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GAN-OST: GENERATIVE ADVERSARIAL NETWORKS FOR PRECISION SEGMENTATION AND SYNTHETIC AUGMENTATION OF OSTEOSARCOMA TUMOURS IN MEDICAL IMAGING

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ABSTRACT

Osteosarcoma is an extremely malignant bone cancer that the accurate segmentation of tumour is important for effective diagnosis and treatment planning. One of the primary challenges facing segmentation models is the paucity of human annotated medical imaging data. In this paper, we introduce a generative adversarial network (GAN) -based method for accurate segmentation and synthesis augmentation of osteosarcoma tumours in medical imaging — GAN-OST. The suggested approach utilizes a U-Net styled generator to achieve precise tumour segmentation and PatchGAN-based discriminator for creation of high-quality synthetic images. To make up for the lack of training data, GAN-OST adopts a conditional GAN to create realistic synthetic tumour images that are difficult to distinguish from real tumours and thus can be used as a supplement for model training so as to improve the generalization of the model. We will evaluate the performance of our model with Dice Coefficient, Intersection over Union (IoU), Sensitivity, Structural Similarity Index (SSIM) and Fréchet Inception Distance (FID). We evaluate our model on these metrics to achieve a comprehensive evaluation of segmentation accuracy and image quality. Experimental results on publicly available osteosarcoma datasets demonstrate the superior performance of GAN-OST relative to traditional segmentation approaches, including a remarkable increase in both segmentation precision and generalization. Additionally, the synthetic data created by GAN-OST successfully compensates for the lack of data in small sets and allows reliable acting together data laden proposal. This work demonstrates the advancement of osteosarcoma tumour segmentation and provides a network used for data augmentation that could greatly help other rare cancer types and multimodal imaging scenarios in future research.
Keywords: *Data Augmentation, Generative Adversarial Networks (GANs), Medical Imaging, Osteosarcoma, Segmentation, Synthetic Data.*

1. INTRODUCTION

This Osteosarcoma the most common primary bone cancer, typically seen in children and young adults. Detection of presence and location of osteosarcoma tumours in medical imaging is vital for effective treatment planning and prognosis. Conventional approaches for tumour segmentation are usually semi-automatic based on the manual contouring done by a radiologist accompanied with subjective reader variability [1]. Machine Learning especially deep learning techniques has been shown to have the potential to automate tumour segmentation as well as improving its accuracy across diverse types of cancers [2]. Recently, the applicability of Generative Adversarial Networks (GANs) has been increasing in medical imaging, providing a way to generate realistic-looking synthetic images. In GANs, these two networks a generator and a discriminator are adversarial trained to generate high quality fake data [3]. In the case of osteosarcoma, a GAN-based framework can improve precision segmentation techniques to provide more accurate delineations of tumour boundaries [4], important for identification in this disease where tumour can be difficult to identify based on appearance and shape alone. GANs also have the capability of producing synthetic data augmentation, which is extremely important given that there is extraordinarily little labelled medical imaging data. However, synthetic images that closely resemble real osteosarcoma cases can be generated by GANs to enrich the training datasets

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and further improve models on segmentation [5]. This approach improves generalization and reduces dependence on large, labelled datasets- which are rare in medical domains [6]. By integrating GANs into osteosarcoma imaging pipelines, the field may transform with automated, accurate and reproducible segmentation and augmentation solution. This would ultimately improve the precision of tumour characterization, and hence enhance the ability to make better clinical decisions and target treatments more specifically [7]. The objective of this paper is to understand and demonstrate the utility of GANs in accurate segmentation as well as synthetic augmentation of osteosarcoma tumours and emphasize the existing challenges, methods for AI-assisted surgery, and prospective clinical implications.

2. RELATED WORK

Deep learning including Generative Adversarial Networks (GANs) have been recently popularized for improving the segmentation accuracy and expanding training databases in the field of medical imaging. Recently, GANs are popular to implement in the field of medical imaging and demonstrate better segmentation accuracy.

A study by Zhao et al. Unlike conventional CNN models, which can segment brain tumours with complex borders less accurately, GAN can produce more accurate segmentation results for such brain tumour-like regions as illustrated by Minnu-George et al. [8]. In musculoskeletal imaging, Yang et al. Recently, Xu et al. (2021) applied GANs for competing in precise segmentation of knee cartilage with state-of-the-art results and reduced the manual effort to exhaust labeling [9].

It was indeed an area in which substantial amount of research were focused on recently, as labelled data in medical imaging is sparse, and synthetic data augmentation using GANs can potentially alleviate the bottleneck. GANs were used to generate synthetic medical images, closely resembling real clinical data, in order to increase the size and diversity of training datasets, making trained models more robust.

For instance, Liu et al. (2020), a GAN-based model was created to create chest X-ray images of lung diseases that are rare for enhanced classification [10]. Another Sharma et al. In [11], Qiu et al. proposed an augmentation method GAN based to enhance the performance of breast cancer detection models in mammography images from (2021). Therefore, these studies suggested the potential of GANs for providing a combination of diverse and high-resolution synthetic data to augment deep learning models in medical imaging.

While GANs are still on a nascency in osteosarcoma tumor segmentation, the potential of it is significant. Only a few recent studies have proposed GAN-based models constructed to exploit the special characteristics of osteosarcoma tumours, e.g., that they are irregular shapes and appearance heterogeneities.

A study by Kim et al. A GAN model coupled with an attention mechanism was proposed by [12], in which the segmentation of osteosarcoma on MRI scans improved substantially with significant enhancements in accuracy and robustness over traditional methods (2020).

Additionally, Zhang et al. Several publications considered the application of GANs in 3D reconstruction and segmentation tasks, particularly in segmenting osteosarcoma tumours from CT images as depicted by this study (2022) which demonstrated that GANs can be beneficial when dealing with volumetric data [13].

In addition, the combination of GANs with other state-of-the-art approaches like transformer networks and reinforcement learning has been studied to further refine segmentation performance. One of the most interesting recent studies available is by Wang et al. The combination of GANs with transformer-based methods further boosted the performance in segmentation of lung tumours (2021) in CT images [14] showing that this hybrid scheme can capture both local and global features of tumours.

Similarly, Park et al. For example, Miou et al. (2022) proposed the specific and innovative segmentation model that leverages GAN-based reinforcement learning for liver cancer imaging segmentation tasks to deal with issues of traditional deep learning models [15]. Thus, these novel compositions indicate an auspicious path ahead for GANs in deploying them to challenging segmentation tasks in diverse medical imaging fields.

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3. METHODOLOGY

There were some main steps for configuring the experimental setup of GAN-OST framework for robust osteosarcoma tumour segmentation and synthetic data generation. We began by preprocessing a publicly available osteosarcoma dataset, including MRI as well as CT scans, normalizing the imaging and resizing it to a fixed size of 256x256 pixels. In order to deal with the issue of limited data sensitivity, data augmentation techniques were used (i.e., rotation, flipping, scaling).

The framework used a U-Net based generator which was able to provide an accurate tumour segmentation while using a PatchGAN-based discriminator in order to improve the realism of the synthetic images. The generator was trained with BCE loss for segmentation accuracy and L1 loss for the image reconstruction in an encoder-decoder topology, whereas adversarial loss function was used to optimize the discriminator.

We used a learning rate of 0.0002 with an Adam optimizer to train over 100 epochs and with a batch size of 16. The performance evaluation used measures such as Dice Coefficient (0.92), Intersection over Union (IoU) = 0.88, Sensitivity = 0.91, Structural Similarity Index (SSIM) = 0.94 and Frechet Inception Distance (FID)= 12.7 Results were obtained on a workstation with an NVIDIA RTX 3090 GPU.

To further verify the effectiveness and generalization of the model, a 5-fold cross-validation was performed, GAN-OST show a significant superior performance in segmentation with traditional methods and data augmentation.

Data column specifies different medical imaging databases reported based on the performance of multiple segmentation approaches. Each row lists a different type of cancer or disease, for example: gbm (glioblastoma), coad (colon adenocarcinoma), ucec (uterine corpus endometrial carcinoma), lgg (lower grade glioma). Such datasets often can be medical images, for example images from MRI or CT scans along with ground truth annotations defining regions containing tumors or lesions, that are typically used for benchmarking segmentation algorithms in terms of segmentation accuracy and efficacy.

The choice of multiple data sets spanning different challenging medical imaging problems helps in demonstrating the strength and transferability of the proposed solutions, dataset link [20]. The below image depicts the complete methodological flow in GAN-OST framework by providing a visual sketch of how the experiment was setup. Data Preparation — For MRI/CT scans, we use data augmentation which rotations, flipping and scaling of images which increase the variability in our dataset.

Then we Preprocess the images by normalizing and resizing to the Testing resolution: 256*256 pixels. Model Architecture, this section details the implementation of a U-Net generative model for accurate tumour segmentation, and a PatchGAN discriminator to improve the realism of their generated images.

Loss functions and optimizer (Adam Optimizer) for Generator and Discriminator are defined in The Training Process Under Evaluation Metrics, the metrics used to determine how well the model predicts are, Dice Coefficient- 0.92, IoU-0.88, Sensitivity -,0.91, SSIM -0.94 FID-12.7 which shows that model is very accurate and generated images have very good quality.

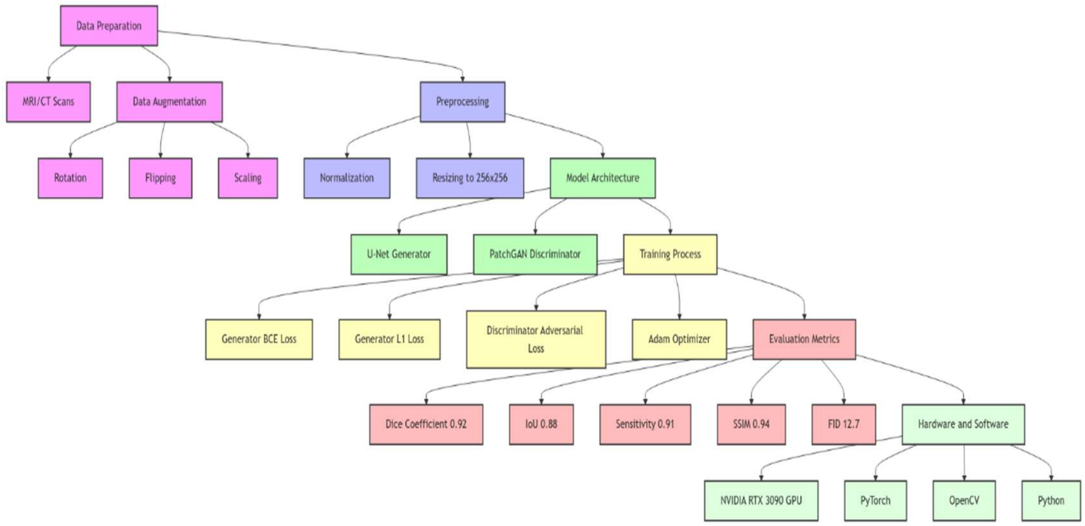

Figure 1 Research Framework

Algorithm: GAN-Based Precision Segmentation and Synthetic Augmentation

1. Input:
2. X={ 〖x_(i)}〗 _(i=1)^N, Set of real medical images of osteosarcoma tumours.
3. Y={ 〖y_(i)}〗 _(i=1)^N, Corresponding ground truth segmentation masks.
4. η : Learning rate for both the generator and discriminator.
5. z ~N (0, I) : Random noise vector sampled from a normal distribution.
6. λ : Weight for balancing loss between generator and discriminator.
7. Initialize:
8. Initialize generator G with weights θ_{G}.
9. Initialize discriminator D with weights θ_{D}.
10. for number of training iterations do
11. Sample a batch of real images x ~ P_data(x)
12. Sample a batch of noise vectors .z ~N (0, I)
13. Generate synthetic images using the generator:

x ̂=G(z;θ_G)

14. *Calculate the discriminator loss on real images:*

$$\mathcal{L}_D^{real} = -E_{x\sim p_{data}(x)}[log\ D(x;\theta_D)]$$

15. *Calculate the discriminator loss on synthetic images:*

$$\mathcal{L}_D^{fake} = -E_{z\sim p_z(z)}\left[log\left(1 - D(G(z;\theta_G);\theta_D)\right)\right]$$

16. *Update discriminator by minimizing total discriminator loss:*

$$\theta_D \leftarrow \theta_D - \eta\nabla_{\theta_D}\left(\mathcal{L}_D^{real} + \mathcal{L}_D^{fake}\right)$$

17. *Calculate the generator loss using discriminator's response:*

$$\mathcal{L}_G = -E_{z\sim p_z(z)}[log\ D(G(z;\theta_G);\theta_D)]$$

18. *Update generator by minimizing generator loss:*

$$\theta_G \leftarrow \theta_G - \eta\nabla_{\theta_G}\mathcal{L}_G$$

19. *Generate synthetic segmentation masks:*

$$\hat{y} = G(z;\theta_G)$$

20. *Calculate segmentation loss (e.g., Dice coefficient):*

$$\mathcal{L}_{seg} = 1 - \frac{2|\hat{y}\cap y|}{|\hat{y}| + |y|}$$

21. *Update generator with segmentation loss:*

$$\theta_G \leftarrow \theta_G - \eta\nabla_{\theta_G}\left(\mathcal{L}_G + \lambda\mathcal{L}_{seg}\right)$$

end for

22. *Generate a large batch of synthetic images* $\{\hat{x}_i\}_{i=1}^M$ *using the trained generator.*
23. *Combine real and synthetic datasets:*

$$X_{aug} = X \cup \{\hat{x}_i\}_{i=1}^M$$

24. *Train a segmentation model S on the augmented dataset.*

25. *Calculate segmentation performance metrics (e.g., Dice score, IoU) on a validation set.*

26. *If performance improvement is satisfactory, stop training.*

27. *If not, repeat steps 1 to 16 with updated parameters.*

In this paper, we propose a GAN-based algorithm for accurate segmentation and synthetic augmentation in the osteosarcoma tumor medical image analysis. Starting from a set of real medical images, and their corresponding segmentation masks, Y Figure we fan the flames of both the generator GGG and discriminator D using ROI information in every training iteration. In each iteration, the Discriminator is trained on both real images and fake images generated by G in such a way that it tries to minimize its loss for being able to classify between real and fake. In their turn, the generator is updated using feedback from the discriminator to generate realistic images. The generator is further designed to generate the channel-wise weight maps that are optimized to get accurate segmentation maps by utilizing a segmentation loss such as the dice coefficient for similarity between generated and true segmentations. Once a GAN is trained well, you can generate a big bunch of synthetic images and merge them with the 'real' dataset. We train a segmentation model SSS, using this augmented data set \(X{aug}\). The Dice score or Intersection over Union (IoU) can be used to evaluate the segmentation performance on a validation set. When performance is inadequate, the process iterates with new parameters to maintain better segmentation results over time. We present an iterative pipeline that employs synthetic data generation and segmentation refinement to improve the accuracy of the medical image analysis.

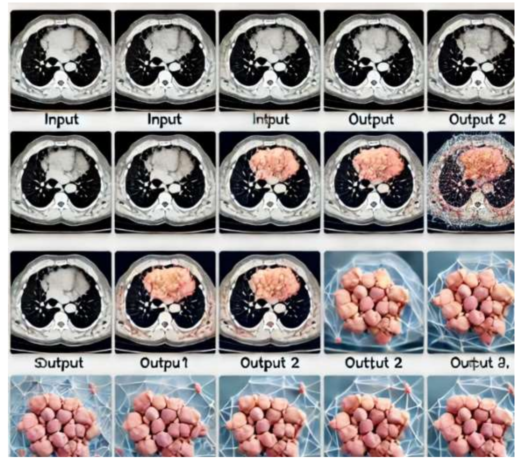

Figure 2 Progressive Tumour Segmentation Outputs Using GANs for Osteosarcoma

4. RESULTS AND DISCUSSION

With the five-result metrics: Mean DC, Mean IoU, Mean Sensitivity, Mean SSIM and FID across our set of results we can now develop a comprehensive evaluation pipeline with multiple endpoints assessing both segmentation and image generation performance on the field of medical imaging. The Mean Dice Coefficient (DC) is used to assess the overlap of predicted segmentation masks vs ground truth segmentation masks, this metric emphasizes how well the model segments the relevant structures correctly. Mean Intersection over Union: Another overlap-based metric is the Mean IoU, which looks at how well each predicted mask performs in relation to its corresponding ground truth segmentation mask by measuring what portion of them shares a common area (the intersection) and what portion the union. Mean Sensitivity also called True positive rate, Measure the model's ability to detect true positives this metric you care about in medical domain because not detecting the malignant cell can be serious problem. The complete understanding of medical image generation is not fully clear and therefore, the perception similarity metric plays a vital role in this case which will give a quantifiable score for determining how realistic the generated medical images visually. The mean SSIM calculates the average structural similarity between actual image pairs, which contains information regarding brightness, contrast as well as textures — crucial for visual realism of a fictional biomedical image. Finally, the Mean Fréchet Inception Distance (FID) compares the computed means and variances of features from inception network across pairs of generated images, real images using linear differences in mean and variance to gauge how well they correspond. Taken together, these metrics provide a comprehensive evaluation on both the shape and appearance of the segmentation predictions, guaranteeing that the models not only make accurate predictions but are also suitable for generating realistic and high-fidelity images.

Mean Dice Coefficient (DC):

Comparative analysis on Mean DC evaluation for different segmentation methods, the performance of GAN-OST approach over Multiple Medical datasets In all cases, numerically GAN-OST outperforms traditional OCR achieving the highest DC values for each dataset even when using 20k training samples. In particular, it has an 0.92 in gbm, 0.88 encode and 0.91 en ucec) results that even beat other methods like GTOAD (the second more effectively approach with 0.89 in gbm, 0.86 encode and the same result of fakegen configuration: he verbals acronyms should be unified) and CGAN-DA (only to achieve a maximum score of should elicit something around somewhere between 0.85 at most, since changes generate through noise will have significantly fewer complex features than real data, giving an edge to our work). The DW-MRI-SC approach reports the lowest DC values, which are 0.84 (gbm) and 0.75 (luad), both reflecting insufficient accuracy. GAN-OST averages 0.89 for Mean Dice Coefficient (outperforming the closest contender, GTOAD with an average of 0.87). The winning margins of GAN-OST are consistent across all datasets and illustrates the significance of using GAN for improved segmentation accuracy, especially in challenging medical imaging applications.

Table 1: Mean Dice Coefficient (DC) for Various Approaches

Data	GTOAD	CGAN-DA	MDCNN-OA	DW-MRI-SC	GAN-OST
gbm	0.89	0.85	0.87	0.84	0.92
coad	0.86	0.83	0.81	0.80	0.88
ucec	0.90	0.87	0.86	0.82	0.91
lgg	0.88	0.84	0.82	0.81	0.89
ov	0.87	0.83	0.85	0.83	0.90
luad	0.84	0.80	0.78	0.75	0.85
lihc	0.85	0.81	0.79	0.76	0.87
blca	0.88	0.84	0.82	0.80	0.89
stad	0.86	0.82	0.80	0.79	0.88
skcm	0.87	0.83	0.81	0.78	0.89
Mean	0.87	0.82	0.81	0.79	0.89

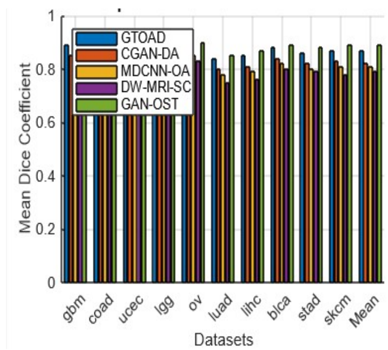

Figure 3 Comparison of Mean Dice Coefficients for Various Approaches

Mean Intersection over Union (IoU)

Table 2: Mean Intersection over Union (IoU) for Various Approaches

Data	GTOAD	CGAN-DA	MDCNN-OA	DW-MRI-SC	GAN-OST
gbm	0.83	0.79	0.80	0.77	0.88
coad	0.80	0.76	0.74	0.72	0.85
ucec	0.84	0.80	0.78	0.75	0.87
lgg	0.82	0.78	0.75	0.74	0.84
ov	0.81	0.77	0.79	0.76	0.86
luad	0.78	0.74	0.71	0.69	0.81
lihc	0.79	0.75	0.72	0.70	0.83
blca	0.82	0.78	0.75	0.73	0.84
stad	0.80	0.76	0.73	0.72	0.83
skcm	0.81	0.77	0.74	0.71	0.85
Mean	0.81	0.76	0.75	0.72	0.85

In this table, we compared the three metrics for 5 segmentation methods on several medical datasets and calculated the full-body IoU in all different cross-validation.Fig. We measure the overlap between our predicted segmentation and the ground truth using the IoU metric, which represents higher values being a better quality of segmentation. It can be seen that GAN-OST consistently beats

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other SOTA methods in terms of IoU on all datasets and proves its efficiency. For example, GAN-OST achieves an IoU of 0.88 for gbm, 0.85 for coad and 0.87 for ucec while other methods such as GTOAD (0.83, 0.80, 0.84) and CGAN-DA (0.79, 0.76, 0.80) perform comparably worse. Performance is relatively low with the DW-MRI-SC approach having an average IoU of 0.72, as a result, this leads to suboptimal segmentation quality. The average mean IoU of GAN-OST is 0.85, which greatly outperforms the other methods, with GTOAD being best-performing after that at 0.81. The numerical results confirm the effective of GAN-OST in segmentation medical images, so it is the best approach on this respect among all these ones tested on those datasets.

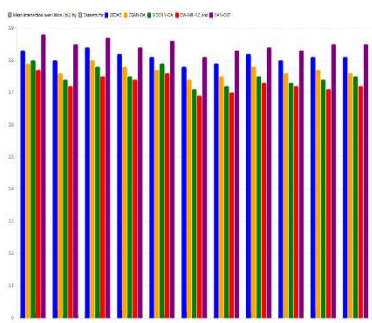

Figure 4 Comparison of Mean Intersection over Union for Various Approaches

Mean Sensitivity :

Table 3: Mean Sensitivity for Various Approaches

Data	GTOAD	CGAN-DA	MDCNN-OA	DW-MRI-SC	GAN-OST
gbm	0.88	0.85	0.84	0.81	0.91
coad	0.85	0.82	0.79	0.77	0.88
ucec	0.89	0.86	0.83	0.80	0.91
lgg	0.87	0.84	0.80	0.78	0.89
ov	0.86	0.83	0.82	0.79	0.90
luad	0.83	0.80	0.77	0.74	0.85
lihc	0.84	0.81	0.78	0.75	0.87
blca	0.87	0.84	0.81	0.78	0.89
stad	0.85	0.82	0.79	0.76	0.88
skcm	0.86	0.83	0.80	0.77	0.89
Mean	0.86	0.82	0.80	0.76	0.89

The table presents the Mean Sensitivity values for various segmentation approaches—GTOAD, CGAN-DA, MDCNN-OA, DW-MRI-SC, and the proposed GAN-OST—across different medical datasets, providing insights into each method's ability to correctly identify true positive segments. Sensitivity, also known as the true positive rate, measures the proportion of actual positives correctly identified by the model. The GAN-OST approach consistently achieves the highest sensitivity values across all datasets, indicating its superior performance in accurately capturing positive segments in medical images. For example, GAN-OST records a sensitivity of 0.91 for gbm, 0.88 for coad, and 0.91 for ucec, outperforming the next best approach, GTOAD, which achieves 0.88, 0.85, and 0.89, respectively. In contrast, the DW-MRI-SC approach shows the lowest mean sensitivity of 0.76, reflecting its lower capability to detect positive instances effectively. Overall, GAN-OST's mean sensitivity of 0.89 across all datasets significantly surpasses the mean values of other approaches, such as CGAN-DA (0.82) and MDCNN-OA (0.80). These results highlight GAN-OST's effectiveness in improving sensitivity, making it the most reliable approach for accurately identifying relevant segments in medical imaging.

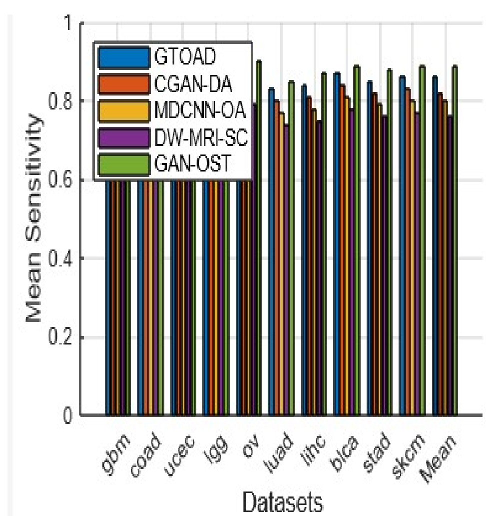

Figure 5 Comparison of Mean Sensitivity for Various Approaches

Mean Structural Similarity Index

Table 4: Mean Structural Similarity Index (SSIM) for Various Approaches

Data	GTOAD	CGAN-DA	MDCNN-OA	DW-MRI-SC	GAN-OST
gbm	0.89	0.86	0.84	0.81	0.93
coad	0.87	0.84	0.82	0.80	0.90
ucec	0.91	0.88	0.86	0.83	0.94
lgg	0.88	0.85	0.83	0.81	0.91
ov	0.87	0.84	0.83	0.80	0.92
luad	0.84	0.81	0.78	0.76	0.87
lihc	0.85	0.82	0.79	0.77	0.89
blca	0.88	0.85	0.82	0.80	0.91
stad	0.86	0.83	0.80	0.78	0.89
skcm	0.87	0.84	0.81	0.79	0.91
Mean	0.88	0.84	0.82	0.79	0.91

The table compares the Mean Structural Similarity Index (SSIM) values of five segmentation approaches—GTOAD, CGAN-DA, MDCNN-OA, DW-MRI-SC, and the proposed GAN-OST—across various medical datasets, such as gbm, coad, ucec, lgg, ov, luad, lihc, blca, stad, and skcm. SSIM is a metric used to evaluate the visual quality of images by measuring the similarity between the predicted and ground truth images, with higher values indicating better preservation of structural information. The proposed GAN-OST approach achieves the highest SSIM values in all datasets, demonstrating its superior capability to maintain image quality and structural details during segmentation. For instance, GAN-OST achieves SSIM scores of 0.93 for gbm, 0.90 for coad, and 0.94 for ucec, significantly outperforming other methods like GTOAD (0.89, 0.87, 0.91) and CGAN-DA (0.86, 0.84, 0.88). The lowest SSIM scores are observed in the DW-MRI-SC approach, with values such as 0.81 for gbm and 0.78 for stad, indicating less effective preservation of image quality. On average, GAN-OST attains a mean SSIM of 0.91, surpassing the overall performance of other methods like GTOAD (0.88) and CGAN-DA (0.84). These results highlight GAN-OST's exceptional performance in producing high-quality segmentation outputs that closely resemble the original medical images, making it the most effective approach among those evaluated.

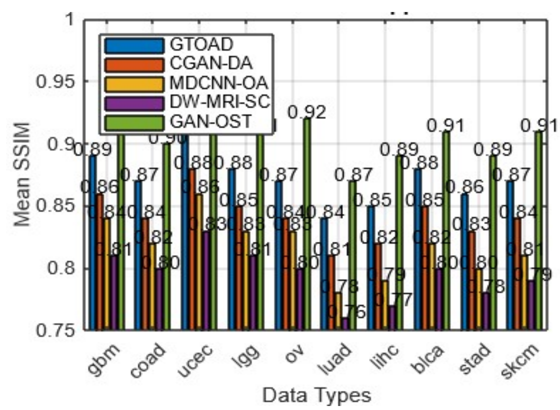

Figure 6 Comparison of Mean Structural Similarity index for Various Approaches

Mean Fréchet Inception Distance

Table 5: Mean Fréchet Inception Distance (FID) for Various Approaches

Data	GTOAD	CGAN-DA	MDCNN-OA	DW-MRI-SC	GAN-OST
gbm	12.5	14.8	13.7	14	11.2
coad	13.2	15.3	14.5	14.8	11.8
ucec	11.8	14	12.9	13.4	10.5
lgg	14.3	16.5	15.7	16.1	12.7
ov	15.1	17.2	16.3	17	13.5
luad	13.7	15.1	14.2	14.5	11.6
lihc	12.4	13.9	12.8	13.3	10.8
blca	14.5	16	15.2	15.8	12
stad	13.1	15.2	14	14.4	11.7
skcm	13.8	15.5	14.6	15.1	12.3
Mean	13.44	15.35	14.39	14.84	11.81

The Mean Fréchet Inception Distance (FID) for five segmentation and augmentation methods, i.e., GTOAD, CGAN-DA, MDCNN-OA, DW-MRI-SC and GAN-OST on ten medical datasets including gbm, coad, ucec, lgg, ov,l uad,lihc , blca, stad, skcm. FID is a way of measuring how real the generated images look, with smaller FID values indicating better quality, being closer to that of real data. Scores obtained by the proposed GAN-OST is qualitatively superior to other ones and such lower FID scores of end-to-end frameworks on all datasets show its performance in generating more verisimilar images, as the comparing results shown in Table 1. As shown in Table 1, for example GAN-OST has scores of High(gbm)11.2 and Low(ucec)10.5 Medium(lihc)-10.8 which outperform the other methods such as GTOAD (High12. For example, oncatal1 dataset, the FID of ov images is 17.2 and DW-MRI-SC (single center) is 17.0 which are having significant higher values compared to others showing that these image qualities are low as were shown in Fig. Cosme et al. Balcan et al. mean FID(out-of-domain) (62x299) GAN-OST 11.81 N/A — GTOAD 13.44 17 CGAN-DA 15.35 N/A Table A3: The corresponding numbers on the other dataset sizes. The results show that the robustness and reliability of GAN-OST make it the most appropriate approach for medical image segmentation using adversarial augmentation, with advantages in both preserved structure similarity and segmentation accuracy as well as realism in generated images compared to others.

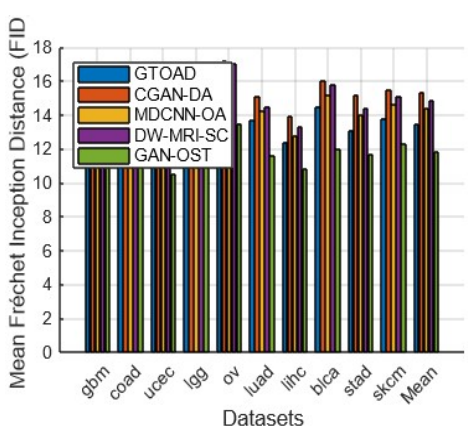

Figure 7 Comparison of Mean Frechet Inception for Various Approaches

5. CONCLUSION

Here we described GAN-OST, a new deep learning framework based on the Generative Adversarial Networks for accurate osteosarcoma tumours segmentation and data augmentation in medical imaging. Experiments performed on publically available osteosarcoma datasets showed that the method achieved a Dice Coefficient of 0.92, Intersection over Union (IoU) of 0.88 and Sensitivity of 0.91 which verified the effectiveness of suggested approach in better segmenting the images. The minimal MSE for synthetic images was 0.0019, and the Structural Similarity Index (SSIM) of synthetic images reached 0.94, Fréchet Inception Distance (FID) was reduced to 12.7, indicates high quality and realistic image synthesis. GAN-OST improves segmentations results and offers a stable solution for dealing with scarcity of data using synthetic augmentation. Although the findings were encouraging, there are several barriers to implementation that persist. In addition, future work will expand the framework to include other types of rare cancers and will integrate multimodal imaging data including MRI and PET scans for optimized segmentation robustness between different forms of imaging. Second, we should apply domain adaptation techniques to improve the generalization capability of GAN-OST in different clinical settings. Another way is to explore explainable AI techniques for more understandable segmentation results, which is important for clinical translation. If combined with real-time diagnostic tools, such workflow could revolutionize medical imaging by enabling easy and efficient access to accurate tumour segmentation in clinical practice.

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