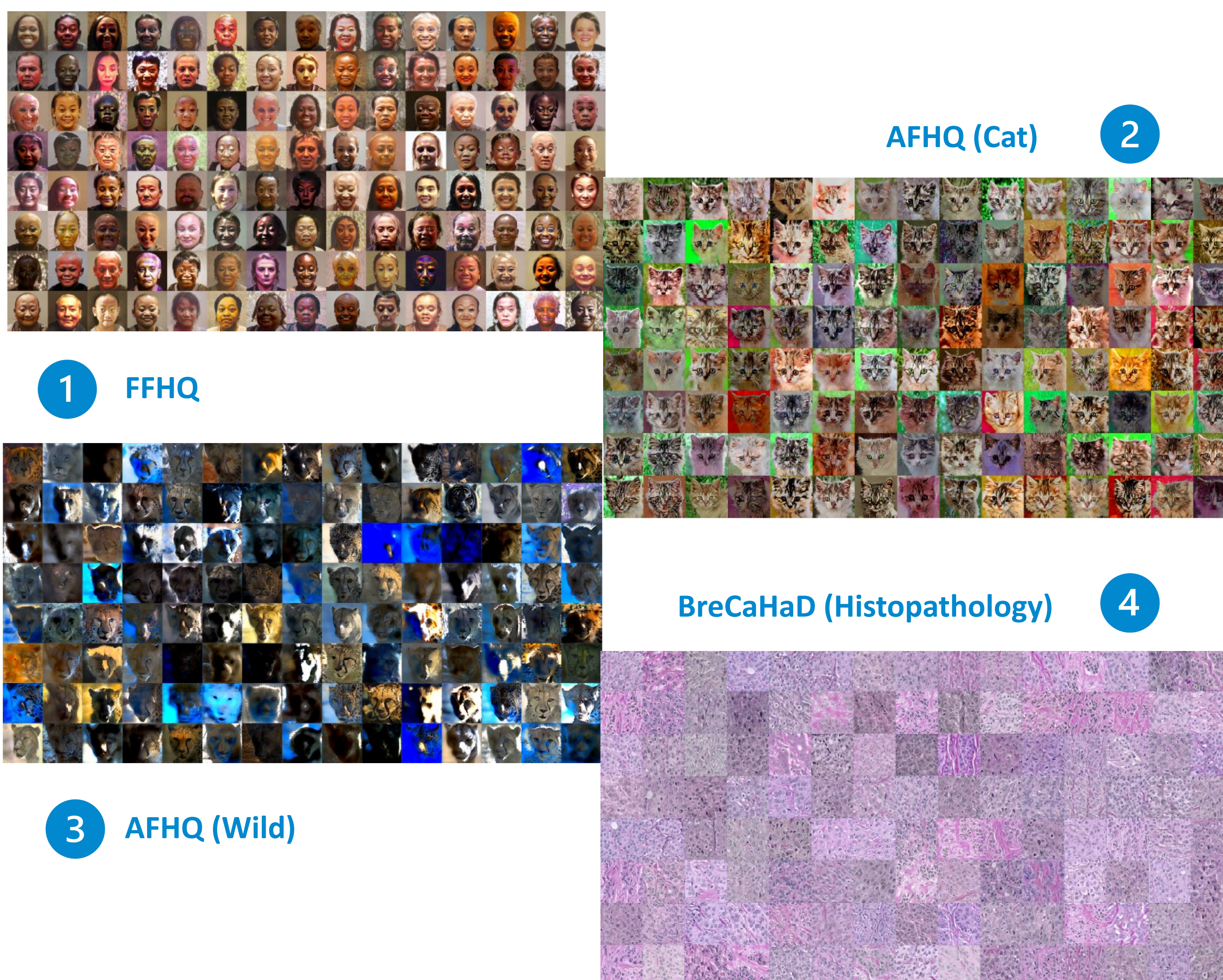
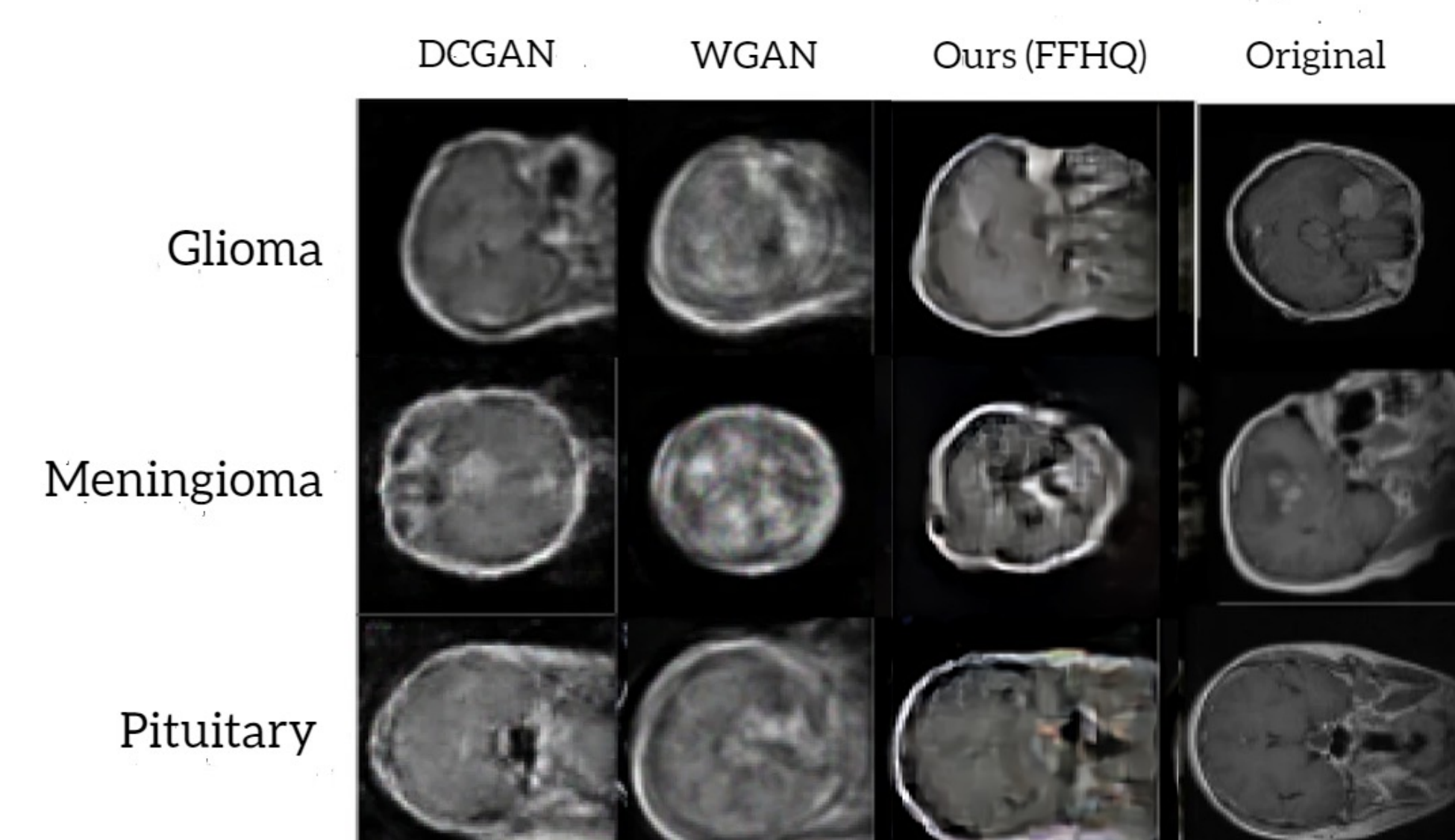


Figure. Samples of initially generated images.
Results show a visualization of the weights of the StyleGAN model trained on FFHQ, AFHQ (Cat), AFHQ (Wild), and BreCaHaD images.

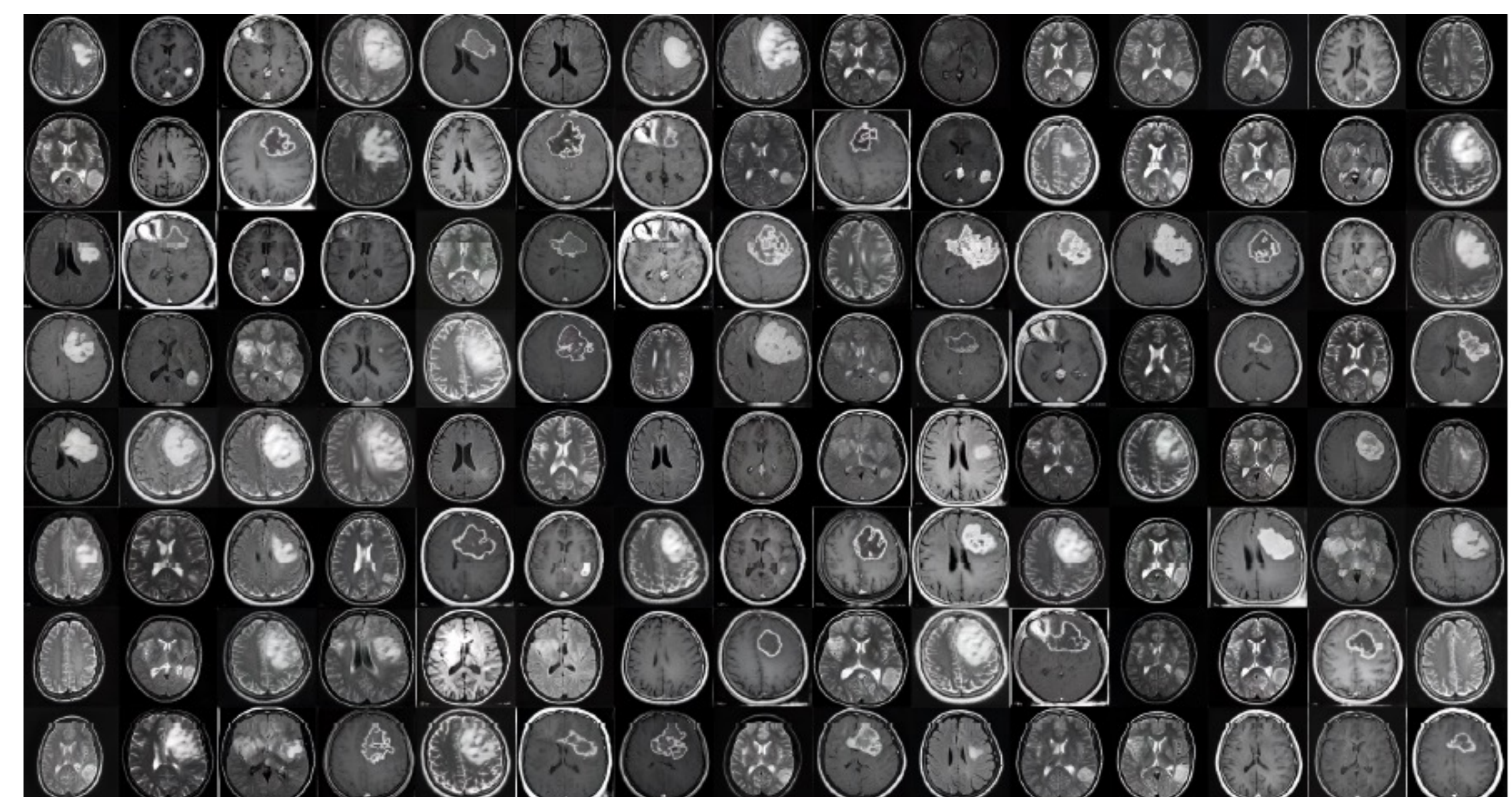
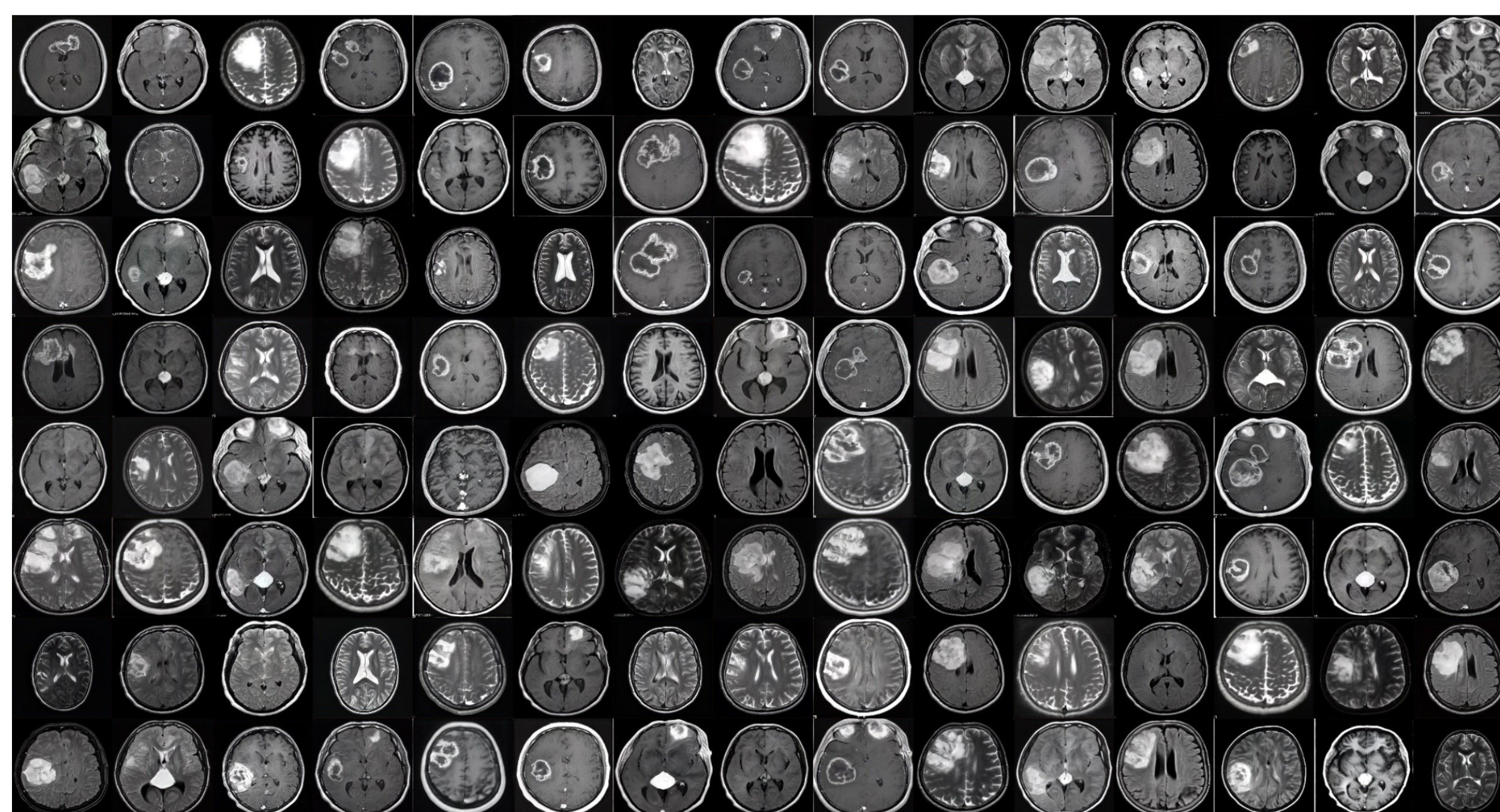
Results



Model	FID	KID
FFHQ	58.1097	0.00862692
AFHQ Cat	60.9486	0.01049849
AFHQ Wild	59.7498	0.0109629
BreCaHaD	67.5336	0.02081763

FID: Fréchet Inception Distance. KID: Kernel Inception Distance

Samples of Synthetic Images



Contact

Hazrat Ali
Hamad Bin Khalifa University, Doha, Qatar
Email: haal2@hbku.edu.qa, hazrat.ali@live.com
Website: alihazrat.weebly.com



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