PROJECT REPORT

UTILIZING GENERATIVE ADVERSARIAL NETWORKS (GANs) FOR SYNTHETIC MRI DATA AUGMENTATION IN BRAIN TUMOR DETECTION

ABSTRACT-

This project explores the use of Generative Adversarial Networks (GANs) for image augmentation, specifically employing the Deep Convolutional GAN (DCGAN) architecture to generate synthetic brain MRI images. The generated images were used to train deep learning models, including ResNet and MobileNet, with the goal of enhancing the models' ability to classify real brain MRI images. By using generated images for training and real data for validation, the project ensures that the synthetic images approximate the distribution of real images, thereby aiding the model in learning critical features. The ResNet model achieved an accuracy of 72.19%, highlighting the potential of GAN-based data augmentation to improve classification performance. This suggests that further exploration of GANs in medical image classification could yield promising results.

INTRODUCTION-

Generative Adversarial Networks (GANs) have emerged as a powerful tool in artificial intelligence, particularly for tasks involving synthetic data generation. At their core, GANs consist of two networks: the generator, which creates new data samples, and the discriminator, which evaluates whether the generated samples are real or fake. This unique framework has shown remarkable success across various domains, including healthcare, where data scarcity often limits the performance of machine learning models. By generating synthetic data that closely mirrors real data distributions, GANs can help address issues related to limited datasets, especially in fields such as medical imaging.

In medical imaging, early detection and classification of conditions like brain tumors play a crucial role in improving patient outcomes. Brain tumors, one of the leading causes of death globally, are typically diagnosed through imaging techniques like Magnetic Resonance Imaging (MRI). However, manually annotating and segmenting MRI images for tumor detection is time-consuming and requires significant expertise, which can be a barrier in healthcare settings with limited access to specialized professionals. The application of machine learning, and more specifically deep learning models, has proven to be highly effective in automating these tasks, providing faster and more accurate diagnoses.

One of the primary challenges in medical image classification is the need for large, diverse datasets. In many cases, acquiring sufficient annotated images can be difficult. This is where data augmentation techniques, such as GANs, become particularly valuable. By generating synthetic MRI images, GANs can increase the volume of training data available, helping to improve model accuracy and robustness. This study focuses on leveraging the DCGAN architecture to generate synthetic brain MRI images, which are then used to train deep learning models for tumor classification. By validating the model performance using real MRI data, this approach aims to explore the effectiveness of GAN-generated images in enhancing the training process, demonstrating that GAN-based augmentation could be a promising avenue for future research in medical image classification.

LITERATURE REVIEW-

Generative Adversarial Networks (GANs) have shown promise in medical imaging, especially for augmenting datasets with limited MRI images. Han et al. (2019) improved tumor detection sensitivity from 93.67% to 97.48% using two-step GANs. Other studies, like those by Ge et al. (2020), used Pairwise GANs for better tumor classification performance by combining real and synthetic images. Ghassemi et al. (2019) achieved 98.57% accuracy with pre-trained GANs, improving diagnostic efficiency across multiple hospitals.

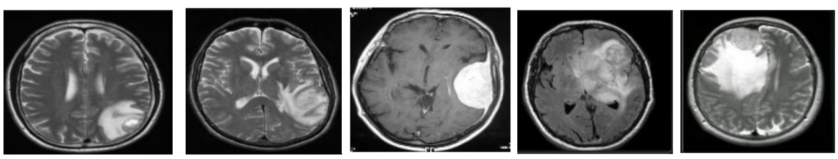
Chenjie et al. (2019) and Sivadas et al. (2019) demonstrated that GANs like MSG-GAN and PGGAN could generate realistic tumor images with high accuracy (88.7% and 91.08%, respectively). Additionally, Changhee et al. (2021) used MADGAN for anomaly detection, achieving high accuracy for conditions like Alzheimer’s and brain metastases.

Recent studies, such as Sandhiya et al. (2021), applied Faster Regional CNNs, achieving 93% accuracy, and Dhaniya et al. explored Cyclic GANs for enhanced tumor classification. These studies underline the potential of GANs in improving brain tumor detection and classification by augmenting datasets and enhancing model performance.

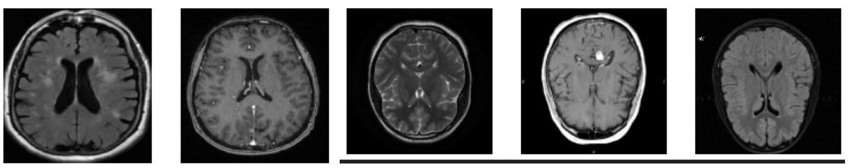
DATASET-

The data consists of two folders, named yes and no respectively. “Yes” contains MRI images containing tumors in them whereas “no:” contains healthy brain MRI images. The dataset has 155 and 98 images for each class respectively. A few sample images from each of the two classes are attached.

Tumor images



Normal images



Model Description

- **Data Preprocessing and Loading:**
  - Images are loaded from two directories (yes for tumor and no for normal) and resized to 128x128 pixels.
  - The images are converted to grayscale and normalized to the range of -1 to 1 for better model performance.
- **Generator and Discriminator Creation:**
  - A **Generator Model** is built to generate synthetic images from random noise, using transposed convolution layers and batch normalization for stable learning.
  - A **Discriminator Model** is created to classify images as either real (from the dataset) or fake (generated), utilizing convolution layers and dropout for regularization.
- **GAN Architecture:**
  - A **Combined GAN Model** is constructed by linking the Generator and Discriminator, where the Generator tries to create realistic images and the Discriminator tries to differentiate real from generated images.
  - The GAN model is trained by updating the weights of the Generator based on the Discriminator's feedback and vice versa.
- **Training Process:**
  - The model is trained using noise vectors (random data) to generate images, with both the Generator and Discriminator being updated iteratively.
  - For each epoch, the Discriminator is trained to differentiate between real and generated images and the Generator is trained to produce increasingly realistic images.
  - Every 100 epochs, sample-generated images are displayed to track progress.
- **Model Saving:**
  - After training, the Generator, Discriminator, and Combined GAN Model are saved for future use and evaluation.
- **Handling Normal Data:**
  - A similar process is repeated for "normal" MRI images, training another GAN to generate normal brain images.
  - Both the tumor and normal generated images are combined, along with their respective labels, to form the final dataset.
- **Augmentation and Final Model Training:**
  - Data augmentation is applied to the generated images to create additional variety, including rotations, shifts, and flips.

- We have tried both ResNet152V2 and MobileNetV2 architectures (pretrained on ImageNet) to use the generated images for classifying tumors in the original data (used here as validation data). Both models were fine-tuned on the generated data to classify MRI images into tumor and normal categories.

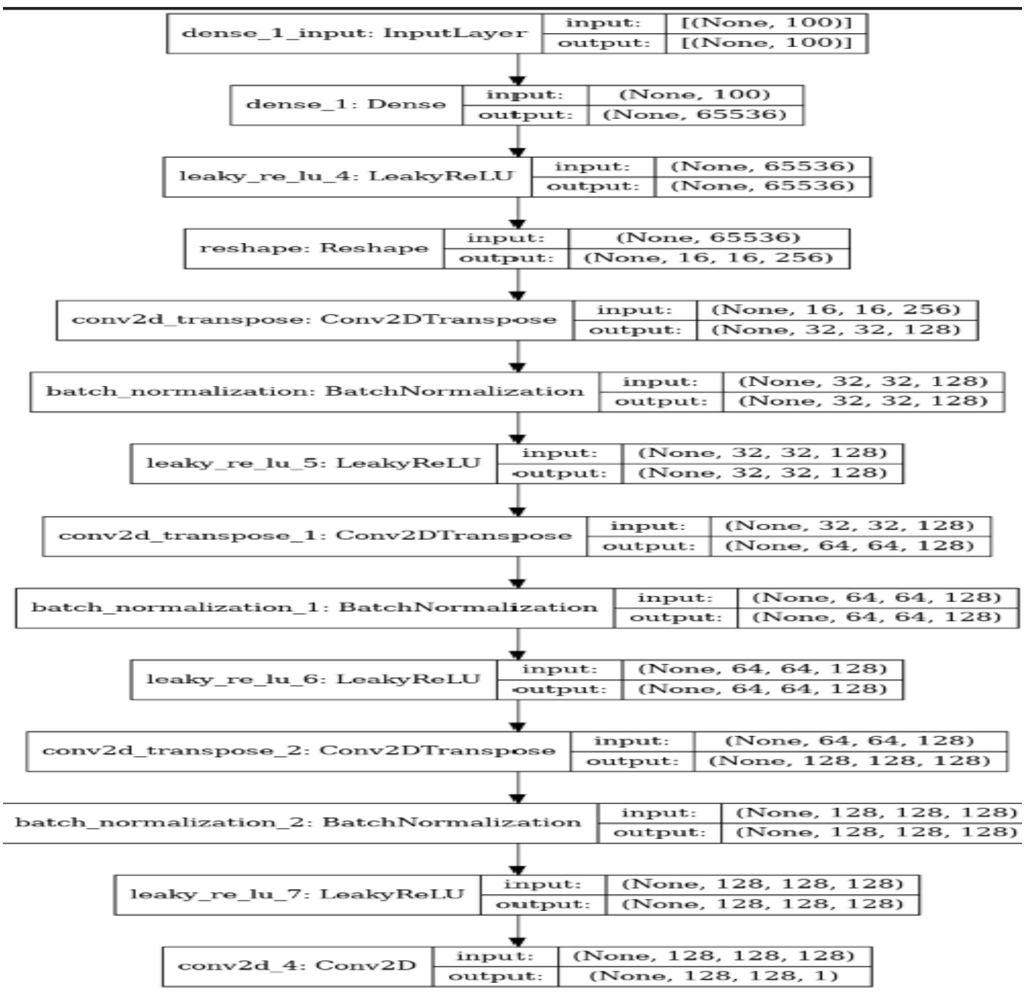
GENERATOR MODEL-

The generator model is a deep convolutional network designed to generate synthetic MRI images from random noise. It starts with a dense layer to reshape the input noise vector into a 16x16x256 feature map. Following this, several transposed convolutional layers (Conv2DTranspose) with batch normalization and LeakyReLU activations are used to upsample the image while maintaining spatial coherence. The final layer is a 2D convolutional layer with 'tanh' activation, producing images with the same number of channels as the target images (typically 1 for grayscale images). The Adam optimizer with a learning rate of 0.0002 and beta 1 set to 0.5 is used to train the model, minimizing binary cross-entropy loss.

Total params: 7,671,681

Trainable params: 7,670,913

Non-trainable params: 768



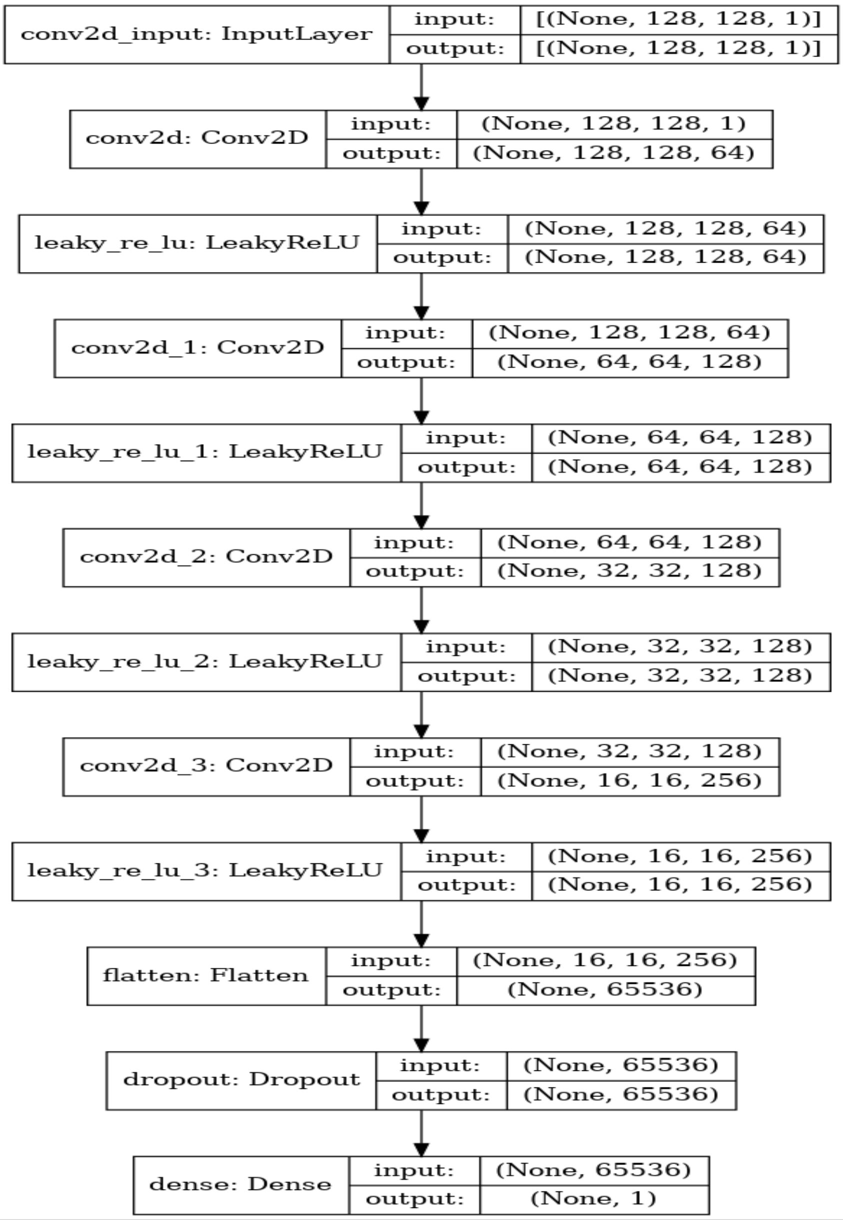
DISCRIMINATOR MODEL-

The discriminator model is a convolutional neural network designed to distinguish between real and generated MRI images. It begins with a 2D convolutional layer that processes the input image with a 'same' padding, followed by several convolutional layers with increasing filter sizes (64, 128, 256) and LeakyReLU activations to capture hierarchical features. The model uses strided convolutions to reduce the spatial dimensions progressively. After the convolutional layers, the output is flattened and passed through a dropout layer to prevent overfitting. The final layer is a dense layer with a sigmoid activation that outputs a probability, classifying the image as either real or fake. The model is trained using binary cross-entropy loss and the Adam optimizer.

Total params: 582,785

Trainable params: 582,785

Non-trainable params: 0

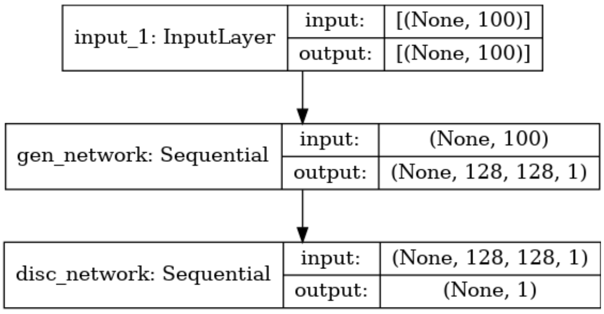


COMBINED GAN NETWORK-

Total params: 8,254,466

Trainable params: 7,670,913

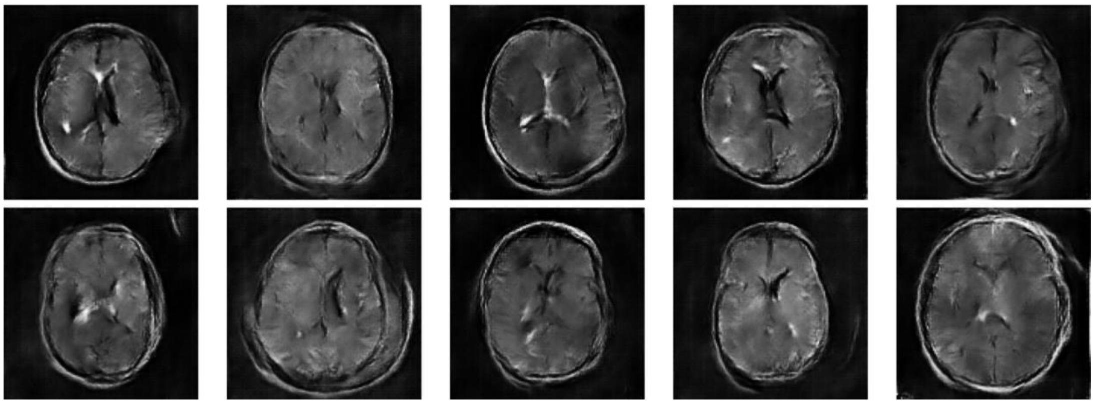
Non-trainable params: 583,553



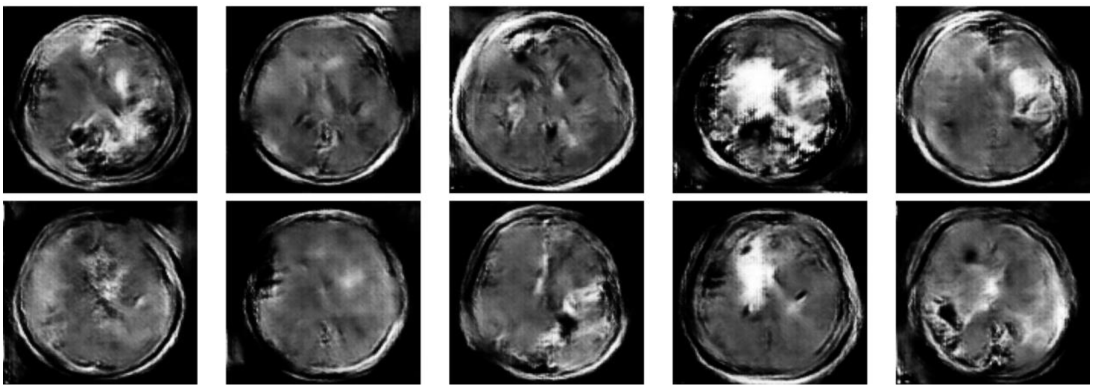
GAN RESULTS-

After training the model for 1000 epochs, these were the outputs generated.(We generated 400 samples for each category, some of them are shown below.

For normal data(without tumor)

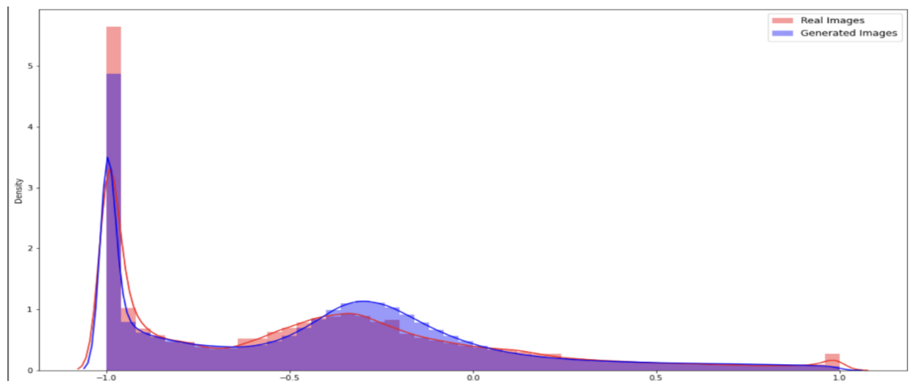


For tumor data(We can see that the model is trying to generate tumor regions)

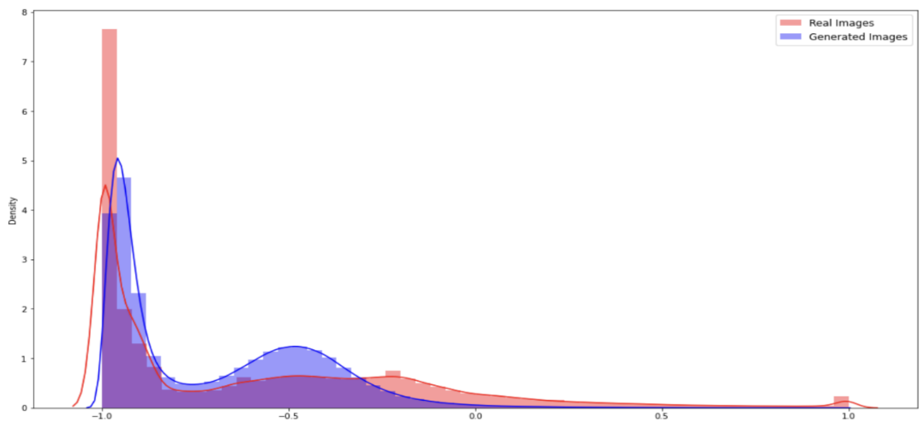


We compare the pixel intensity distributions of real tumour images (red) and generated tumour images (blue). While this is not the best way to find the similarity between real and generated images, plotting both distributions gives us a preliminary idea of whether or not the generator is going in the right path.

DIST PLOT FOR NORMAL DATA



DIST PLOT FOR TUMOR DATA



CLASSIFICATION RESULTS-

Both models were trained using the generated dataset comprising normal and tumor images, while the original dataset was utilized as validation data to evaluate their accuracy in classifying real-world images. This approach inherently assesses the quality and realism of the GAN-generated images by determining their effectiveness in improving classification performance on real-world data

RESNET152v2 model architecture-

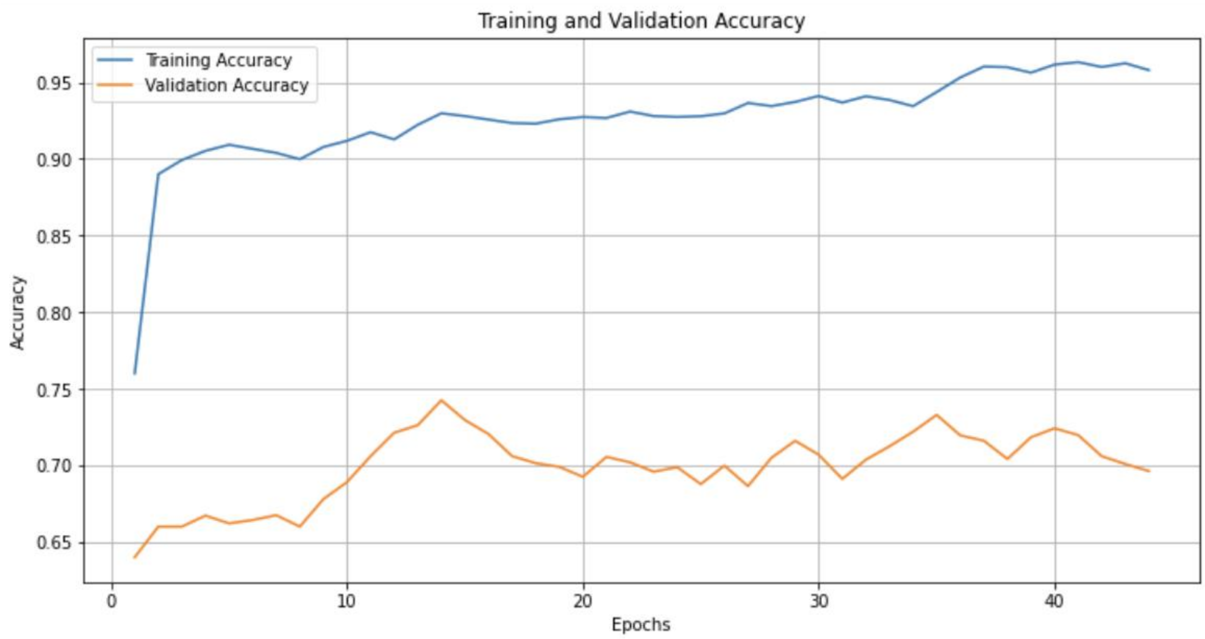
```
RESNET
_________________________________________________________________
Layer (type)              Output Shape              Param #
=================================================================
conv2d_19 (Conv2D)        (None, 128, 128, 3)       6
_________________________________________________________________
resnet152v2 (Functional)  (None, 4, 4, 2048)        58331648
_________________________________________________________________
flatten_4 (Flatten)       (None, 32768)             0
_________________________________________________________________
dense_7 (Dense)           (None, 256)               8388864
_________________________________________________________________
dropout_4 (Dropout)       (None, 256)               0
_________________________________________________________________
dense_8 (Dense)           (None, 1)                 257
=================================================================
Total params: 66,720,775
Trainable params: 8,389,127
Non-trainable params: 58,331,648
_________________________________________________________________
```

ACCURACY ACHIEVED – 72.19%

MOBILENET MODEL ARCHITECTURE-

```
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
conv2d_303 (Conv2D)         (None, 128, 128, 3)       6
_________________________________________________________________
mobilenetv2_1.00_128        (None, 4, 4, 1280)        2257984
_________________________________________________________________
global_average_pooling2d_4 ( (None, 1280)             0
_________________________________________________________________
dense_16 (Dense)            (None, 512)               655872
_________________________________________________________________
dropout_13 (Dropout)        (None, 512)               0
_________________________________________________________________
dense_17 (Dense)            (None, 1)                 513
=================================================================
Total params: 2,914,375
Trainable params: 656,391
Non-trainable params: 2,257,984
```

ACCURACY ACHIEVED- 68.79%



CONCLUSION-

The results of this study highlight the potential of Generative Adversarial Networks (GANs) in generating synthetic medical images, specifically for augmenting datasets in tumor classification tasks. While the outcomes are encouraging, they clearly indicate room for significant improvement. This underscores the versatility of GANs as a tool in the medical imaging domain and their ability to address the challenge of limited datasets.

To further enhance the performance of GANs, several improvements can be explored. Utilizing more complex architectures, such as GANs with attention mechanisms or progressive growing GANs, could improve the quality and diversity of the generated images. Running the models for additional epochs, with techniques such as adaptive learning rates or scheduled learning rate decay, can allow for better convergence and refinement of the synthetic data. Furthermore, employing advanced loss functions like Wasserstein loss or perceptual loss may help stabilize the training process and yield more realistic outputs.

In addition, fine-tuning the balance between the generator and discriminator during training and incorporating domain-specific augmentations could enhance the representational quality of the synthetic images. Exploring methods like semi-supervised learning or transfer learning to integrate real and synthetic data more effectively can further boost classification performance.

The findings of this work suggest that GANs have immense potential in addressing data limitations in medical imaging and beyond. Future studies should focus on refining these techniques to maximize their impact, paving the way for more reliable and accurate applications in tumor detection and classification.