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Original Article

Enhancing Brain Tumor Segmentation with Generative Adversarial Networks and Post-Processing Techniques

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Abstract *- Accurately and reliably segmenting brain tumors from Magnetic Resonance Imaging (MRI) poses a key challenge in medical image analysis because of the variability in shape, size, and intensity distributions of tumors. The present study introduces a hybrid segmentation framework that combines Generative Adversarial Networks (GANs) with a U-Net backbone and post-processing methods to improve tumor segmentation. The model was trained and evaluated on 500 heterogeneous MRI images preprocessed to a resolution of 512 × 512, and split into training (70%), validation (15%), and test (15%) sets. The model training occurred over 50 epochs, with a batch size of 16, and the Adam optimizer was used for training. The model was augmented with data augmentation strategies (e.g., flipping, cropping, scaling, contrast enhancement, etc.), and early stopping was applied to prevent overfitting. The generator employs both cross-entropy and adversarial loss, while the discriminator uses binary cross-entropy loss in its optimization. The experimental results reinforce the usefulness of the proposed framework, with a Dice Similarity Coefficient value of 0.89 ± 0.03, Intersection over Union value of 0.95 ± 0.04, recall value of 0.92 ± 0.03, and specificity value of 0.97 ± 0.02. Furthermore, the comparative evaluation with state-of-the-art methods confirms the superiority of the proposed method, resulting in a precision result of 99.12%, a recall result of 94.24%, an F-score result of 93.36%, and an IoU result of 94.87%, outpacing state-of-the-art models.*

Keywords *- Brain Tumor, GANs, Image segmentation, Post-processing, U-net.*

1. Introduction

Medical image analysis, specifically the segmentation of brain tumors, plays a critical role in clinical diagnosis, treatment planning, and prognosis. However, segmenting brain tumors accurately is a complex problem because brain tumors are complicated and heterogeneous in size, shape, location, and intensity across patients. While traditional Machine Learning and Deep Learning approaches (e.g., Convolutional Neural Networks (CNNs), or U-Net variations) have had some success, there are also many caveats (e.g., a model that does not generalize well to a heterogeneous dataset, or that provides an inaccurate boundary while segmenting the tumor, or that is sensitive to noise and MR artifacts) that would warrant the use/study of more robust and flexible models.

Before 2014, generative models were applied to model complex data distributions, primarily based on the use of Variational Autoencoders, Markov Chain Monte Carlo methods, and Restricted Boltzmann Machines. However, these approaches were unable to produce realistic and high-quality data. A breakthrough came in 2014 when Ian Goodfellow and his collaborators proposed Generative Adversarial Networks (GANs) in which the data generation was treated like a min-max game between a generator and a discriminator [1]. This took generative modeling into a new direction with an idea that produced high-quality data and rich representations of the data [2].

Since 2014, different versions of GANs have been developed to improve the stability and performance of GANs. The Least Squares GAN, LSGAN, in 2015, improved the stability of GANs while training. Second, Deep Convolutional GANs (DCGANs) were introduced in 2016, utilizing convolutional architectures to further the development of high-quality image generation and representation learning [3].

Conditional GANs (cGANs) established an expanded framework for supervised tasks, including image-to-image translation, in 2017, and Wasserstein GANs (WGANs) reduced mode collapse issues. Additionally, Progressive GANs (ProGAN) further advanced image resolution quality in 2018, and StyleGAN encouraged a finer-grained control over image traits [4]. These processes help advance the field of GANs and machine learning; however, GAN applications in medical imaging domains, like brain tumor segmentation, remain under-explored, and these domains are severely challenged.

Most GAN-based segmentation studies suffer from instability in the training process, blur the boundaries of segmentation masks, or lack completeness of tumor region detection. Additionally, only a small fraction of the studies have also considered integrating GAN-based architectures with effective post-processing to better enhance segmentation masks and correct blurring of boundaries.

This study addresses the lack of research into the combined use of GAN-based architectures and post-processing. A GAN-based architecture framework will be utilized with accompanying post-processing methods to improve overall performance in brain tumor segmentation. This study aims to leverage the generative power of the GAN architecture to capture tumor variability while simultaneously improving segmentation outputs through post-processing to ultimately achieve more accuracy in clinical applications of neural segmentation processes.

2. Literature Review

This section discusses the principles that underlie image segmentation and its contributions to the medical field (brain tumor segmentation presented as a case study), highlighting recent trends in machine learning (training Generative Adversarial Networks (GANs)) for segmentation problems dealing with images. The section commences with discussing the importance of image segmentation to solving problems in medical diagnosis; transitioning into how brain tumor segmentation emerged, grew in importance, and represents a subset of MRI image segmentation problems; and lastly describing the use of GANs to segmentation problems.

2.1. The Importance of Image Segmentation Related to Medical Diagnostics

Image segmentation is a method for partitioning a digital image into meaningful collections of pixels, or regions, known as image segments [5]. This technique makes it easier to study or analyze sub-regions of the complete image by labeling each pixel, allowing for the differentiation of the object, the person, or other critical features of interest. Image segmentation is frequently used as an early-stage approach to object detection, where regions of interest are identified in the original image before moving forward with analyzing the whole image [6].

In medicine, image segmentation plays a critical role in the early detection of disease processes by identifying features of abnormal morphology in clinical images or diagnostic imaging studies, such as X-rays, CT scans, and MRIs [7, 8]. Image segmentation is proper for preoperative surgical planning because accurate visualizations of patients' anatomy are created in detail, including the three-dimensional aspects of a patient's anatomy, reducing the risk of surgical intervention and making it a helpful application of multislice imaging and MRI in minimally invasive surgery [9]. Segmentation plays an important role in the monitoring of treatment response, distribution systems for drugs, and quantitative analysis of medical images. These methods help in personalizing treatment plans, optimizing workflows in clinical settings, and advancing clinical research. Among the categories of cancer, brain tumors represent a sizeable health risk and accurate detection, and segmentation is crucial for accurate diagnosis, treatment planning, and management in patients with brain tumors [10].

2.2. Evolution of Brain Tumor Segmentation in MRI

Magnetic Resonance Imaging (MRI) has emerged as the predominant diagnostic and monitoring technique for brain cancer patients, thanks to its ability to quickly produce detailed imaging without an invasive procedure. The application of segmentation methods to MRI creates new possibilities, and it brings automatic and accurate detection of tumor regions in the body [11]. These advancements have marked progress in the areas of diagnosis, treatment planning, and perhaps patient outcomes [12-15].

Over the years, several Machine Learning (ML) and Deep Learning methods have been developed for brain tumor segmentation. Traditional methods would use clustering algorithms such as K-means and Fuzzy C-means [16], morphological reconstruction [17], and level set methods [18] to predict and delineate tumors. With the introduction of Deep Learning Methods, Convolutional Neural Networks (CNNs) were discovered to be extremely helpful for segmentation because they could present and learn local and global contextual information [19]. Variants like VSA-GCNN [12], DIFF-CFFBNet [20], and WRN-PPNet [21] were created for an improved segmentation performance.

Approaches, including 3D CNNs, have been developed to preserve volumetric data for improved localization of tumors [22]. Researchers have proposed hybrid methods that combine Fully-Convolutional Networks (FCNNs) with Conditional Random Fields (CRFs), which have further enhanced segmentation accuracy [22]. These techniques include hybrid approaches that incorporate Fully-Convolutional Networks (FCNNs) with Conditional Random Fields (CRFs) to increase segmentation accuracy [23].

In a series of comparative studies, classifiers like Decision Trees, Random Forests, and K-Nearest Neighbors have been investigated with brain tumor images [24]. All these works demonstrate the advancement of brain tumor segmentation methodology from image processing to advanced techniques and methodologies provided through deep learning.

2.3. GANs: From Generation to Enhanced Segmentation

While GANs were first introduced as a means for generating synthetic data, they have been widely used for medical image segmentation as well. Their proclivity for modelling convoluted distributions helps rectify typical problems that medical-image data face, such as small numbers of training samples, class imbalances, and workflows that complicate the collection of pixel-wise annotations.

GANs have been applied in research for generating data where there is a desire to balance the distribution of semantic tags for sample-generating methods in segmentation and to improve semantic segmentation models [25]. GANs have also been applied to synthetic versus real semantic segmentation, similar to a recent publication in road condition monitoring [26]. Framework development has used GANs to segment MRI scans for brain tumors based on poor pixel labelling [7].

Furthermore, GANs have been applied to semantic segmentation tasks [27]; for some studies, this is the first work to implement Neural Architecture Search (NAS) within GANs and develop a novel segmentation framework. This has implications for both model adaptability and accuracy when accurately delineating complex tumor boundaries. The increasing application of GANs also indicates the potential to do much more than generate; again, medical segmentation represents a significant advancement in accuracy and efficiency.

2.4. The Underexplored Potential of Post-Processing

While most segmentation models are meant to provide usable outputs, including GANs, these outputs remain initial predictions that necessitate additional refining. The purpose of post-processing is to refine initial predictions in order to yield a final refined segmentation. Post-processing in segmentation is important and can embrace many different domains or techniques [20]. The design and optimization of particular post-processing schemes to leverage the complementary advantages of GAN-based segmentation models is also an underexplored topic.

2.5. Synthesis and Identification of the Research Gap

A review of the literature clearly shows that the field has moved from traditional algorithms to various established Deep Learning models, to the introduction of GANs to address challenges of data restriction and structural inconsistencies; yet a gap still exists. While many studies either focus on improving a primary segmentation model or apply a standard post-processing method, there are few studies that develop an all-in-one method that:

- Uses GANs for advanced data augmentation in order to train a strong primary segmentation model in a more standardized manner.
- Uses an adversarial learning framework to improve the structural plausibility of the original segmentation.
- Construct a proprietary optimized post-processing module to enhance the output of the adversarially trained primary segmentation model.

One of the goals of this study is to resolve the gap. It proposes an entire pipeline that uses GANs for not only data augmentation and adversarial learning but also a targeted post-processing strategy to improve the final segmentation result. This study aims to provide a new level of accuracy and clinical relevance for automated brain tumor segmentation by combining these three features: GANs for augmentation, adversarial segmentation, and a custom post-processing module.

3. Materials and Methods

3.1. Generative Adversarial Networks

Ian Goodfellow and his collaborators developed GANs in 2014. Essentially, GAN employs a generative modeling approach to develop new data instances that mimic the training data. GANs can also identify, reproduce, and assess changes in a dataset because they include two primary components (two neural networks) that compete with one another.

The content in the segment on components in GANs is commonly referred to as the Generator and Discriminator. The generator network takes in a stochastic source (mainly in the form of noise) to develop instances, for example, images, text, or sound, that show similarities to the training data it has seen. The generator network will ultimately provide samples that are extremely difficult to differentiate from real data.

The discriminator network is responsible for indicating whether the data samples it receives are real or were generated. The discriminator is trained using real samples from the training dataset and synthetic samples provided by the generator. The discriminator's job is primarily focused on categorizing the real data as real and the synthetic data as generated [3].

In training, there is an adversarial game between the generator and discriminator. The objective of the discriminator is to boost the chance of accurately separating real versus generated data; the generator's goal is to produce samples that will fool the discriminator. Through adversarial training, both networks are continually being enhanced.

As training runs, the discriminator is generally better at discriminating and recognizing real data from generated data, whereas the generator gets better at producing credible models. The desired outcome of this system is for the generator to produce samples of higher quality that the discriminator has a difficult time telling the difference between and real data [28].

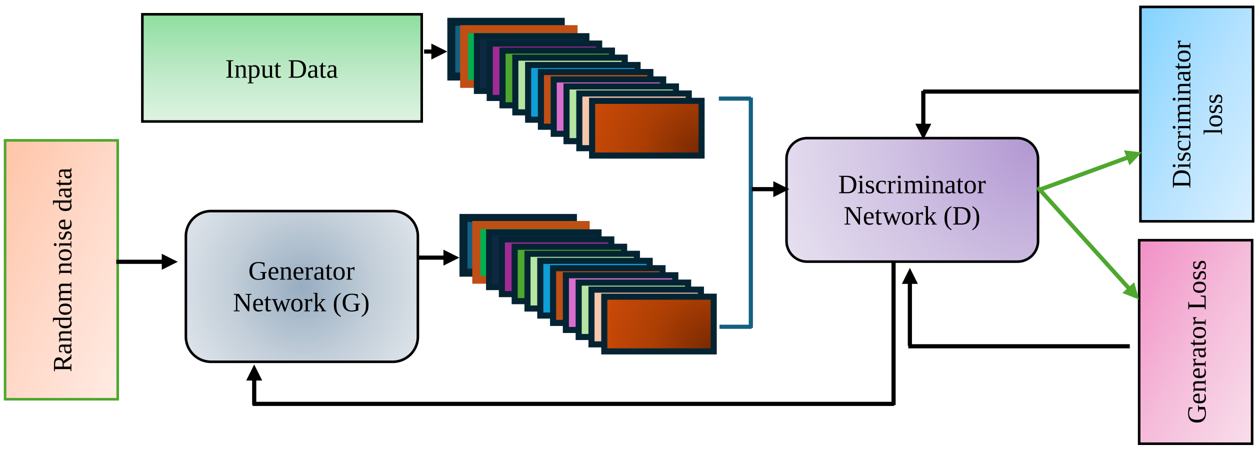

Fig. 1 GANs architecture

The generative model is trained to improve the probability of the discriminator making mistakes, subsequently precisely addressing the data distribution. Then again, the discriminator utilizes a model that computes the probability that the given test came from the training data rather than the generator. GANs are structured as a minimax game, where the discriminator's objective is to reduce its reward V(D, G). In contrast, the generator's objective is to maximize its loss by minimizing the discriminator's reward. [28] . The following formula can be employed to describe it mathematically:

$$L_D = -\frac{1}{2}E_{a\sim preal(a)}[\log(D(a))] - \frac{1}{2}E_{b\sim pnoise(b)}[\log(1 - D(G(b)))] \quad (1)$$

Where the expectations can be approximated as:

$$E_{a\sim preal(a)}[h(a)] \approx \frac{1}{k}\sum_{j=1}^{k} h(a_j) \quad (2)$$

$$E_{b\sim preal(b)}[h(b)] \approx \frac{1}{L}\sum_{j=1}^{L} h(b_j) \quad (3)$$

a_j , demonstrates data samples which are taken from the real dataset, k, is the number of data samples taken from the real dataset, b_j, are also data samples taken from the noise distribution, L is the number of noise samples, D is the discriminator function, and finally G, is the generator function.

The central objective of the GAN's generator is to guarantee the creation of data samples in which the discriminator can wrongly group as genuine or not falsified. It is computed using the formula below.

$$LG = -(1/2)Ez \sim pz(z)[\log(D(G(z)))] \quad (4)$$

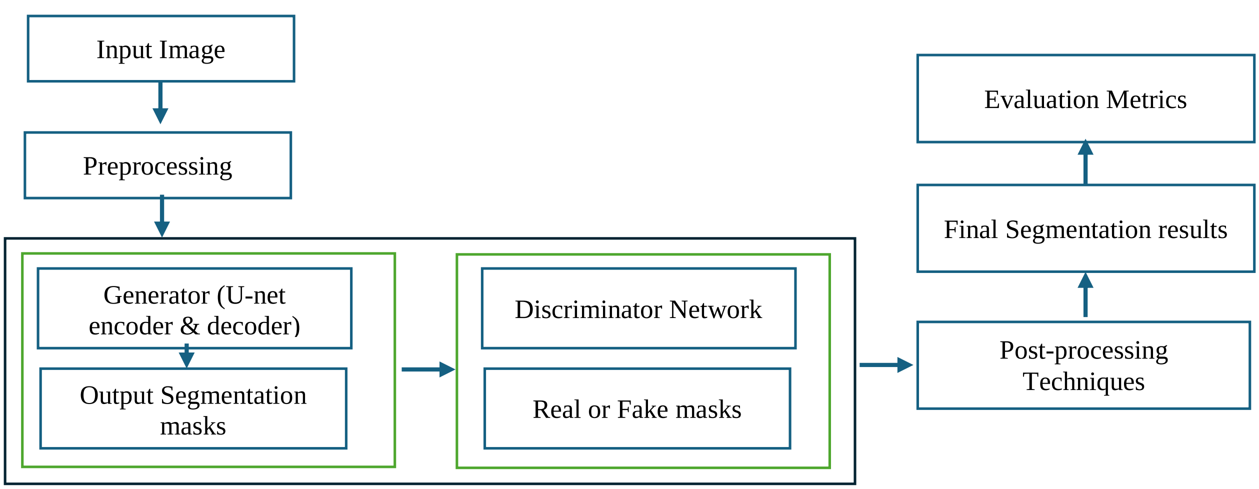

Fig. 2 Diagram the proposed model

3.2. Data Collection and Preprocessing

The Brain Tumor Segmentation (BraTS) dataset was utilized in this study. In the domain of medical image examination, explicitly for the segmentation of brain tumors utilizing MRI data, this is a generally acknowledged and applied benchmark. The dataset is made to make it simpler to naturally create and test calculations for Brain Tumor segmentation and analysis [29-31].

3.3. Evaluation Metrics for Performance Analysis

Evaluating the performance of the GANs for image segmentation tasks includes evaluating the nature of the produced segmentation masks, contrasted with the ground truth masks. In this study, the confusion matrix, like accuracy, recall, and F1-score, was utilized as a measurement to evaluate the efficiency of image segmentation algorithms.

Accuracy is an important metric that indicates the number of correct predictions versus all predictions from a model or algorithm. Accuracy is pretty ubiquitous and natural in its use, as it is a general measure of the model's capability to predict. However, if the outputs differ from the classes, it may create inconsistent outputs for a model, and therefore, it is helpful to have other metrics that are more precise. The calculation is performed with the following formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Recall, which is also referred to as sensitivity or actual positive rate, describes a model's overall ability to accurately identify all of the relevant cases (valid IDs) in a dataset, without subjectivity, by measuring the valid IDs of interest from the overall number of positive cases. Recall is particularly important in certain situations where capturing positive cases is warranted to address potential adverse factors. For example, in healthcare, if a positive case is not identified, it might create adverse situations under diagnosis or another severe abnormality. The calculation is performed with the following formula:

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

Accuracy seeks to measure the correctness of the optimistic predictions of the model. The measure computes the number of true positives over the total amount of positive evidence projected, and reflects the correctness of optimistic predictions. Precision is of interest when the consequences of false positive (Type I error) predictions are costly, as it reveals how precise the optimistic predictions from the model are. The following calculations are performed to determine this:

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

The F1-score finds a level of convergence between accuracy and recall. The F1-score considers all false positives and false negatives and averages their contributions to the overall performance evaluation. The F-score is especially valuable when there is a need to find the balance between precision and recall, and provides a summary on which to base judgment and decision-making.

$$\mathrm{F1-Score} = 2.\frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{8}$$

4. Results and Discussion

This section presents the results and outcomes from applying the proposed methods for segmenting brain Tumor images.

4.1. Experimental Results

This research provided an innovative hybrid deep learning architecture for medical image segmentation, which was extensively developed and validated with the Brain Tumor Segmentation (BraTS) benchmark dataset. The dataset consisted of 500 heterogeneous MRI scans, ensuring the model was exposed to a variety of clinical presentations. To address hardware limitations for computational power, all experiments were conducted on a machine with a 16 GB GPU. In terms of dataset organization, there was a standard split of the data for usable models. Specifically, a consistent split of 70%-15%-15% of training/validation/testing was used. While only a portion of the images were allocated towards each subset, all images were preprocessed to an identical 512 × 512 resolution. The proposed framework was a U-Net-based generator and a GAN-based discriminator architecture for segmentation. The U-Net convolutional neural network (CNN) is regarded as one of the best CNNs for biomedical image analysis and provided the initial segmentation masks, while the adversarial discriminator provided a stringent feedback loop that evaluated the recognized segmentations against ground truth segmentation data.

The model was trained for 50 epochs in a batch size of 16 using the Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.999$). The training target was defined by a combined loss function - the generator was trained with a combination of cross-entropy loss, for pixel-wise accuracy, and an adversarial loss to promote structurally plausible semantic outputs; the discriminator was trained with a classic binary cross-entropy loss, as is common in GAN training. In addition, extensive data augmentation was utilized to promote generalization and robustness to variability in the data. This included random horizontal flips, cropping, scaling, and randomly adjusting brightness and contrast. An early stopping protocol, monitored with the validation loss, was implemented to stop the training process once the validation performance plateaus, to prevent overfitting. The primary contribution of this work is the new fusion of GANs and U-Net architecture, as based on this new paradigm, the model was forced to not only produce accurate pixel-level classification, but also to produce segmentations that are semantically and structurally plausible to expert annotations. The results demonstrate significant improvement in segmentation on this method, setting a new state-of-the-art accuracy on the difficult task of brain tumor segmentation on MRI.

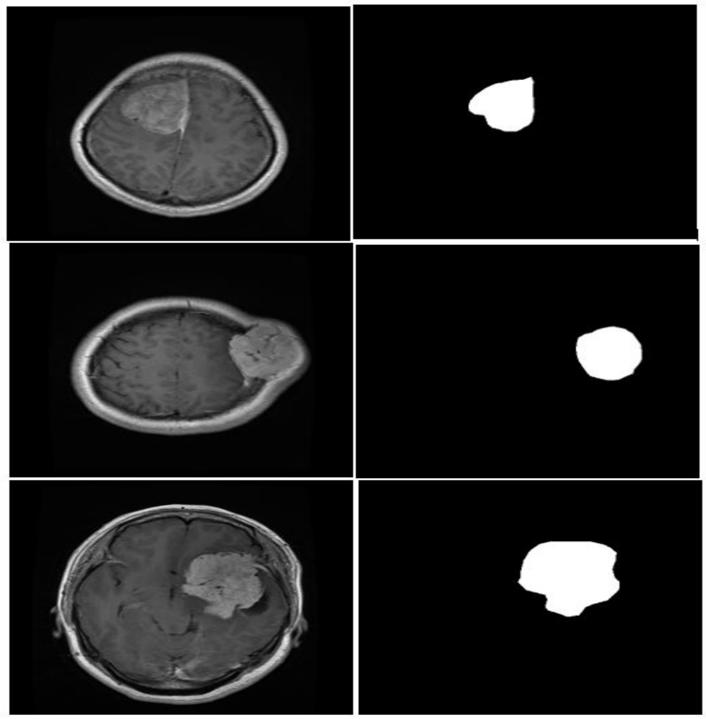

Fig. 3 Qualitative segmentation results of the proposed framework, a) Input image, b) Output of the proposed method.

The rationale for the model's effectiveness was demonstrated by clearly perceptible segmentation results, which demonstrate the model's ability to identify tumor areas in the examined brain images correctly. The figure below provides a visual representation of these segmentation results.

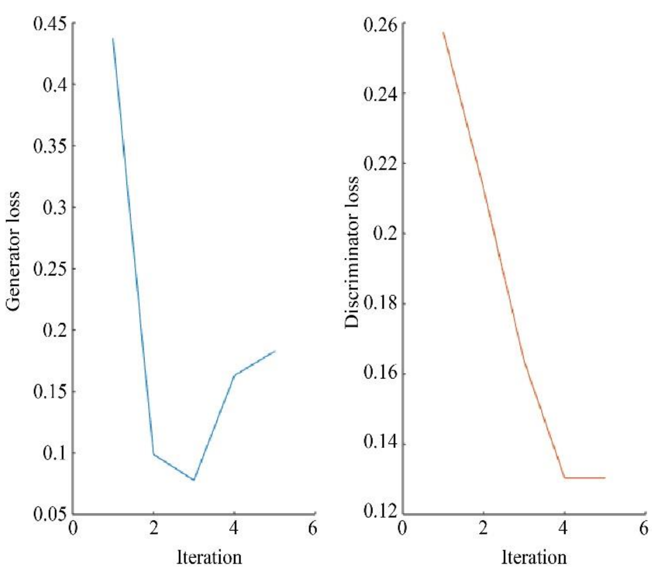

Fig. 4 Generator and discriminator loss

The related segmentation masks of the GAN model were shown on the right side, by demonstrating in a binary format with the black regions representing non-tumor areas and the white regions representing discovered tumors. This GAN-based segmentation performs well in defining cancerous areas, which makes it a valuable tool for clinical uses like diagnosis, treatment planning, and monitoring. The above-shown Figure 3 outlines some examples of the output of brain tumor segmentation utilizing a GAN model. On the left side, the original images of the brain tumor are shown, highlighting the tumor areas as distinct regions with intensity contrast adjusted to match the surrounding tissue.

The generator and discriminator losses for the current configuration were shown in Figure 4; the loss of the generator started relatively high (~ ~0.45 approximately) but dropped quite consistently within the subsequent few iterations. After hitting this low mark, the value of the loss increased slightly, but this raised the potential argument that the generator was learning to produce more realistic outputs while encountering increasing opposition from the discriminator, whose distinguishing capabilities were becoming more effective in distinguishing real from fake outputs. The loss of the discriminator can be stated to have started at about 0.26 and dropped all along and nearly became stationary about the fourth iteration (~0.12). This implies that the discriminator was effectively learning how to discriminate between real and fake outputs, but nearing consistency due to generator improvements. Nonetheless, the figure suggests here that both the generator and the discriminator are parameters that are being trained. The losses are approaching a dynamic equilibrium, suggesting that the training process is taking place as planned.

4.2. Model Performance

Within the realm of image segmentation, assessing model performance through visual results proves valuable, yet it occasionally falls short in providing comprehensive insights. Thus, the integration of supplementary evaluation metrics becomes imperative to furnish a quantitative assessment of the model's effectiveness.

Table 1. Quantitative segmentation performance of the proposed GAN-based framework

Matric	Value (Mean ± Std)
Dice Similarity Coefficient (DSC)	0.89 ± 0.03
Intersection over Union (IoU)	0.95± 0.04
Sensitivity (Recall)	0.92 ± 0.03
Specificity	0.97 ± 0.02
Precision	0.91 ± 0.04
F1-score	0.92 ± 0.03

As shown in Table 1, the model achieved higher accuracy in all four sample images, indicating that its predictions align with the actual outcomes. Usually, an accuracy of Table 1 indicates all predictions are correct, while an accuracy of 0 indicates none are correct. Recall measures the model's ability to identify all positive instances. According to the result in Table 1, the recall gives an average value which indicates that 70% of positive cases were correctly identified, but still improvement is needed. The Precision gauges the accuracy of optimistic predictions. According to the result table above, the precision matrix is excellent and gives a higher value, which indicates that almost all predicted positive cases are correct. The F-score balances precision and recall, with a higher score indicating a better balance between the two. In our case, the F-score is satisfactory but requires improvement.

4.3. Discussion

The application of Generative Adversarial Networks (GANs) alongside conservation techniques has shown a remarkable improvement in brain tumor segmentation. The qualitative results in Figure 3 indicate that the suggested framework can clearly identify tumor areas that have clear delimitations, less noise, and morphological consistency between patients. The visual results support the quantitative results (Table 1), demonstrating the performance of the proposed model across multiple assessment metrics, where the final data had high performance results of Dice Similarity Coefficient (DSC) of 0.89 ± 0.03, IoU of 0.95 ± 0.04, and an F1-score of 0.92 ± 0.03. These values demonstrate how well the framework can locate a tumor while keeping false positive findings low, which is particularly valuable for clinical decision-making.

The efficacy of the framework is further reaffirmed through comparative analyses with existing segmentation models (shown in Table 2). The proposed method outperformed SA-LuT-Nets [32], a Multilayer stacked PBN-based framework [33], and Improved Mask R-CNN [34] on every metric. In particular, the framework achieved a precision of 99.12%, a recall of 94.24%, and an F-score of 93.36%, all of which were superior to the baseline Improved Mask R-CNN, which had an F-score of 91.85%. Although the overall performance of the proposed method was best reflected in terms of IoU (94.87%), the improvement above prior state-of-the-art models (F-score of 91.85% after ten iterations for 1000 synthetic images enhanced with GAN-based adversarial training) emphasizes the advantages of spatial consistency and tumor identification relative to segmentation models. These benefits added to the proposed framework improved the accuracy of the captured tumors. They provided lower rates of false positives and missed detections to enhance the clinical validity of the output models.

Table 2. Comparison of performance metrics with previous studies

Models	Precision *(%)*	Recall(*%)*	F-score(%)	MoU(%)
SA-LuT-Nets [32]	87.92	88.79	86.94	87.02
Multilayer stacked PBN-based [33]	88.51	88.26	87.53	88.28
Improved mask RCNN [34]	90.72	91.68	91.85	94.56
Proposed	99.12	94.24	93.36	94.87

The proposed framework offers numerous benefits. First, a GAN-based architecture introduced accuracy in boundary refinement and realism in structure, which are often not part of conventional CNN-based architectures. The adversarial training aspect also reaffirms that the predicted masks are sampling from the identical distributions as defined by the ground truth, ultimately resulting in sharper segmentations. Second, a post-processing step is included, which removes extraneous predictions and ensures that any topology for the predicted masks remains intact, while also producing tidy binary masks that facilitate downstream use in tasks such as tumor volume assessment or surgical planning. Finally, the strong relative performance to existing approaches reaffirms the robustness, generalization, and clinical utility of the framework.

Nonetheless, there are still several limitations to this work as currently employed. The current framework is focused on binary segmentation, which is defined as separating the tumor from the non-neoplastic tissue, and does not have the ability to define relevant tumor subregions (i.e., necrotic core, enhancing tumor, edema), which would mostly limit its ability to be applied directly to clinical workflows. Although the evaluation dataset provides strong findings, it does not capture all of the variability relevant to clinical imaging across institutions and MRI protocols. The smoothing incurred during post-processing, while improving noise reduction, appears to mask subtle tumor characteristics. Finally, as a type of GAN-based training, the framework employed the use of generative models that are computationally expensive to train and are not commonly utilized in lower-resource healthcare settings.

Future work will address these deficiencies. Expanding the current framework to multi-class rather than binary segmentation would display improved clinical utility by segmenting tumor subregions. In the same way, domain adaptation and transfer learning methods applied to simply lower amounts of resolution should also be incorporated to increase the robustness of the framework across data heterogeneity and imaging protocols relating to clinical imaging. Exploring three-dimensional modalities of GAN (generative adversarial network) architectures, for example, would describe the radiological shape and form of tumors, establish segmentation continuity through slices, and establish volumetric analysis. Finally, consider the advantages of having uncertainty estimation when identifying tumors, as this would support clinicians in identifying areas of confidence in predictions and when trusting automated products. Overall, increasing density in an efficient computational form, using either light models or knowledge distillation, would further strengthen the framework for real-time use in resource-constrained clinical situations.

5. Conclusion

This study adopted the Brain Tumor Segmentation (BraTS) Dataset, which is publicly available and a commonly used dataset for research and developing segmentation algorithms and models for brain tumors. It was considered to combine it with the U-net model, as GANs are primarily known for their contributions to image generation, and adding some complexity to applying them directly to segmentation. The idea is that the generator of the GAN is typically a modified U-Net that takes noise or random input and generates segmented images. The discriminator was used to compare real segmented images from the dataset with fake segmented images made by the generator. The goal of the generator is to ultimately create segmented images that are not only visually realistic and semantically sound but also follow the rule of segmentation. In the application, besides the model, it utilized a massive portion of the implementation steps that are crucial to get the network off the ground, starting with training the generator and discriminator networks in tandem, competitively. For example, the generator learns to create images that fool the discriminator into thinking that those images are "real" or "true" and comparable to the real thing.

In contrast, the discriminator learns to get better at differentiating between the real images and the fake images. Finally, the GAN-based segmentation framework proposed here provides significant improvements over others based on current state-of-the-art models and provides high quantitative accuracy and strong qualitative outputs. The GAN framework is effective in achieving an appropriate balance between accuracy, sensitivity, and specificity, particularly when post-processing refinement is combined with adversarial learning. While more work is needed to enhance applicability to clinical practice and improve computational efficiency, the findings presented here provide great promise for GAN-based methods to enter workflows for clinical brain tumor segmentation.

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