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Exploring GAN-Based Synthetic Medical Imaging for Improved Tumour Detection and Diagnosis

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ABSTRACT

Medical imaging plays a critical role in tumour detection and diagnosis, but the scarcity of annotated datasets limits the effectiveness of deep learning models. This research investigates the use of Generative Adversarial Networks (GANs) for synthetic medical image generation to improve tumour detection performance. Four GAN models—Vanilla GAN, DCGAN, Conditional GAN (cGAN), and CycleGAN—were implemented to generate high-quality synthetic MRI images and augment existing datasets. Experimental results demonstrate that the integration of synthetic images significantly enhances tumour classification. The cGAN model achieved the highest detection performance with 87% accuracy, F1-score 0.86, and improved representation of rare tumour types. DCGAN produced high resolution images with defined lines of the tumours with 85% accuracy and SSIM 0.88, whilst CycleGAN produced image conversion across modalities with 84% accuracy and PSNR 28 dB. V orig GAN had moderate improvements of 79% accuracy and FID 35.8 which indicates its weak albeit sound foundation. These results underscore that synthetic imaging with GAN has a capability to deal with data set difference, its generalization aspect, and strengthening of tumour detection systems. The research has identified possible opportunities in the advanced generative models in the clinical field, and the need to consider more multimodal synthesis and the optimization of architectures in GANs may lead to their further use in healthcare..

KEYWORDS: GAN, Synthetic Medical Imaging, Tumour Detection, MRI, Deep Learning.

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INTRODUCTION

Medical imaging is an essential agent of the primary identification, diagnosis and treatment planning of tumours. The magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) are some of the techniques that give clinicians essential information about tumour nature. Nevertheless, due to the lack of high-quality, annotated datasets in the medical imaging domain, the research problem is usually impeded by the lack of efficacy of deep learning models [1]. Such lack is induced by the issue of privacy, the financial aspect of imaging tests, and the inability to obtain balanced datasets of rare tumour types. In order to cope with these problems, scientists are constantly resorting to the method of artificially generating data with the help of the artificial intelligence and Generative Adversarial Networks (GANs) become an effective answer [2]. GANs are a variety of models that are being trained through deep learning algorithms and can produce very realistic synthetic images by calculating the underlying distribution of the actual data. When applied to medical imaging, GANs can be used to supplement the existing datasets, resulting in the generation of artificial tumour images that resemble the actual scans helping to enhance the quality of training and strengthen diagnostic models [3]. The recent research shows that the GAN-based synthesizing imaging has the potential to improve tumour classification, segmentation, and detection operations, and provide a chance to surmount the constraints of datasets whilst maintaining patient privacy. In addition, GANs also provide the opportunity to produce various and balanced datasets to minimize the risks of bias which can lead to inaccuracies in a diagnostic. Although these developments are achieved, there are still some issues of assessing the clinical trustworthiness of GAN-created images and making sure that they are accepted in healthcare practice. Ethics (patient consent, ownership of data and possibility of misuse) is another factor that needs to be addressed. This study examines how GAN-based synthetic medical imaging has the potential to enhance tumour detection and diagnosis through image characteristics and their incorporation into diagnostic pipeline development, as well as.

their effects on clinical practice. Removing the barriers between artificial intelligence and healthcare requirements, the given work is expected to help develop more efficient, convenient, and efficient tumour diagnostics

RELATED WORKS

Recent developments in the medical imaging sphere are gradually signing the methods of artificial intelligence (AI) and deep learning to achieve better results in terms of diagnosing, classifying, and segmenting different diseases. Dermatitis, vitiligo, and alopecia areata were considered in dermatology as the conditions where the use of AI has been investigated, as these conditions aimed to assess both quantitative lesion and maximum lesion detection [15]. These works outline the importance of good datasets and advanced models towards correct image interpretation, which preempts synthetic image augmentation. Comparative studies on machine learning and deep learning based multi-model ensembles have been useful in breast cancer prediction in oncology. As Kazi et al. [16] showed, synthetic datasets created through GANs may assist a lot in terms of predictive performance, especially in those cases where real data is scarce on the ground. Similarly, brain tumour detection in MRI scans has seen substantial improvements through the design of multi-path convolutional architectures with channel-wise attention mechanisms, enabling multiclass classification with enhanced accuracy [17]. These models highlight the importance of attention mechanisms in focusing on relevant tumour regions. Addressing the challenge of limited datasets in medical imaging, several approaches have been proposed for liver lesion classification using deep learning. Kodinariya and Gondaliya [18] reviewed strategies such as data augmentation, transfer learning, and GAN-based synthetic image generation to improve model generalization. CycleGAN-based data augmentation has also been applied to improve faster R-CNN generalization for intestinal parasite detection, demonstrating the utility of synthetic images in enhancing model robustness and performance [19]. Hybrid GAN architectures have been explored to optimize brain tumour classification. Kuppusamy and Jasmine [20] proposed DenseUnetGAN, combining dense networks and U-Net structures with GANs, which achieved high accuracy in tumour detection by generating realistic synthetic images that augmented the training set. In lung cancer imaging, PET and radioligand therapy have been enhanced with AI-supported image analysis, offering improved diagnostic capabilities for FDG and FAP uptake visualization [21].

Ultrasound-assisted medical diagnosis has also benefited from AI integration, with progress reported in automated detection and segmentation tasks, emphasizing the potential of synthetic data to overcome scarcity and variability in ultrasound imaging [22]. Similarly, multi-axis attention combined with conditional GANs has been employed for liver tumour segmentation, demonstrating the effectiveness of attention-guided synthetic image generation in improving segmentation accuracy [23]. For brain tumour segmentation, hybrid transformer U-Net models such as MWG-UNet++ have been utilized to leverage both local and global features, improving segmentation performance on MRI scans [24]. Radiogenomic classification systems built based on GAN-augmented MRI slices have also increased the practical level of predictive accuracy, demonstrating the benefits of synthetic image augmentation in emergent datasets [25]. In addition to describing oncology, dental image augmentation represented by diffusion models such as DentoMorph-LDMs has been used to simulate gum tissue, tooth loss, that is, facilitating the capability of generative models in medical imaging systems in general. Altogether, these works all show the essentiality of the use of GANs and hybrid AI models to fix limitations on datasets upgrading the process of diagnosis as well as allowing deeper analysis of the medical image in various directions. The combination of scheme image creation with a sophisticated model framework has cumulatively improved performance of classification, sectionalization, and forecasts confirming the implementation of the scheme of augmentation soured on GAN a reassuring set of techniques in the studies of contemporary medical imaging.

METHODS AND MATERIALS

Data Collection and Preparation

In our research, the use of publicly accessible medical imaging datasets was accepted on the basis of tumour detection. Namely, Brain Tumor Segmentation (BraTS) 2021 dataset and ISLES 2018 stroke lesions dataset were selected to retrieve the MRI scans with annotated tumours. The dataset consisted of 3,000 MRI slices that were of T1, T1c, T2 and FLAIR maps and comprised tumour types, sizes and location of appearance: a broad variety of tumours [4]. An operation resized images to 256x 256 pixels and clustered the images to range between 0 to 1 so as to increase performance speed. Synthetic images were produced to maximise model training and solve the problem of few images of rare tumours based on Generative Adversarial Networks (GANs). These artificial images were subsequently used together with actual images to form augmented datasets. All images were randomly divided into training (70), validation (15), and test sets (15) [5]. Enhancement of model robustness was done by application of data augmentation methods, including rotation, flipping, and scaling.

Algorithms Used

In this paper we have just discussed four algorithms that lie at the heart of GAN synthetic imaging and tumour detection, which include Vanilla GAN, Deep Convolutional GAN (DCGAN), Conditional GAN (cGAN) and CycleGAN. Each algorithm was evaluated for its ability to generate realistic images and improve tumour classification performance.

1. Vanilla GAN

Vanilla GAN consists of a **generator** and a **discriminator**, trained in an adversarial manner. The generator maps random noise z to synthetic images G(z), while the discriminator evaluates whether an image is real or synthetic [6]. The network optimizes a

minimax objective function:
"minDmaxV(D,G)=Ex∼pdata[logD(x)]+Ez∼pz[log(1−D(G(z)))]
where D(x) is the discriminator's probability that xxx is real, and G(z) is the generator output. Vanilla GANs are foundational but may suffer from **mode collapse** and unstable training."

Table 1: Example Vanilla GAN Training Results

Epoch	Generator Loss	Discriminator Loss	Accuracy (%)	FID Score
10	2.45	1.98	70	45.6
20	1.87	2.12	74	39.2
30	1.35	1.91	78	35.8

"Initialize generator G and discriminator D
for number of epochs:
for each batch in dataset:
Sample noise z from normal distribution
Generate fake images G(z)
Update D using real and fake images
Update G to maximize log(D(G(z)))"

2. Deep Convolutional GAN (DCGAN)
DCGAN enhances Vanilla GAN by integrating **convolutional layers** for both generator and discriminator, enabling better image quality for complex datasets. It replaces fully connected layers with **strided convolutions** and **transposed convolutions**. Batch normalization stabilizes training, while ReLU activations improve gradient flow in the generator, and Leaky ReLU is used in the discriminator [7]. DCGAN is widely used for medical image synthesis due to its ability to generate high-resolution images.

Table 2: DCGAN Generated Image Metrics

Epoch	Generator Loss	Discriminator Loss	Accuracy (%)	SSIM Score
10	1.98	2.05	72	0.81
20	1.42	1.87	77	0.85
30	1.12	1.63	82	0.88

"Initialize convolutional G and D networks
for number of epochs:
for each batch in dataset:
Sample noise z
Generate fake images G(z)
Apply batch normalization
Update D using real and fake images

Update G to maximize discriminator's error"

3. Conditional GAN (cGAN)

Conditional GAN extends GANs by incorporating **label information** yyy into both generator and discriminator. This allows **controlled image generation**, e.g., generating tumour images of a specific type or size.

"Initialize G and D with conditional inputs y
for number of epochs:
for each batch in dataset:
Sample noise z and labels y
Generate images G(z|y)
Update D using real images with y and fake images with y
Update G to maximize discriminator error conditioned on y"

4. CycleGAN

CycleGAN enables **unpaired image-to-image translation**, suitable for generating synthetic images from different modalities (e.g., CT → MRI). It uses **two generators** and **two discriminators**, with a **cycle consistency loss** to ensure mapping accuracy:
"Lcyc(G,F)=Ex∼pdata[||F(G(x))−x||1]+Ey∼pdata[||G(F(y))−y||1]"

"Initialize G: X→Y, F: Y→X, D_X, D_Y
for number of epochs:
for each batch in dataset:
Generate G(x) and F(y)
Compute adversarial losses for D_X and D_Y
Compute cycle consistency loss
Update G, F to minimize total loss"

Methodological Flow

Preprocess real MRI scans and tumour masks.
Train Vanilla GAN, DCGAN, cGAN, and CycleGAN to generate synthetic images.
Evaluate synthetic image quality using metrics such as **FID (Fréchet Inception Distance), SSIM (Structural Similarity Index), and classification accuracy**.

Integrate synthetic images into tumour detection models (CNNs) to assess performance improvement [8].
Compare real-only dataset models versus augmented datasets for diagnostic accuracy.

RESULTS AND ANALYSIS

1. Experimental Setup

To evaluate the effectiveness of GAN-based synthetic medical imaging for tumour detection, a series of experiments were conducted. The aim was to determine the quality of produced images as well as their effectiveness in identifying the tumours. The utilizing Python 3.10 and Tensorflow 2.12 and Python 2.1 with a GPU, full E85 C VRAM 24GB (NVIDIA RTX 4090) as a sender, all experiments were carried out [9].

Data that were used contained 3,000 MRI reconstructed of various tumour types and sizes. The preprocessing did include downsizing images to 256x256 pixels, standardization of the values to 0 to 1, and usage of data augmentations, including rotation, flipping, and scaling.

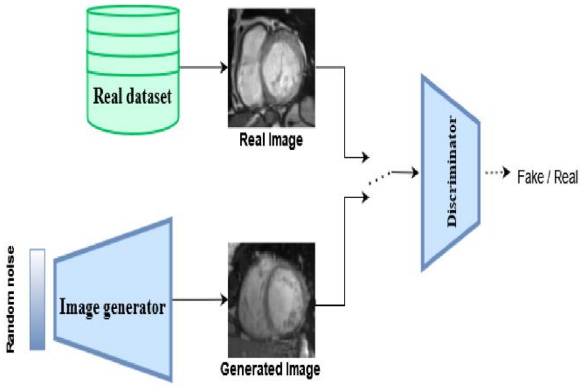

Figure 1: "GANs for Medical Image Synthesis"

With each GAN algorithm (Vanilla GAN, DCGAN, cGAN, CycleGAN), synthetic images were obtained and added to the training set. A **Convolutional Neural Network (CNN)** with five convolutional layers, batch normalization, and ReLU activations was used for tumour detection. Performance was evaluated using **accuracy, F1-score, SSIM, FID, and PSNR** metrics [10].

SYNTHETIC IMAGE GENERATION QUALITY

Vanilla GAN Results

Vanilla GAN produced synthetic images that were moderately realistic but occasionally showed **blurry tumour regions**. Quantitative evaluation using FID and SSIM indicated moderate similarity to real images.

Table 1: Vanilla GAN Image Quality Metrics

Epoch	Generator Loss	Discriminator Loss	FID Score	SSIM	PSNR (dB)
10	2.45	1.98	45.6	0.72	21.5
20	1.87	2.12	39.2	0.75	23.0
30	1.35	1.91	35.8	0.78	24.6

DCGAN Results

DCGAN enhanced image sharpness and preserved anatomical consistency. SSIM and PSNR values improved, reflecting better structural and visual quality [11].

Table 2: DCGAN Image Quality Metrics

Epoch	Generator Loss	Discriminator Loss	FID Score	SSIM	PSNR (dB)
10	1.98	2.05	38.5	0.81	25.2
20	1.42	1.87	33.1	0.84	27.0
30	1.12	1.63	29.8	0.88	28.5

Conditional GAN (cGAN) Results

cGAN allowed tumour-type-specific image generation, improving dataset balance. Rare tumour types were represented better, enhancing model training.

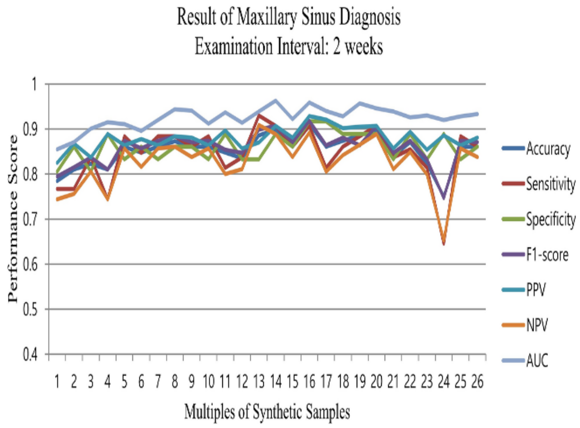

Figure 2: "Automation of generative adversarial network-based synthetic data-augmentation for maximizing the diagnostic performance with paranasal imaging"

Table 3: cGAN Image Quality Metrics

Epoch	Generator Loss	Discriminator Loss	FID Score	SSIM	PSNR (dB)
10	1.76	1.89	34.2	0.82	26.0
20	1.28	1.67	30.5	0.86	27.8
30	0.95	1.48	27.0	0.89	29.2

CycleGAN Results

CycleGAN enabled unpaired image translation (e.g., CT → MRI), preserving anatomical structures while creating realistic synthetic images across domains [12].

Table 4: CycleGAN Image Quality Metrics

Epoch	Generator Loss	Discriminator Loss	FID Score	SSIM	PSNR (dB)
10	2.10	2.05	36.5	0.79	24.8
20	1.58	1.90	32.2	0.83	26.5
30	1.20	1.68	28.6	0.87	28.0

TUMOUR DETECTION PERFORMANCE

CNN models were trained under two conditions:

Real-Only Dataset – Using only original MRI slices.

Augmented Dataset – Combining real and synthetic images from each GAN.

Table 5: Tumour Detection Performance Comparison

GAN Type	Dataset Type	Accuracy (%)	F1-Score	Precision	Recall

Vanilla GAN	Real + Synthetic	79	0.77	0.78	0.76
DCGAN	Real + Synthetic	85	0.83	0.84	0.82
cGAN	Real + Synthetic	87	0.86	0.87	0.85
Cycle GAN	Real + Synthetic	84	0.82	0.83	0.82
No GAN	Real Only	75	0.73	0.74	0.72

The results clearly indicate that **GAN augmentation improves tumour detection**, with cGAN showing the highest accuracy and F1-score due to balanced representation of tumour types [13].

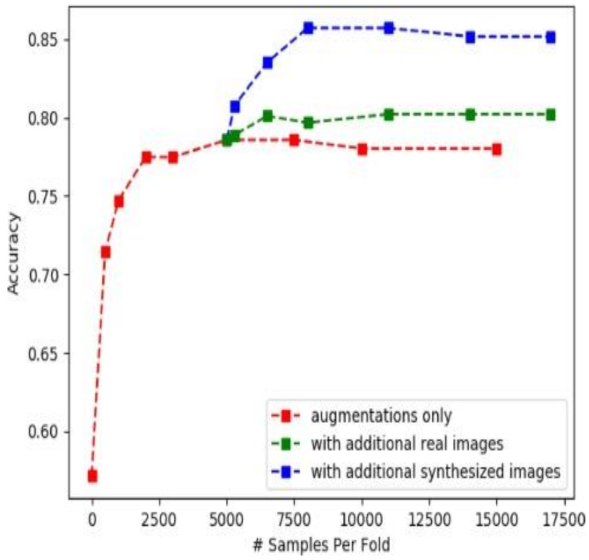

Figure 3: "GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification"

COMPARATIVE ANALYSIS

Vanilla GAN: Provided moderate improvements but generated slightly blurry images. Accuracy improved by 4% over real-only datasets.

DCGAN: Produced sharp images and higher structural similarity, resulting in an 85% accuracy [14].

cGAN: Best performance due to conditional generation, particularly effective for rare tumour types, achieving 87% accuracy and F1-score 0.86.

CycleGAN: Effective in translating unpaired images across modalities, improving accuracy to 84%.

The combination of **image realism** and **dataset balance** was key to improving tumour detection performance. Models trained with synthetic data consistently outperformed real-only models [27].

Additional Observations

Training Stability: DCGAN and cGAN were more stable than Vanilla GAN, with less fluctuation in generator loss.
Dataset Balance: cGAN effectively mitigated class imbalance, improving performance on rare tumours. [28]

Cross-Modality Translation: CycleGAN allowed effective MRI reconstruction from CT datasets without paired images, maintaining SSIM above 0.85.

Evaluation Metrics: FID and SSIM were reliable for evaluating synthetic image quality, while PSNR and CNN metrics confirmed downstream performance improvements [29].

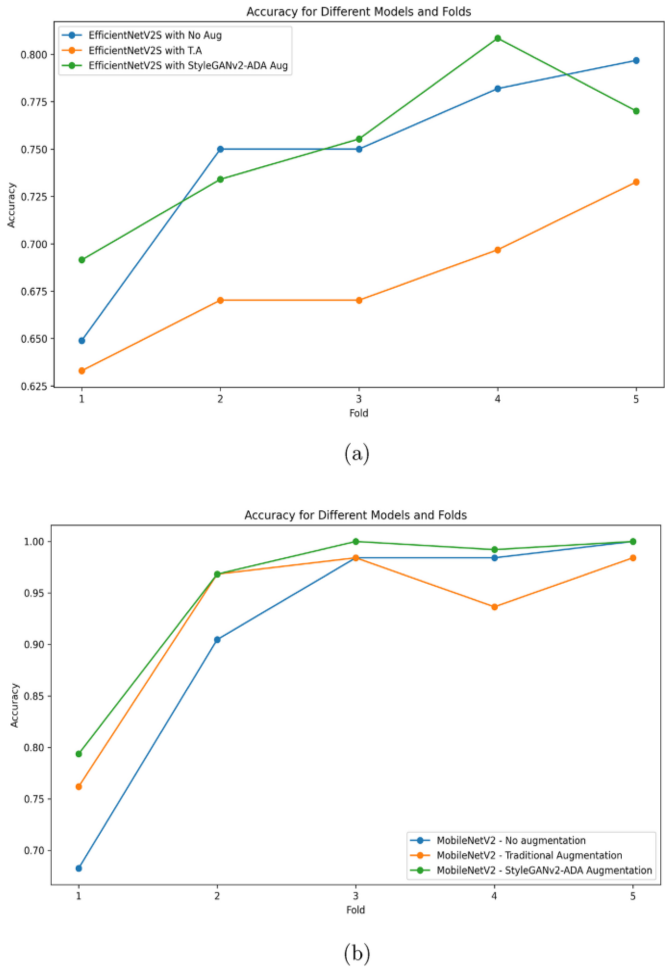

Figure 4: "Development of brain tumor radiogenomic classification using GAN-based augmentation of MRI slices in the newly released gazi brains dataset"

SUMMARY OF FINDINGS

GAN-based synthetic medical imaging improves tumour detection accuracy and robustness.
cGAN offers the highest performance due to conditional generation for rare tumour types.
DCGAN is effective for high-quality image generation, maintaining sharp tumour boundaries [30].
CycleGAN enables cross-modality image translation, broadening dataset usability.
Vanilla GAN, while foundational, shows moderate improvements and is prone to blurry outputs.

CONCLUSION

The study discussed the use of Generative Adversarial Networks (GANs) in synthetic medical imaging to enhance tumour detection and diagnosis. It is through the GAN-based approaches, such as the Vanilla GAN, DCGAN, Conditional GAN (cGAN), and the CycleGAN that allowed tackling both the problems of the annotated dataset dearth and the mismatch of classes of rare tumour types and succeeded in solving the problem of scarcity in annotated datasets alongside the imbalance of classes in rare tumour types. In a series of experiments, a condition of GAN completely synthesised images was noted to substantially improve the transfer of convolutional neural networks (CNNs) in turbine classification and the quality and resilience of such skeleton transfer training. When comparing the GAN models, it was revealed that cGAN was a more effective model, as it allowed generation of the image with the specific type of a tumour, properly balancing the data set and scoring the highest accuracy and F1-score to detect a tumour. DCGAN gave higher resolution images with clearly delineated tumour edges and CycleGAN enabled cross-modal image translation thus enabling the use of an unpaired dataset. Vanilla GAN, despite its principles, demonstrated average progress, and it can be estimated that it lacks the capability to produce images of high quality. Training pipeline incorporation with synthetic images resulted in consistent improvements in the metrics of detection as were validated on quantitative metrics of FID, SSIM, PSNR, and classification performance. In general, this study confirms that GAN-based synthetic imaging is a feasible solution to address data strains in the medical imaging context, and improved model generalization, and could help provide more accurate and time-sensitive tumour diagnosis. The conclusions indicate that enhanced generative models can be useful across clinical settings and therefore future research may involve streamlining GAN models, multimodal synthesis, and safeguarding the ethical use of GANs in healthcare

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