# Brain Tumor Classification Using a Pre-Trained Auxiliary Classifying Style-Based Generative Adversarial Network

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## Abstract

Computer Vision's applications and their use cases in the medical field have grown vastly in the past decade. The algorithms involved in these critical applications have helped doctors and surgeons perform procedures on patients more precisely with minimal side effects. However, obtaining medical data for developing large-scale generalizable and intelligent algorithms is challenging in the real world as multiple socio-economic, administrative, and demographic factors impact it. Furthermore, training machine learning algorithms with a small amount of data can lead to less accuracy and performance bias, resulting in incorrect diagnosis and treatment, which can cause severe side effects or even casualties. Generative Adversarial Networks (GAN) have recently proven to be an effective data synthesis and augmentation technique for training deep learning-based image classifiers. This research proposes a novel approach that uses a Style-based Generative Adversarial Network for conditional synthesis and auxiliary classification of Brain Tumors by pre-training. The Discriminator of the pre-trained GAN is fine-tuned with extensive data augmentation techniques to improve the classification accuracy when the training data is small. The proposed method was validated with an open-source MRI dataset which consists of three types of tumors - Glioma, Meningioma, and Pituitary. The proposed system achieved 99.51% test accuracy, 99.52% precision score, and 99.50% recall score, significantly higher than other approaches. Since the framework can be made adaptive using transfer learning, this method also benefits new and small datasets of similar distributions.

## Keywords

Generative Adversarial Image Classification, Image Synthesis, Magnetic Resonance Imaging, Medical Imaging, Networks.

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## I. Introduction

THE healthcare industry has evolved tremendously because of the growing demands and population. It has become highly challenging for doctors to meet the velocity and volume of patients requiring diagnosis and treatments. The numerous realtime advances in Computer Vision and Artificial Intelligence in the medical field have been a game-changer in how fast and accurate most medical procedures are carried out. This has made doctors save time and establish treatments for patients early [1], [2]. While most of the algorithms in hand are not perfect, they are still helpful in real-time for gathering inferences at various stages of diagnoses and treatments.

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Classification of Brain Tumors has been a difficult task. It is one of the most crucial steps and required information in diagnosis, presurgical planning, and treatment. While radiologists accurately identify and annotate these tumors for further steps, it is highly impossible for them to do the same at a large scale. Identifying the brain tumors and their type also depends on several scan parameters like the scan's modality, isotropy, magnetic field strength, and other acquisition parameters [3], [4]. The scan acquisition also depends upon several socio-economic and demographic factors. Hospitals in a highly developed country may have 7 Tesla Magnetic Resonance Imaging machines. In contrast, countries with a not-so-similar economy and infrastructure may have only 1.5 Tesla Magnetic Resonance Imaging machines. These fields can vastly impact the manual and automated process of scan analysis during the diagnosis and planning of the treatment.

The recent development of several deep learning architectures like

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convolutional neural networks and transformers has helped solve and automate processes in several critical domains like healthcare, autonomous driving, and cybersecurity. Hence, deep learning can play a massive role in classifying brain tumors. The algorithms are also multi-disciplinary, enabling people to solve problems or invent in any field. However, the performance of these algorithms can be easily biased or degraded when it is not trained correctly with massive datasets using the appropriate methods. Obtaining medical datasets is challenging due to numerous legal procedures and factors like patient consent and the prevalence of disorder or disease. Geography also plays a vital role since people from different locations have different physical and mental attributes. This can cause the deep learning-based solutions can have less accuracy or bias based on the mentioned factors, leading to improper diagnosis and treatment that can result in side effects or even death. Several existing solutions have high false positive and negative rates for the same reasons. Furthermore, high accuracy or almost 100 % accuracy is expected in the healthcare industry since the algorithm's results are going to be used on patients for different purposes.

The groundbreaking invention of Generative Adversarial Networks (GAN) by Goodfellow et al. [5] has led to many creative applications and usage of image synthesis. GANs have also been popularly used as a data augmentation method that can improve the performance of image classifiers by oversampling. In this study, a framework that uses a Conditional Style-based Generative Adversarial Network with auxiliary classification [6], [7], [8], [9], [10] for pre-training the GAN and fine-tuning the Discriminator to improve the performance of auxiliary classification with extensive augmentation methods has been proposed. Fig. 5 displays a simplified architecture diagram of the system, giving an overview of how the proposed method works in real-time.

The proposed system uses an open-source dataset compiled by J. Cheng et al. [11] that comprises T1-weighted Magnetic Resonance Images with a magnetic field strength of 1.5 Tesla of many patients with three types of tumors: Glioma, Meningioma, and Pituitary. By training the proposed framework with extensive augmentation techniques during preprocessing, the system achieved a test accuracy of 99.51% and several other crucial validation metrics using the fine-tuned auxiliary classifying Discriminator of the pre-trained GAN. This method is advantageous when the availability of datasets is limited and can be fine-tuned using transfer learning for other datasets with similar distributions like scans from 3 Tesla or & Tesla machines.

This research article has been split into the following sections based on the experimental investigations:

1. The related research work that motivated the development and implementation of the proposed method.
2. Analysis of the dataset and the augmentation techniques was used as preprocessing for training the given framework.
3. A detailed description of the proposed architecture and its working with the training and validation strategies, hyperparameter settings, and optimization techniques that were followed.
4. The various evaluation metrics that were used to evaluate the model with the obtained results.
5. Discussion of the proposed system's results, advantages, and limitations.

## II. Related Works

For this study, a deep analysis of the related research works and state-of-the-art methods for brain tumor classification was conducted, which helped in developing a novel and improved method for classifying brain tumors. Xiao et al. [12] proposed a method presenting the brain tumor classification with Dual Suppression Encoding and Factorized Bilinear Encoding with ResNet50 to differentiate minor features extracted from various MRI images belonging to different types of brain tumors. This achieved an excellent performance of 98.02% in classifying the exact features of brain tumors. While the feature engineering and the convolutional neural network architecture are amazing, the accuracy is comparatively lesser than some other methods.

Yerukalareddy et al. [6] introduced an intriguing method based on deep learning to classify brain tumors on MRI scans by pre-training MSGGAN to classify tumor types using the auxiliary block of the Discriminator. This approach obtained an accuracy of 98.57%, proving to be better than other methods. Our system uses a similar pre-training technique with significant changes in the neural network architecture, data preprocessing, and optimization strategies. Diaz-Pednas et al. [13] presented a multiscale approach using convolutional neural networks that used images at different resolutions and stages to learn feature representations to perform the classification. It was 97.3% successful in classifying meningioma, glioma, and pituitary types of tumors. Mohan Karnati et al. [14] presented a multi-scale deep convolutional neural network for detecting COVID-19 from X-rays with an accuracy >99%. This research works highlight the dynamicity and adaptability of neural networks to learn from any form of data.

Kumar R.L. et al. [15] have introduced a model that uses ResNet50 and global average pooling and acquired 97.08% and 97.48% efficient performance with and without data augmentation, respectively. While ResNet50 uses global average pooling by default, the authors have implemented a transfer learning-based approach to train the architecture to classify three types of brain tumors. Inspired by this approach, our framework was benchmarked with and without augmentation. Singh R. et al. [16] developed a Gabor-modulated convolutional filter-based tumor classification in the brain to classify Low-grade and High-grade Glioma. However, the number of network parameters is high, and it can only classify within the same tumor type. Likewise, Abd El Kader et al. [17] have derived a differential deep-CNN model to classify low-grade and high-grade glioma from brain MR images with an accuracy of 99.25%.

Kang et al. [18] presented a brain tumor classification method with an ensemble of features (DenseNet-169) using pre-trained convolutional neural networks, extracting the features of the tumor from MRI images using learned representations. They have achieved an accuracy of 93.72 % by using the CNN for feature extraction and Quasi-Support Vector Machine for classification. Alshayeji et al. [19] proposed an automatic classification of brain tumors by integrating two CNN structures and Bayesian optimization, resulting in higher performance with 97.37% correctness. Arbane et al. [20] used CNN architectures such as ResNet, Xception, and MobilNet-V2 based on transfer learning. They have compared these methods and concluded that MobilNet-V2 gave the best accuracy of 98.24% and an F1-score of 98.42%. Ayesha et al. [21] have invented a deep learning and improved particle swarm optimization-based algorithm to classify brain tumors using multiple MRI modalities with an accuracy of 99.9 %. Amjad Rehman et al. [22] proposed a 3D Convolutional Neural Network to extract brain tumors and employed a correlation-based feature selection to create a classification algorithm that achieved >92% on BraTS datasets. These research works helped in assessing the possible biases and challenges associated in training our algorithm.

Deepak S. et al. [23] adopted an approach of CNN with a support vector machine and attained a classification exactness of 95.82%. The system seems novel, but it is underperforming compared to other state-of-the-art methods. To classify the tumor, Singh R. et al. [24] have used a wavelet transform technique, which is fed to a kernel-

based support vector machine. This algorithm yielded an accuracy of 98.87%, better than the deep neural-network approach. Ghassemi et al. [7] have used the GAN technique with a deep neural network pre-training process, resulting in high accuracies of 93.01% and 95.6% on the introduced and random splits, respectively, while classifying the meningioma, glioma, and pituitary tumors. The approach proposed in our study uses some motivations from this research work, and a robust framework was built like this.

Badza et al. [25] presented a new Convolutional Neural Network algorithm using a 10-fold cross-validation approach on the brain tumor databases. It produced 96.56% accuracy and claimed to have a decent generalization capability and execution speed. Deepak S. et al. [8] have used multi-scale gradient GAN to synthesize images of meningioma tumors. This approach has produced results close to the source dataset [26] but only for the Meningioma tumor type. Nonetheless, this method justifies the benefits of Generative Adversarial Networks in training image classifiers by using synthesized images for oversampling. Rehman A. et al. [27] have compared Convolutional Neural Network architectures like AlexNet, GoogLeNet, and VGGNet to extract distinguishable features and patterns from MRI images to obtain 98.69% accuracy using the VGG16 network. A. Seal et al. [28] proposed two probabilistic models using Logistic Regression (LR), Linear Discriminant Analysis (LDA) and a predictive model using Multilayer Perceptron (MLP) with a Fuzzy C-Means clustering algorithm for feature extraction of lesions in the human liver to predict whether a person has cancer in their liver or not. The MLP model achieved the lowest accuracy of 94.4 % when compared to the other models. This methodology would help extend the study's proposed method to accommodate for benign and malignant classification of the tumor in the future.

Our proposed method has used a similar approach to Oeldorf et al. [9], who have leveraged Conditional Style-based Generative Adversarial Networks to synthesize logos images. This is highly beneficial for synthesizing images based on desired class or condition and can be adapted to any appropriate dataset. Oeldorf et al. [9]'s paper was based on the Style-based Generative Adversarial Network proposed by Karras T. et al. [29], [30] from NVIDIA, improving the quality of the synthesized image using progressive growing of GANs, adaptive instance normalization, and style mixing using latent vectors. Karnewar et al. [31] have introduced a Multi-Scale Gradient Generative Adversarial Network for synthesizing high-resolution images, which uses images at different resolutions/scales at various stages to learn and synthesize images using unsupervised learning. Karnewar and team [32] have also improved their approach by generating synchronized multi-scale images using concatenation operation, limiting forced mixing regulation.

Sajjad M. et al. [30] have presented a Multi-Grade approach using a Deep Convolutional Neural Network, improving the correctness up to 94.58% using data augmentation and deep learning. This is useful in classifying the tumor grades, and the classification of tumor types of their method is sub-optimal. Seetha J. et al. [33] proposed an automated tumor detection mechanism using Convolutional Neural Networks with small kernels. Their approach attained an accuracy of 97.5% with minimum complication. Balasooriya M. et al. [34] developed a sophisticated deep learning method using CNN, performing with improved accuracy of 99.68%. Afshar P. et al. [35] have proposed to equip CapsNet incorporating raw and surrounding brain tissues, producing 90.89% accuracy. J. Cheng et al. [11] from Southern Medical University, Guangzhou, China open-sourced a brain tumor dataset containing T1- weighted contrast-enhanced images containing three types of tumors: glioma, meningioma, and pituitary. This dataset was used to train and benchmark the performance of the proposed method. Jun-Yan Zhu et al. [26] have proposed an approach for translating an image from a source domain to a target domain, and quantitative comparisons were demonstrated.

Goodfellow et al. [36] have designed a new way to synthesize non-linear probability distributions by using two neural network models that learn adversarially to improve each other;s performance with different goals called Generative Adversarial Networks. Kaiming et al. [28] presented a residual learning network called ResNet that uses skip connections at different convolutional blocks to improve feature learning and classification performance. Most of the related work and work done so far was using Convolutional Neural Networks using the figshare dataset provided by J. Cheng [11]. Despite multiple similar approaches with different training and hyper-parameter optimization-based strategies, most of the works' accuracies are not up to the mark. The GAN pre-training-based approaches [6], [7] have achieved almost perfect classification results without using the images synthesized for oversampling and training different network architectures. The literature survey of related works has been summarized in Table I.

TABLE I. Summary of Related Work

| Authors | Method | Accuracy | Description | Limitations |
|---|---|---|---|---|
| Xiao et al. [12] | Dual Suppression Encoding and Factorized Bilinear Encoding | 98.02% | A complex and robust feature extraction technique yielding good accuracy | The approach produced results very similar to other methods, and accuracy is sub-optimal |
| Yerukalareddy et al. [[6] | MSG-GAN pre-training and fine-tuning discriminator | 98.57% | Advanced implicit feature learning by using GAN pre-training and fine-tuning the discriminator with augmented data | Generator and Discriminator requires up-sampled and down-sampled images at multiple stages to produce good results. |
| Diaz-Pednas et al. [13] | Multi-scale Convolutional Neural Networks | 97.3% | Residual-like operation using source images at different resolutions at multiple stages to improve feature extraction | Requires sub-sampled images at multiple stages to produce good results. |
| Kumar R.L. et al.[15] | ResNet50 | 97.08%, 97.48% | Transfer learning with ResNet50 architecture on augmented and non-augmented data | ResNet50's pre-trained weights are of ImageNet dataset which does not have learned features from MRI scans thus having decent results. |
| Singh R. et al. [24] | Wavelet-based transformation with a kernel-based Support Vector Machine | 93.72% | A different feature extraction technique based on image processing having good results using SVM. | Convolutional Neural Networks have proven to be better at learning kernels dynamically but the proposed SVM has achieved sub-par results. |
| Ghassemi et al. [7] | ACGAN based pre-training and fine-tuning of the discriminator | 95.6% | Advanced implicit feature learning by using GAN pre-training and fine-tuning the discriminator with data of different splits. | The GAN architecture is based on DCGAN which upon training can be unstable and can cause mode-collapse with limited samples. |

These research works helped in developing a sophisticated system that can classify three types of tumors using an auxiliary classifying style-based generative adversarial network. While most of the related works have used deep learning-based approaches, the usage of different architectures, datasets, hyperparameters, preprocessing, and training strategies have led to models with variable biases and high false positive/negative rates in different cases. In Section III, the research methodology has been explained in detail, giving an overview of the dataset, preprocessing techniques, and proposed system implementation. The results obtained from the conducted experiments were validated using different strategies and evaluation metrics, which have been discussed in Section IV. The advantages, limitations, and analysis against several state-of-the-art methods have been briefly discussed in Section V. Finally, the proposed research and the future works to overcome the drawbacks of the proposed method have been summarized in Section VI.

## III. Methodology

The proposed method uses an Auxiliary Conditional Style-based Generative Adversarial Network for pre-training and usage of the pre-trained Discriminator of the GAN by fine-tuning for classifying Glioma, Meningioma, and Pituitary tumors from a given MR Image. The experiments were conducted on a system with Ubuntu OS with 54 GB RAM and eight 16 GB NVIDIA V100 graphic processing units for faster training using distributed computing. Python was used to develop experiments with the help of libraries like PyTorch, NumPy, Matplotlib, Seaborn, Pandas, and Scikit-Learn. The methodology and experiments performed on the dataset, preprocessing steps, and neural network architectures have been explained in detail in the following sub-sections.

### A. Dataset

The system was trained and benchmarked using a dataset open-sourced on Figshare in 2017 by J. Cheng et al. [11] containing T1-weighted Magnetic Resonance Images of Glioma, Meningioma, and Pituitary tumors. There are 3064 contrast-enhanced images presented as 2D MRI scans from 233 patients. The images appear to be of 1.5 Tesla Magnetic Field Strength and are of 512x512 resolution in coronal, axial, and sagittal views, as seen in Fig. 1. However, the number of images across all three modalities is low and can lead to a biased or less accurate classification rate upon training deep learning or machine learning algorithms. Table II describes the dataset in detail with supplemental information.

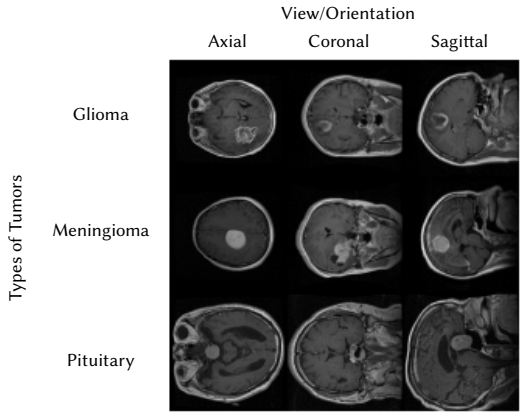


Fig. 1. T1-Weighted MR Images of tumor types in different views.

### B. Preprocessing & Preparation

The dataset was downloaded from figshare as uploaded by J. Cheng et al. [11]. The MR Image slices were extracted from big data file format (.h5) and saved as png images under the corresponding folder as their class name, denoting the type of brain tumor. Convolutional neural networks perform better when the resolution of the image is higher. However, most MR Images are obtained in 256x256 resolution as most scanners have 256 as their frequency and Field-of-View (FOV) parameters since it takes less time for acquiring a T1-weighted MRI. MR Image scanners are also susceptible to noise during scan acquisition, and the noise produced is mostly Gaussian or non-linear. A matrix is randomly sampled from Gaussian distribution as described by (1) and (2) and is added to the input image to introduce noise in the source MR Image.

TABLE II. T1-Weighted Brain Tumor MRI Dataset Details

| Type of Brain Tumor | Number of Patients | Number of MR Image slices | View/Orientation | | | Ground Truths | |
|---|---|---|---|---|---|---|---|
| | | | Axial View | Coronal View | Sagittal View | Tumor Labels | Tumor Masks |
| **Glioma** | 89 | 1426 | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Meningioma** | 82 | 708 | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Pituitary** | 62 | 930 | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Total** | 233 | 3064 | | | | | |

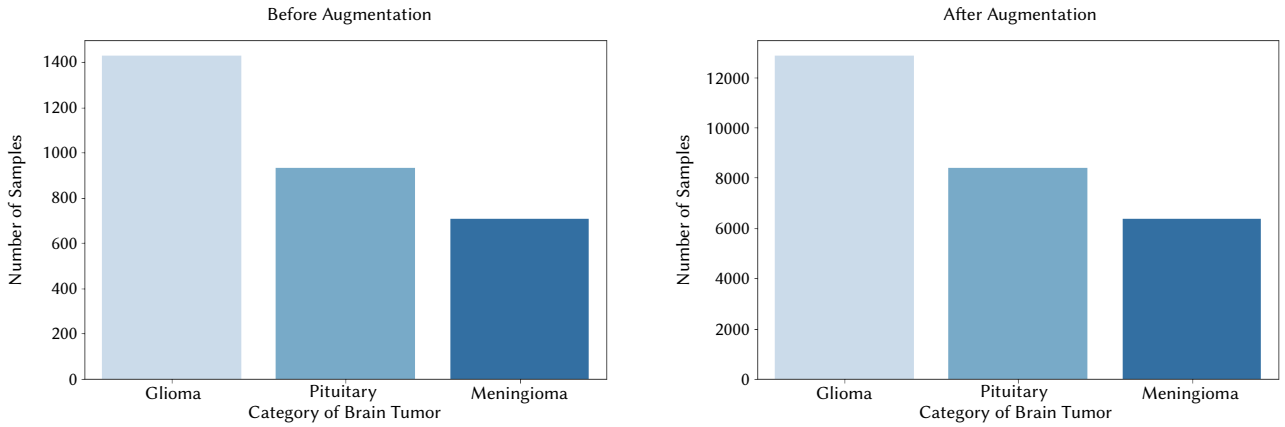


Fig. 2. Count Plot of samples before augmentation (up) and after augmentation (down).

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \quad (1)$$

$$f(x) = \begin{bmatrix} P(z_{11}) & P(z_{12}) & P(z_{13}) & \dots & P(z_{1n}) \\ P(z_{21}) & P(z_{22}) & P(z_{23}) & \dots & P(z_{2n}) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P(z_{d1}) & P(z_{d2}) & P(z_{d3}) & \dots & P(z_{dn}) \end{bmatrix} + \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{d1} & x_{d2} & x_{d3} & \dots & x_{dn} \end{bmatrix} \quad (2)$$

Histogram equalization was performed on the data to standardize the distribution and equalize intensity values, removing any bias fields. Finally, angular augmentations were performed on the image to get resultant images in 45, 90, 120, 150, 180, 270, 300, 330 degrees. Even though the scans in the real world would be in -90 to 90, -180 to 180 degrees in axial, coronal, and sagittal views, this type of augmentation would help the model learn the kind of tumors at different places and orientations. The labels were then one-hot encoded to create sparse tensors representing the tumor type. Fig. 2 depicts the dataset's sample distribution pre and post data augmentation.

These were the augmentation techniques performed for preprocessing the MR Images in general. However, two types of preprocessing with different augmentation techniques were performed for training the GAN and then fine-tuning the Discriminator of the pre-trained GAN:

1. Strategy 1: The augmentation technique used for training the GAN is resizing the input image to 256x256 resolution, applying random center cropping, random translation of the image towards left or right randomly, and histogram equalization. This augmentation resulted in 3064 images with some source images randomly cropped and translated.
2. Strategy 2: The augmentation techniques followed for fine-tuning the discriminator model were resizing the input image to 256x256 resolution, applying random center cropping, random Gaussian noise, histogram equalization, and angular augmentation. This augmentation resulted in 27576 images that contained source images, and the augmentation applied images.

The preprocessing can be done on the fly based on any given batch size using PyTorch Datasets and DataLoaders to save memory and GPU usage. A stratified 5-fold cross-validation was performed on the dataset, which splits the given dataset into five random subsets while preserving the ratio of the number of samples per class in each subset where the algorithm is trained by combining four of the subsets and evaluating it against the remaining set in all permutations and combinations. These approaches were used for pre-training the GAN and fine-tuning the Discriminator using corresponding augmentation methods.

## C. Algorithm

The suggested method is based on a conditional Style-based Generative Adversarial Network with an auxiliary classification block that performs the tumor classification. It comprises two significant portions: pre-training the GAN and fine-tuning the pre-trained discriminator network with heavy data augmentation. The style-based generator is a modified architecture proposed by Karras T. et al. [10] with conditional input support to help the generator learn and produce distributions based on specified input classes like the method proposed by Oeldorf et al. [9]. The generator of the GAN uses convolutional blocks of decreasing filter size (256 -> 128 -> 64 -> 32) with a 3x3 kernel followed by adaptive instance normalization and leaky relu activation with bilinear upsampling. The Discriminator of the GAN is a simple convolutional neural network comprising of convolutional layers with growing filter size (16 -> 32 -> 64 -> 128 -> 256) followed by leaky relu (4) and max-pooling, with two final output layers: adversarial fully-connected layer (5) for image legitimacy prediction and an auxiliary fully-connected layer for tumor classification. The hyperparameters for the convolutional blocks in both Generator and Discriminator are set to grow progressively as suggested by Karras T. et al. [37] to have better learning fidelity. Furthermore, the convolutional layers' filter size can grow from 16 to 1024, for a target image resolution of 1024x1024. A detailed architecture diagram of the described generator and discriminator neural networks is displayed in Fig. 3 and Fig. 4.

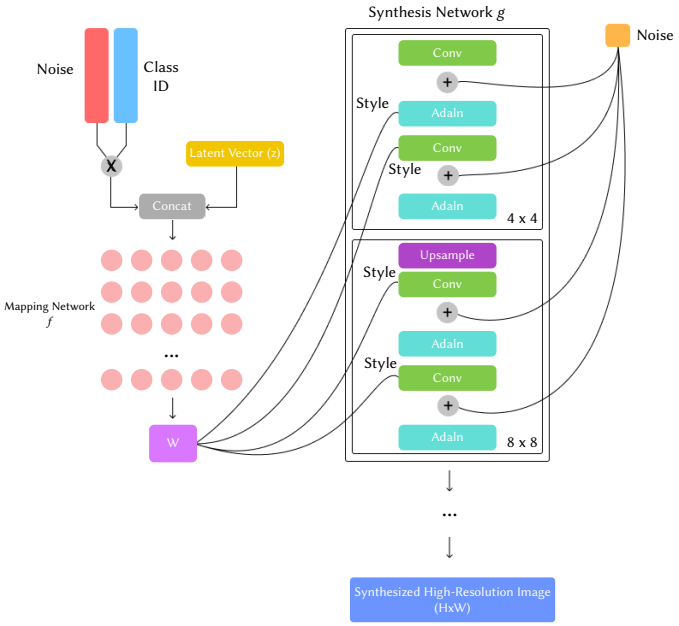


Fig. 3. Conditional Generator for the Style-based Generator Adversarial Network.


Fig. 4: Discriminator of the Style-based Generative Adversarial network with an auxiliary output block for tumor classification.

The process of the Generative Adversarial Network can be formulated as (3). Unlike Yerukulareddy et al. [6], the proposed generator uses a concatenated noise vector containing class representations and the latent vector as an input instead of classwise embedding, represented in Fig. 3. This makes the input latent vectors less sparse and leads to better feature identification and learning since the input has class details with a random distribution to generate the images.

$$\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log\ D(x)] + \mathbb{E}_{z\sim p_{\text{generated}}(z)}[1-\log\ D(G(z))] \tag{3}$$

$$R(z) = \begin{cases} z & z > 0 \\ \alpha z & z <= 0 \end{cases} \tag{4}$$

$$\hat{y} = W^T.X + b \tag{5}$$

The concatenated input latent vectors are passed through a fully connected network, called the mapping network, which maps styles or feature representations to the synthesis network for conditional image generation. The progressive growth or upsampling of the images combined with the mapping network, adaptive instance normalization (6) [38], and latent vectors with random and class representations helps the generator to learn classwise features adversarially with feedback received from the Discriminator regarding the image legitimacy and correctness of the tumor image generated.

$$\text{AdaIN}\ (\boldsymbol{x}_i, \boldsymbol{y}_i) = \boldsymbol{y}_{s,i}\left(\frac{\boldsymbol{x}_i - \mu(\boldsymbol{x}_i)}{\sigma(\boldsymbol{x}_i)}\right) + \boldsymbol{y}_{b,i} \tag{6}$$

The Discriminator has two objectives: the adversarial fully connected block predicts image legitimacy, and the auxiliary fully connected block predicts tumor type. The discriminator is a progressively growing convolutional neural network with a two-way output channel, as seen in Fig. 4. The adversarial fully connected block is activated with a sigmoid (7) to output probability-like values within the range of 0 to 1. Softmax (8) was used to activate the auxiliary fully connected block to output a vector of 3 probability-like values representing the type of tumor where the index with maximum probability can be mapped to the tumor's name.

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{7}$$

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_j}} \tag{8}$$

Binary Cross-entropy (9) is used as the loss function for the adversarial outputs, and categorical cross-entropy (10) is used as the loss function for the auxiliary outputs. These two losses are averaged and used for backpropagation with gradient penalty, similar to WGAN-GP [39]. The GAN's discriminator loss and the combined loss function with gradient penalty are represented by (11) and (12).

$$\text{BinaryCrossentropy} = \text{bee}\ (y,p) = -(y\log\ (p) + (1-y)\log\ (1-p)) \tag{9}$$

$$\text{CategoricalCrossentropy} = cce(y,p) = -\sum_{c=1}^{M} y_{o,c}\log\left(p_{o,c}\right) \tag{10}$$

$$Discriminator\ Loss = \nabla_{\theta D}\left[f_{\theta D}\left(\left(bce(y,\hat{y}) + cce(y,\hat{y})\right)/2\right) - \sum_{c=1}^{M} y_{o,c}log(p_{o,c})\right] \tag{11}$$

$$\text{Combined Loss}\ =\ \text{Discriminator Loss}\ + \lambda\left[\left(\|\nabla_{\hat{x}} D(\hat{y},y)\|_2 - 1\right)^2\right] \tag{12}$$

Pre-training of the GAN was done with a latent size of 512 for 1000 epochs with a batch size of 128 at a learning rate of 0.005 using the first augmentation strategy mentioned in section 3.2. Once the GAN is trained, the pre-trained Discriminator's weights were frozen for all the layers except the auxiliary classification layer. This Discriminator was then fine-tuned with a batch size of 64 at a learning rate of 1e-4 with the second augmentation strategy given under section 3.2 and without any augmentation using categorical cross-entropy (10) as loss function. Later, Adam optimizer [40] for optimization while training the GAN and fine-tuning the pre-trained discriminator network. Table 3 presents the optimization parameters for training the GAN and fine-tuning the Discriminator.

TABLE III. PARAMETERS USED FOR OPTIMIZING THE NETWORK DURING PRE-TRAINING AND FINE-TUNING

| Hyper-parameters | GAN Pre-training | Discriminator Fine-tuning |
|---|---|---|
| Optimizer | Adam | Adam |
| Loss Function | Combined Loss (9) | Categorical Crossentropy (7) |
| Latent Size | 512 | - |
| Epochs | 1000 | 10 |
| Batch Size | 128 | 64 |
| Augmentation Strategy | Strategy 1 given in section 3.2 | Resizing images to 256x256, no augmentation strategy<br>Strategy 2 given in section 3.2 |
| Learning Rate | 0.005 | 1e-4 |

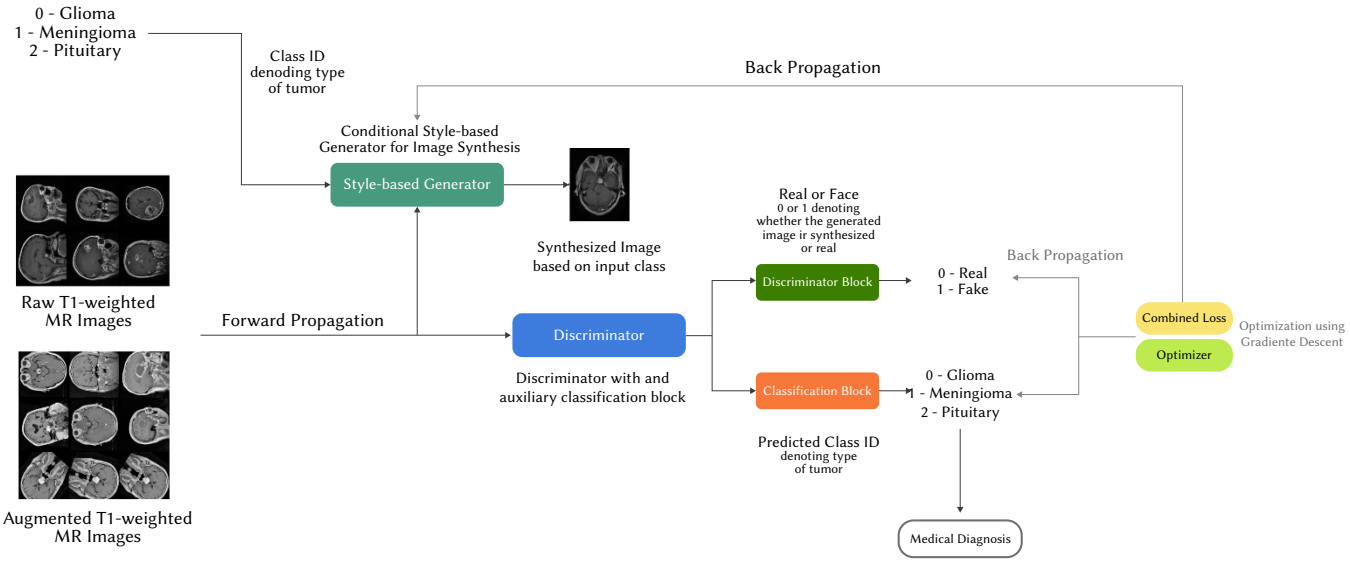


Fig. 5: System Architecture Diagram.

The entire system's architecture in a real time setting can be seen in Fig. 5. In the upcoming sections, the evaluation metrics used for evaluating the proposed classifier and the achieved results are discussed, with a comparison of it against the other existing state-of-the-art methods.

## IV. Results

The benchmarking experiments were done using the Discriminator network of the pre-trained GAN framework on the test samples of 5-fold cross-validation sets with and without augmentation, as mentioned in section III.B. A brief description of the evaluation metrics used is discussed in section IV.I, and the obtained results using the experimental setup are displayed in section IV.II.

### A. Evaluation Metrics

The following evaluation metrics have been used for analyzing the results of the proposed method to understand the algorithm's performance and limitations:

As seen in Table IV, the confusion matrix has been used to understand the model's classification performance and derive other metrics that can give insights into bias and limitations of the algorithm in place.

TABLE IV. Typical Confusion Matrix

| | **Positive** | **Negative** |
|---|---|---|
| **Positive** | True Positive | False Negative |
| **Negative** | False Positive | True Negative |

The correctness of the model can be defined by accuracy, which tells how right the model has done the classification.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

The ratio of true positives to the sum of true positives and false positives is precision. The ratio of true positives and the sum of true positives and false negatives are known as recall. The balance between these scores is known as the F1 score. These scores help us understand the true classification rate of the classifier in depth.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{14}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{15}$$

$$F1 = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 * TP}{2 * TP + FP + FN} \tag{16}$$

The rate of true positives against false negatives is described by a Receiver Operating Characteristic (ROC) Curve, which can tell how well a classifier is good at producing true positives. A classification algorithm performs better when its ROC Area Under the Curve (AUC) score is higher.

$$\text{Sensitivity} = \text{Recall} = \frac{TP}{TP + FN} \tag{17}$$

$$\text{Specificity} = \frac{TN}{FP + TN} \tag{18}$$

$$AUC = \frac{\text{Specificity} + \text{Sesnsitivity}}{2} \tag{19}$$

### B. Model Evaluation

The discriminator network of the pre-trained GAN was fine-tuned on the 5-fold cross-validation sets with and without augmentations using different seed values for sampling and internal shuffling. The predictions were converted to sparse tensors containing one at indices with maximum confidence/probability values in the output tensor that denote the type of tumor using the argmax operation (20).

$$\text{result} = \arg\max_{\theta} g(x) \tag{20}$$

Tables V and VI display the model's performance data on the mentioned test sets with accuracy, precision, recall, and F1 scores as evaluation metrics.

TABLE V. Fine-tuned Discriminator's Performance on Non-augmented Test Sets of All the Five Folds

| **Fold/Evaluation Metrics** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1 Score (%)** |
|---|---|---|---|---|
| **Fold 1** | 99.80 | 99.68 | 99.42 | 99.55 |
| **Fold 2** | **99.83** | **99.88** | **99.76** | **99.82** |
| **Fold 3** | 99.45 | 99.56 | 99.40 | 99.48 |
| **Fold 4** | 98.98 | 99.03 | 98.88 | 98.95 |
| **Fold 5** | 99.63 | 99.72 | 99.54 | 99.63 |
| **Mean** | 99.53 | 99.57 | 99.40 | 99.48 |

TABLE VI. Fine-tuned Discriminator's Performance on Augmented Test Sets of All the Five Folds

| **Fold/Evaluation Metrics** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1 Score (%)** |
|---|---|---|---|---|
| **Fold 1** | 98.78 | 98.49 | 98.56 | 98.52 |
| **Fold 2** | 99.1 | 98.95 | 99.02 | 98.98 |
| **Fold 3** | **99.51** | **99.52** | **99.50** | **99.51** |
| **Fold 4** | 99.42 | 99.44 | 98.39 | 98.91 |
| **Fold 5** | 99.27 | 99.26 | 99.23 | 99.24 |
| **Mean** | 99.216 | 99.13 | 98.94 | 99.03 |

Table VI shows that the fine-tuned model obtained a whopping accuracy of 99.83% on the test set of non-augmented Fold 2 and 99.51% accuracy on the test set of augmented Fold 3. The mean accuracy of the model on non-augmented and augmented sets is around 99.53% and 99.21%. The results of the fine-tuned discriminator network of pre-trained GAN on the test sets of the best-performing fold with and without augmentations are highlighted in Tables 5 and 6.

Fig. 6 and Fig. 7 are the confusion matrix and Receiver Operating Characteristic Curve for all the classes, obtained using the second subset of non-augmented 5-fold stratified cross-validation set. Only one image was misclassified in the test set, and the ROC-AUC scores are higher, suggesting that the model is great at classifying between the three types of tumors. Fig. 8 displays the classwise ROC curves with their corresponding AUC scores.

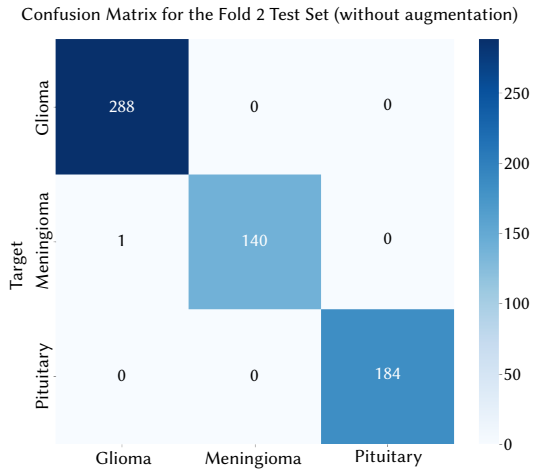


Fig. 6. Confusion Matrix for the non-augmented test set (Fold 2).

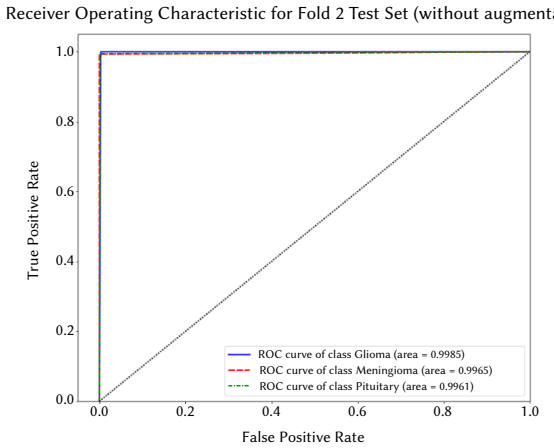


Fig. 7. Receiver Operating Characteristic (ROC) curve for the non-augmented test set (Fold 2).

The confusion matrix and Receiver Operating Characteristic Curve for all classes are shown in Fig. 9 and Fig. 10, obtained using the third fold's test set of the augmented 5-fold stratified cross-validation set. Out of the 5514 images in the test set, there were only 27 that were incorrectly classified. The model's ROC-AUC scores are also high, indicating that the model is very good at classifying the three types of tumors. The classwise ROC curves with their corresponding AUC scores are shown in Fig. 11.

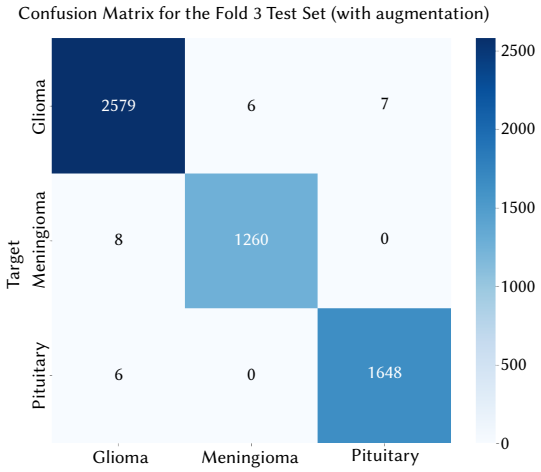


Fig. 9. Confusion Matrix for the augmented test set (Fold 3).

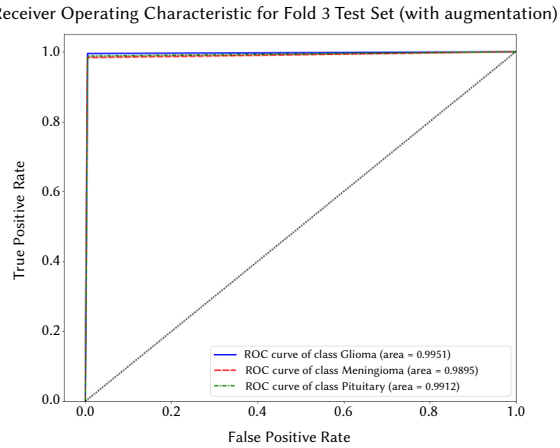


Fig. 10. Receiver Operating Characteristic (ROC) curve for the augmented test set (Fold 3).

## V. Discussion

This section evaluates the model's performance against some state-of-the-art brain tumor classification methods. The neural network architectures of the other methodologies were implemented to compare the results with the proposed method. The experimental investigations showed that the fine-tuned discriminator network has over 99.5% in successfully classifying the three tumor types. Table VII displays some of the evaluation metrics obtained by the proposed method against other existing methods.

From Table VII, it can be said that the proposed method has achieved the best metrics. The pre-training mechanism with minimal augmentation methods, as mentioned in section 3.2, used while training the conditional style-based GAN with auxiliary classification helps the discriminator network learn even the most minor features to identify it is real or fake as well as the type of tumor. This also increases the generator's performance adversarial to synthesize images of tumors. The framework learns to synthesize images and predict image legitimacy and the type of tumor simultaneously while training it for auxiliary classification and image generation. When the pre-trained Discriminator is fine-tuned, all the convolutional layers are frozen, and only the auxiliary classification block is trained to improve the classification performance with extensive augmentation. This makes the fully connected layer use the learned features from the convolutional blocks that act as feature extractors and adapt to the target output classes with features learned during the pre-training for image generation and legitimacy prediction. This also indicates that the model is adaptive and highly beneficial in transfer learning to apply

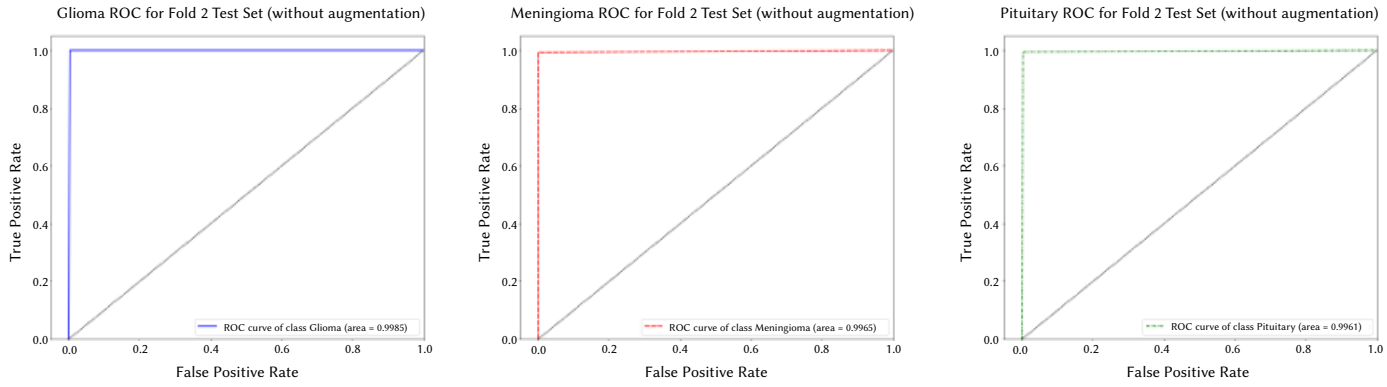


Fig. 8. Classwise ROC curves with AUC values for the non-augmented test set.

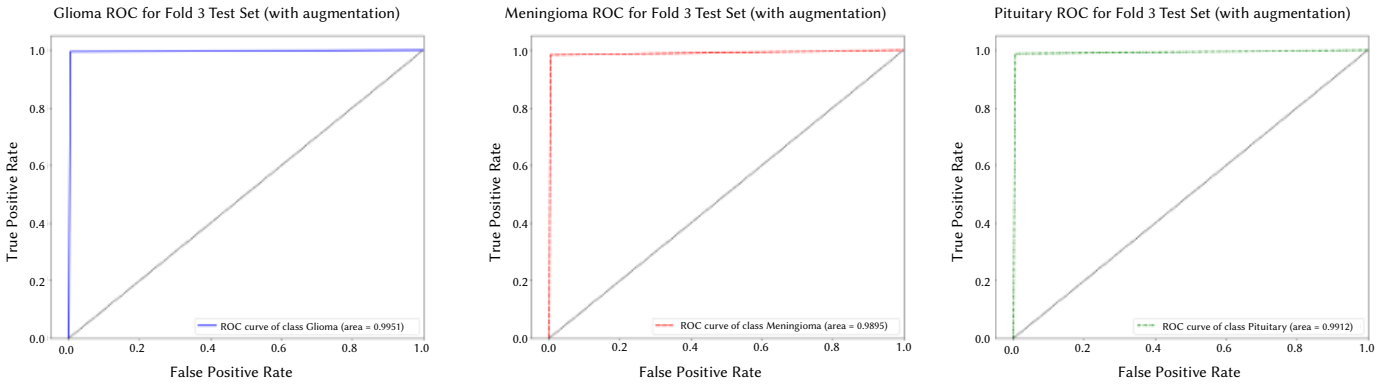


Fig. 11. Classwise ROC curves with AUC values for the augmented test set.

it for datasets of similar distribution like brain MRI or other MRI scans from 3 Tesla machines or 7 Tesla machines. The entire architecture can be retrained on any dataset since deep learning algorithms are naturally adaptive to multifaceted applications.

TABLE VII. Comparison of the Proposed Method Against Existing Approaches

| Method | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| Proposed Method - with the augmented test set | 99.51 | 99.52 | 99.50 |
| Proposed Method - with the raw test set | 99.83 | 99.88 | 99.76 |
| Synergy Factorized Bilinear Network with a Dual Suppression [12] | 97.96 | 97.43 | 97.67 |
| MSG-GAN Pre-trained model [6] | 98.62 | 98.65 | 98.71 |
| Multiscale Convolutional Neural Network [13] | 97.30 | 97.42 | 97.35 |
| ResNet50 with angular augmentation [15] | 97.49 | 97.51 | 97.54 |
| AC-GAN Pre-trained model [7] | 95.60 | 95.29 | 95.10 |

Since the model is pre-trained and fine-tuned on a T1-weighted MRI dataset, it would not perform well for other scan modalities like T2, Flair, Contrast, and functional MRI and scans with different magnetic field strengths. Likewise, the model has not been experimented with other hyperparameters for a different target image resolution (example: 1024x1024, 512x512). However, the framework can be retrained or fine-tuned using an appropriate dataset to improve its performance for other scans or data distributions using transfer learning. The style-based generator synthesizes good images, sometimes producing subpar results. This kind of framework trains datasets with implicit oversampling and improves the classifier's performance. However, the image synthesis of brain tumors may not have any real-world usage apart from using them for oversampling while training deep learning models. Also, the generated images have to be clinically validated by radiologists to know how accurately the GAN can synthesize images of the tumors and how useful it is for doctors. Fig. 12 and Fig. 13 show some of the generated images that were good and those that were bad.

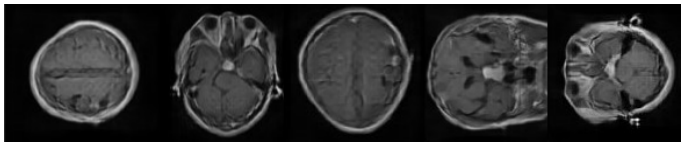

Fig. 12. Generated samples by the GAN.

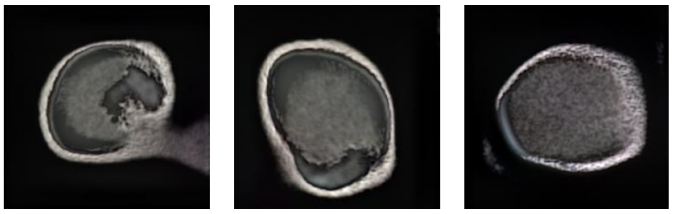

Fig. 13. Badly generated samples by the GAN.

## VI. Conclusion

The proposed approach for the multi-class classification of brain tumors uses pre-training on an auxiliary classifying Style-based Generative Adversarial Network [9, 29, 10] to classify Glioma, Meningioma, and Pituitary tumor types using T1-weighted MR Images. The framework has two major processes: pre-training the conditional style-based GAN and fine-tuning the pre-trained Discriminator with extensive data augmentation to improve the classification performance. Pre-training the GAN with different augmentation strategies helps the algorithm learn feature representations from the data in a semi-supervised approach while also enabling the Discriminator to predict the legitimacy of the image and type of tumor present in the images. The method has achieved an accuracy of 99.51% on the augmented test set 99.83% on the raw test set, which is comparatively better than the other proposed approaches. The system is also sound when the availability of data is less. However, the model must be trained with data from multiple distributions containing different modalities and from machines of different magnetic field strengths like 1.5 Tesla, 3 Tesla and 7 Tesla machines to achieve better generalizability and classification performance, which can be done using transfer learning. To overcome these disadvantages, we plan to introduce few-shot learning or self-supervised architectures with adversarial pre-training and augmentation on a diverse multi-modal dataset to achieve the highest possible performance, fairness, and robustness for classifying brain tumors as well as classifying whether the tumor is benign or malignant [28].

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