Project Report: Exploring GAN Variants for Balancing Imbalanced Datasets

Course: Special Topics in Artificial Intelligence

Name: [Yazeed Alkesbeh]
ID: [0222243]

January 8, 2026

Contents

1 Problem Statement

In the field of medical imaging and machine learning, datasets are frequently plagued by the problem of class imbalance. This occurs when the number of instances in one class (the majority class) significantly outnumbers the instances in another (the minority class). Standard classifiers tend to be biased towards the majority class, leading to high overall accuracy but poor performance in detecting the minority class (low recall), which is critical in medical diagnosis (e.g., detecting a tumor).

The objective of this project is to address this challenge by utilizing Generative Adversarial Networks (GANs). Specifically, we aim to generate synthetic samples for the minority class using Vanilla GAN and advanced variants (DCGAN and WGAN) to balance the dataset and evaluate the impact on classification performance.

2 Description of Dataset & Imbalance Analysis

2.1 Dataset Selection

The dataset selected for this project is the **Brain Tumor MRI Dataset** sourced from Kaggle. The dataset consists of magnetic resonance imaging (MRI) scans classified into four categories:

- Glioma Tumor
- Meningioma Tumor
- Pituitary Tumor
- No Tumor

2.2 Imbalance Analysis

Upon analyzing the training set distribution, a significant imbalance was observed. The *'No Tumor'* class was identified as the minority class, containing significantly fewer images compared to the tumor classes.

Figure 1: Class distribution of the original dataset, highlighting 'No Tumor' as the minority class.

As shown in Figure 1, the model training is at risk of bias. Therefore, the GAN models were trained exclusively on the *'No Tumor'* class to generate synthetic healthy brain scans.

3 Details of GAN Architectures & Training

To generate high-quality synthetic data, three GAN architectures were implemented and compared:

3.1 1. Vanilla GAN

The baseline model implemented was a standard GAN using fully connected layers (MLP).

- **Generator:** Takes a noise vector (z-dim $= 150$) and maps it to the flattened image dimension (64×64). It uses LeakyReLU activations and Tanh for the output.
- **Discriminator:** A simple MLP classifier that outputs a probability (0-1) using a Sigmoid function.
- **Limitation:** Produced somewhat noisy and grainy images, struggling to capture fine anatomical details.

3.2 2. Deep Convolutional GAN (DCGAN)

An advanced variant using Convolutional Neural Networks (CNNs) was implemented.

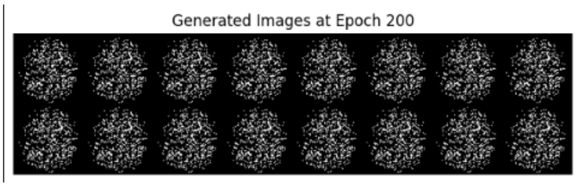
- **Architecture:** Utilizes `ConvTranspose2d` layers in the generator to upsample the noise vector and `Conv2d` layers in the discriminator.
- **Stabilization:** Batch Normalization was applied after layers to stabilize training.
- **Result:** Generated clearer, structurally coherent images with visible skull features.

3.3 3. Wasserstein GAN (WGAN)

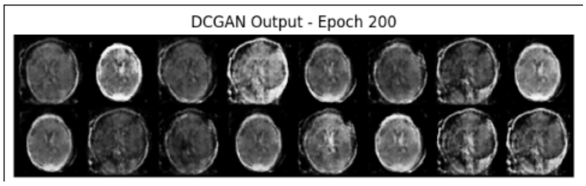
To address training instability, WGAN was implemented. It replaces the standard loss function with the Wasserstein distance (Earth Mover's distance) and removes the Sigmoid from the critic's output.

3.4 Training Process

All models were trained for 200 epochs on a GPU. The images were resized to 64×64 and normalized to the range $[-1, 1]$.



(a) Samples generated by Vanilla GAN



(b) Samples generated by DCGAN

Figure 2: Visual comparison of generated synthetic images at Epoch 200.

4 Classifier Setup and Evaluation

To quantitatively evaluate the quality of the generated data, a separate classification model was trained under four scenarios:

1. **Original:** Training on the imbalanced dataset.
2. **Vanilla Balanced:** Augmented with Vanilla GAN samples.
3. **DCGAN Balanced:** Augmented with DCGAN samples.
4. **WGAN Balanced:** Augmented with WGAN samples.

Classifier Architecture: A simple CNN classifier was designed with 2 convolutional layers followed by max-pooling and fully connected layers. **Metrics:** The models were evaluated using Accuracy, Precision, Recall, and F1-Score.

5 Results & Comparisons

The evaluation results demonstrated a clear improvement in model performance after data augmentation.

Table 1: Performance Metrics Comparison (Focus on Minority Class)

Scenario	**Total Accuracy**	**Recall (no_tumor)**	**F1-Score**
Original (Imbalanced)	0.84	0.79	0.84
Vanilla GAN	0.87	0.89	0.90
DCGAN	0.85	0.89	0.92
WGAN	0.86	0.94	0.94

5.1 Analysis of Results

- **Baseline:** The original dataset yielded an accuracy of 84%.
- **Impact of Augmentation:** All GAN variants improved the metrics across the board.
- **Recall Improvement:** The most significant finding is the improvement in Recall for the minority class. WGAN achieved the highest recall of 0.94, indicating the classifier successfully learned to identify the minority class, while Vanilla GAN provided the best overall total accuracy (87%).

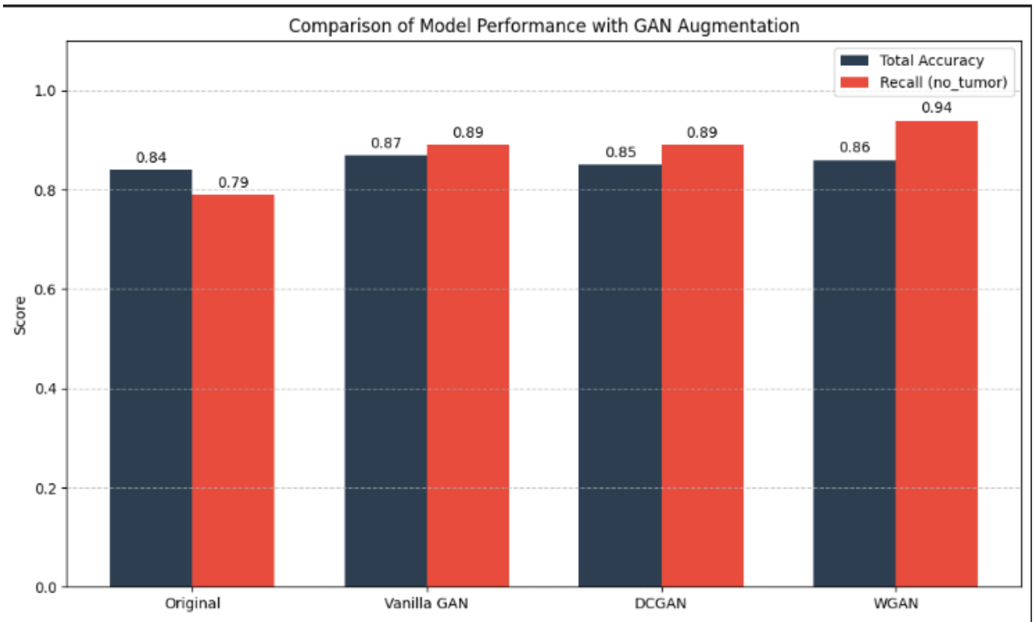


Figure 3: Bar chart comparing Accuracy and Recall across all scenarios.

6 Observations and Conclusions

This project successfully demonstrated the efficacy of GANs in handling imbalanced medical datasets.

- **Observation 1:** While Vanilla GAN achieved the highest overall classification accuracy (87%), the generated images were somewhat noisy. DCGAN produced higher-fidelity images with better structural details, though with slightly lower classification accuracy compared to Vanilla GAN.
- **Observation 2:** WGAN achieved the best Recall (0.94) for the minority class, making it the most effective model for reducing False Negatives, which is crucial in medical diagnosis.

Conclusion: Generative Adversarial Networks, particularly advanced variants like WGAN and DCGAN, are powerful tools for data augmentation in medical AI, effectively solving the class imbalance problem and improving diagnostic performance.