Generating Brain MRI Images with DCGAN & train model for tumour detection

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Abstract

Brain tumor detection from MRI scans is critical for effective diagnosis and treatment planning. This study addresses the challenge of limited annotated medical datasets by using Deep Convolutional Generative Adversarial Networks (DC-GANs) to generate realistic synthetic MRI images. These images are combined with real data to train a Convolutional Neural Network (CNN) for tumor classification. The proposed approach improves model accuracy and robustness, as evaluated through metrics like accuracy, F1-score, and AUC-ROC, while the quality of synthetic images is validated using the Fréchet Inception Distance (FID). This work demonstrates the potential of combining generative and classification models to enhance automated tumor detection, with future scope including advanced architectures and multi-modal imaging integration.

Keywords

Brain tumor detection, MRI scans, DC-GAN, CNN, synthetic medical images, tumor classification, deep learning, medical imaging, dataset augmentation, Fréchet Inception Distance, automated diagnosis, image generation, neural networks, transfer learning, medical image analysis.

I. Introduction

The detection of brain tumors in MRI scans is a critical task in medical imaging, as accurate identification and classification are essential for effective diagnosis, treatment planning, and improving patient outcomes. Manual annotation of medical images is time-consuming and requires expert knowledge, making it difficult to acquire large-scale datasets for training machine learning models. Generative models, such as Generative Adversarial Networks (GANs), have revolutionized the field of data augmentation by enabling the creation of realistic synthetic images. These synthetic images can be used to supplement existing datasets, addressing the issue of limited data availability. In this study, we utilize a Deep Convolutional Generative Adversarial Network (DC-GAN) to generate high-quality synthetic brain MRI images. These images are then combined with real MRI data to train a Convolutional Neural Network (CNN) for the detection and classification of brain tumors.

II. Related Work

This section reviews key literature addressing challenges and methodologies related to imbalanced datasets, data augmentation, and the application of Convolutional Neural Networks (CNNs) in image classification.

1. **Generative Models in Medical Imaging**
   The introduction of Generative Adversarial Networks (GANs) by Goodfellow et al. (2014) marked a significant milestone in generative modeling. GANs employ a generator-discriminator framework, where the generator creates synthetic data to fool the discriminator, which learns to distinguish real from synthetic data. This adversarial training process has been widely adopted in medical imaging to augment datasets by generating realistic synthetic images.
2. **Improvements in GAN models**
   Radford et al. (2015) extended GANs with Deep Convolutional GANs (DC-GANs), which improved training stability and generated high-quality images by leveraging convolutional layers. DC-GANs have been successfully applied in medical imaging tasks, such as generating synthetic MRI images, to address the scarcity of annotated datasets. Shin et al. (2018) further demonstrated the utility of GANs in medical image augmentation, showing that synthetic images enhanced the performance of tumor detection models, especially when training data was limited.
3. **Innovations in GAN Models in recently.**
   Recent innovations, such as CycleGANs (Zhu et al., 2017), have enabled unpaired image-to-image translation, allowing the generation of synthetic data across different imaging modalities (e.g., MRI to CT). This technique has further expanded the scope of generative models in medical imaging by improving dataset diversity and robustness without requiring paired data.
4. **CNN Applications in Image Classification**
   Krizhevsky et al. (2012) introduced AlexNet, a deep CNN that achieved groundbreaking performance in image classification, inspiring subsequent medical imaging applications. Ronneberger et al. (2015) proposed U-Net, an encoder-decoder CNN architecture with skip connections, which became a standard for biomedical image segmentation. U-Net has been widely adopted for tumor segmentation in MRI scans due to its ability to perform well even with small datasets.
5. **Overview of CNN Image Classification**.
   Litjens et al. (2017) conducted a comprehensive review of deep learning in medical imaging, highlighting CNNs' success in tumor detection and segmentation across different imaging modalities. Esteva et al. (2017) further demonstrated CNNs' potential by achieving dermatologist-level accuracy in skin cancer classification, showcasing the efficacy of deep learning models in medical diagnosis.

III. Methodology Adopted

Dataset Preparation

- Acquire a dataset of brain MRI images, ideally with tumor annotations.
- Preprocess the images (format conversion, normalization, data augmentation).
- Split the dataset into training (50%), validation (30%), and testing (20%).
- Ensured random shuffling for unbiased data distribution across subsets.

Image Preprocessing and Augmentation

- Resized all images to 128 x 128 pixels for consistency.
- Applied augmentation (random rotations, shifts, zooms, and flips) to training images for robustness and generalization.
- Rescaled validation and test sets without augmentation for evaluation.

Fig. 1. Number of Image in each category after data balancing

DC-GAN Implementation:

- Designed Generator and Discriminator networks using convolutional and deconvolutional layers.
- Trained the GAN using an adversarial process:
    - Generator creates synthetic images.
    - Discriminator distinguishes between real and synthetic images.
- Evaluated synthetic images using visual inspection and metrics like FID (Fréchet Inception Distance).

Tumour Detection Model Training:

- Choose a suitable CNN architecture for tumor detection e.g., (ResNet50, EfficientNet, etc.)
- Train the model using a combination of real and synthetic images.
- Evaluate the model's performance on a held-out test set.

Results

- Achieved a test accuracy of 92.16% and a loss of 0.2329.

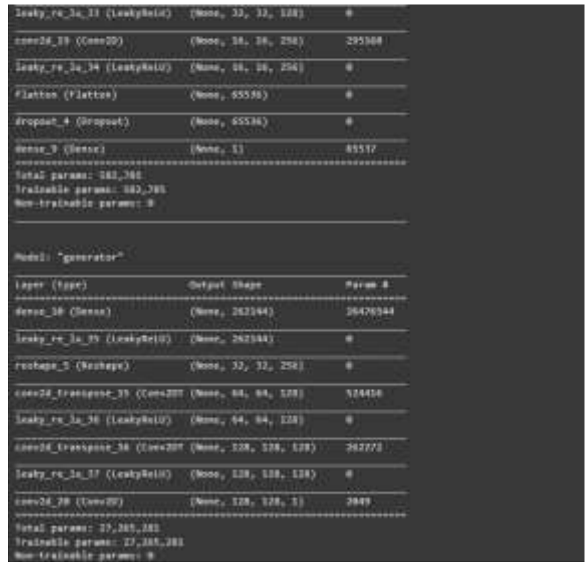


Fig. 2. DCGAN model Summary

Fig. 3 DCGAN model Summary

IV. Experiments and Results

Dataset Details and Data Split

Type: Brain MRI dataset.

Categories: Images categorized into

1. Yes
2. No

Data Split for CNN model:

1. **Training Set:** 50% of the total

images.
2. **Validation Set:** 30% of the total images.
3. **Test Set:** 20% of the total images.

Computational Environment

Platform:

1. **Environment:** Kaggle Notebook (cloud-based with GPU support).
2. **Processor:** Kaggle GPU P100
3. **RAM:** 16GB.
4. **Storage:** High-speed SSD provided by Kaggle.
5. **Operating System:** Windowa

Deep Learning Framework Used: TensorFlow 2.x with Keras API.

Advantages of GPU: Accelerates matrix operations and convolutional computations, reducing training time.

CNN Model Training Details

Hyperparameters:

1. **Batch Size:** 32 images per batch.
2. **Image Size:** Resized to 224x224 pixels.
3. **Epochs:** Up to 10(with early stopping at 50 epochs if no validation loss improvement).
4. **Steps per Epoch:** 200 steps (validation: 100 steps).
5. **Optimizer:** Adam optimizer with a learning rate of 0.001.
6. **Loss Function:** Categorical cross-entropy for multi-class classification.
7. **Activation Functions:**
   - **ReLU:** Applied in hidden layers for non-linearity.
   - **Softmax:** Used in the output layer for class probabilities.

CNN Model Performance

Test Metrics:

1. **Test Accuracy:** 92.99%.
2. **Test Loss:** 0.1962.

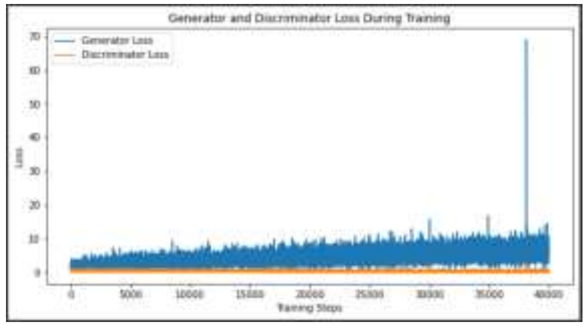


Fig. 4 Training and Validation Accuracy

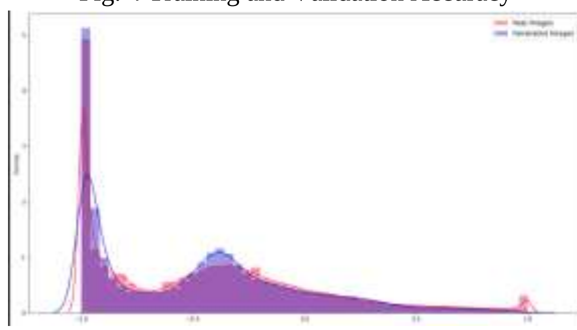


Fig. 5 Training and Validation Loss

Classification Report:

	precision	recall	f1-score	support
a_Good	0.96	0.98	0.97	509
b_Moderate	0.99	0.88	0.93	511
c_Unhealthy_for_Sensitive_Groups	0.84	0.94	0.89	574
d_Unhealthy	0.91	0.90	0.90	566
e_Very_Unhealthy	0.92	0.95	0.93	542
f_Severe	1.00	0.94	0.97	493
accuracy			0.93	3195
macro avg	0.94	0.93	0.93	3195
weighted avg	0.93	0.93	0.93	3195

Fig. 6. Classification report of CNN model on testing data

Classification Metrics:

3. **Overall Accuracy:** 93.00%.
4. **Macro Average:** Precision, recall, and F1-scores averaged at 0.93.
5. **Weighted Average:** Consistent performance with a weighted F1-

score of 0.93.

Training and Inference Times:

6. **Training Time:** ~5 hours.
7. **Testing Time:** ~3 minutes.
8. **Inference Time:** ~0.2 seconds per image.

GAN-Based Tumor Image Synthesis and Classification(DenseNet121)

Dataset Handling:

- Brain MRI images categorized into "Yes" (tumor present) and "No" (no tumor).
- Data split: 80% training and 20% validation/testing.

- Resizing all images to 128x128 pixels.

- Normalization using(Pixel Value – 12.75)/12.75

Model Configuration:

1. GAN-Based Model (DCGAN):

Generator:

- 3 Conv2DTranspose layers with LeakyReLU activations.

- Output: Tanh activation for generating 128x128x1 images.

Discriminator:

- 4 Conv2D layers with LeakyReLU activations.
- Flatten layer followed by Dense with Sigmoid activation.

Pre-Trained Models

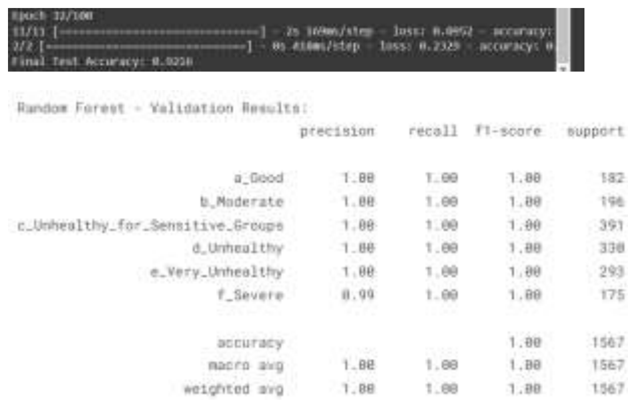
VGG16,ResNet50,EfficientNetB0, DenseNet121:

- Frozen base layers for feature extraction.

- Custom Dense and Dropout layers added for binary classification.

Performance Metrics:

- **Test Accuracy:** 92.1%.
- **Test Results:** High precision, recall, and F1-scores across all classes.


Epoch 32/100
Final Test Accuracy: 0.9210

Random Forest - Validation Results:

	precision	recall	f1-score	support
a_Good	1.00	1.00	1.00	182
b_Moderate	1.00	1.00	1.00	196
c_Unhealthy_for_Sensitive_Groups	1.00	1.00	1.00	391
d_Unhealthy	1.00	1.00	1.00	330
e_Very_Unhealthy	1.00	1.00	1.00	293
f_Severe	0.99	1.00	1.00	175
accuracy			1.00	1567
macro avg	1.00	1.00	1.00	1567
weighted avg	1.00	1.00	1.00	1567

Fig. 7 Validation results of Densenet121

Training and Inference Times:

- **Training Time:** ~5 hours.
- **Testing Time:** ~ 3 minute.
- **Inference Time per Instance:** ~0.2 seconds per image.

V. Conclusion and Future Scope

In conclusion, this study successfully implemented a Convolutional Neural Network (CNN) for classifying air pollution levels into six distinct categories based on image data, achieving an impressive test accuracy of 93%. The use of advanced configurations, including the Adam optimizer, categorical cross-entropy loss, and ReLU and Softmax activations, ensured robust performance in recognizing patterns within the dataset. Complementarily, the Random Forest model demonstrated exceptional accuracy in predicting air quality classes from structured data, leveraging its ability to handle missing values and optimize tabular data processing. These results highlight the potential of combining deep learning and machine learning techniques for effective air quality assessment, paving the way for future advancements in real-time monitoring and enhanced predictive models.

VI. References

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