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GENERATIVE ADVERSARIAL NETWORKS FOR BRAIN IMAGE SYNTHESIS

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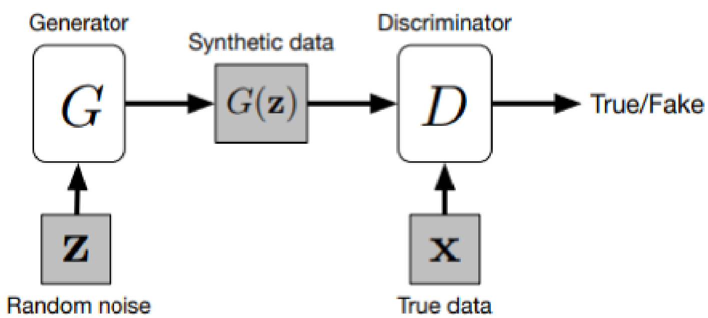
ABSTRACT: The technique of estimating one picture (sequence, modality) from another image (sequence, modality) in medical imaging is known as image synthesis. Multi-modality imaging is essential in medicine since it captures distinct aspects and offers a variety of biomarkers. Although multi-screening is costly and time-consuming to report to radiologists, missing modalities can be artificially generated using image synthesis techniques. High dimensional characteristics may be automatically extracted and captured by deep learning algorithms**.** In particular, one of the most well-liked generative-based deep learning techniques is the generative adversarial network (GAN), which classifies estimated pictures as true or false using a discriminator network and convolutional networks as generators. This review presents GAN-based brain image synthesis. The most current advancements in GANs for cross-modality brain image synthesis—from CT to PET, from MRI to PET, and vice versa—were compiled here.

***KEYWORDS*: Generative Adversarial Networks, Image Synthesis, CT, MRI, PET**

1.INTRODUCTION:

The field of medical imaging is seeing a surge in interest due to artificial intelligence. Artificial Intelligence (AI) has become a leading issue in radiology research, particularly with the rapid advancements in deep learning (DL) and the creation of diverse image processing models. Large Conventional Neural Networks (CNN) are being used in many clinical and scientific applications, including image segmentation, diagnosis, classification, lesion detection, and even interpretation. Radiologists employ a variety of imaging techniques to give a thorough description of a disease and additional information. There are drawbacks to each of these costly, time-consuming imaging methods. Positron emission tomography (PET) scans even include extra radiation exposure, and computed tomography (CT) pictures provide a substantial radiation risk. Magnetic resonance imaging's (MRI) lengthy scanning duration leads in motion artifacts and results in low-resolution imaging. To overcome these constraints, new DL-based techniques are used to create missing imaging modalities from current modalities. With image synthesis, we may expeditiously and affordably get additional information and specifics about the disease while also enhancing the quality and sharpness of imaging exams. Deep neural networks are end-to-end learning models that automatically extract a high number of features from brain images, including CT, MRI, and PET scans. They are capable of learning complex patterns that result in great performance, while statistical methods analyze brain data clinically. Brain image analysis has also made use of deep learning systems. Brain Tumor classification and segmentation for measuring and visualizing the anatomical features of the brain, studying brain changes, and recognizing the form of lesions or tumors in the brain are a few examples of the uses of deep learning models in neuroimages. Images with many modalities can, however, occasionally offer distinct properties that decision-makers might take into account. For instance, screening for Alzheimer's disease at the pre-clinical stage should use simultaneous MRI and PET scans to examine the different biomarkers and enable early identification. The brain's structural features are examined by MRI, whilst amyloid tracers and brain metabolism are measured by PET. Consequently, it would be helpful to employ multi-modality to assess data acquired from many screenings in order to truly make an informed conclusion regarding the condition. Nonetheless, the primary issues with multimodality imaging are the additional scan costs, radiation exposure, and delays in clinical workflow. To get around these restrictions, techniques for image synthesis, or cross-modality image estimation, have been put forth. The process of artificially creating one picture modality from many other modalities is called images synthesis. Techniques for image synthesis offer reduced radiation, fewer scans, and less waiting.



Recently, academics have been paying more and more attention to generative adversarial deep neural networks, or GANs. The generator and discriminator parts of two neural networks are included in the GAN class of machine learning frameworks. In a game where two networks compete with one another, the generative network attempts to create a false picture such that the discriminator component cannot distinguish it from the genuine one. GANs have been used to solve a variety of problems. Image translation is one of GANs' most well-known uses. Since several strategies can translate pictures between modalities or produce new images within the same modality but distinct sequences, translating images across them is the fundamental objective. Creating the T1 sequence from the T2, for instance. When we suffer from a shortage of data, GANs can be utilized to enhance brain imagery since they can produce new data. Another intriguing use for GANs is super resolution, which creates high resolution pictures from low quality ones.
GANs are used to eliminate noise and provide clean pictures since radiologists find it too difficult to comprehend images that are noisy. Another intriguing use of GANs is the automated segmentation of brain lesions and malignancies.
Ultimately, GANs are useful models that may be used to rebuild realistic pictures with extreme accuracy from brain activity.

2. DATA SELECTION:
We have used 411 PET scans (98 AD, 105 NC, 208 MCI) from 479 individuals for our suggested model. The Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu) is where we gathered the data. For our model, we specifically employed the ADNI1 baseline dataset. The age range of the subjects was 55–92. Under the direction of chief investigator Michael W. Weiner, MD, the ADNI began operations in 2003 as a public-private collaboration. The main objective of ADNI has been to determine whether the progression of mild cognitive impairment (MCI) and early Alzheimer's disease (AD) can be tracked using a combination of clinical and neuropsychological assessment, positron emission tomography (PET), serial magnetic resonance imaging (MRI), and other biological markers. The ADNI database's most recent information is available at http://www.adni-info.org [72]

2. GENRATIVE ADVERSIRAL NEURAL NETWORKS:
The term "Adversarial" refers to the fact that adversarial networks, in general, and GANs in particular, are trained to play a minimax game between a generator network that seeks to maximize a given objective function in tandem with a discriminator network that seeks to minimize that same objective function. GANs are taught to optimize the following value function in their most basic form.

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Here, the generator network with parameters θG is denoted as $G(z)$. A random variable, $z \sim pz$, is input to it, sampled from a previous distribution that G attempts to translate to $x \sim pdata$. In order to do this, another network D with parameters θD is trained to distinguish between fictitious samples $\hat{x} p\theta G(x|z)$ created by the generator and genuine samples $x \sim pdata$ from a given dataset. By doing this, the generator is forced to create samples that are increasingly lifelike in an attempt to trick the discriminator into thinking they are real.
Various changes have been proposed to address the problems of vanishing gradients, convergence speed, and model collapse. These include Deep Convolutional GAN, Least Square GAN, Wasserstein GAN, and Style GAN. GANs have been employed as picture estimation for intra-modality applications, even though this study focuses on cross-modality image synthesis and discusses the creation of a modality from another modality (inter-modality) in the brain. For instance, in order to rebuild high resolution from low resolution, the scientists converted the T1 sequence to T2. Diffusion map synthesis from T1 using GAN was carried out by. Additionally, authors synthesized 3T MRI data to create 7T MRI.

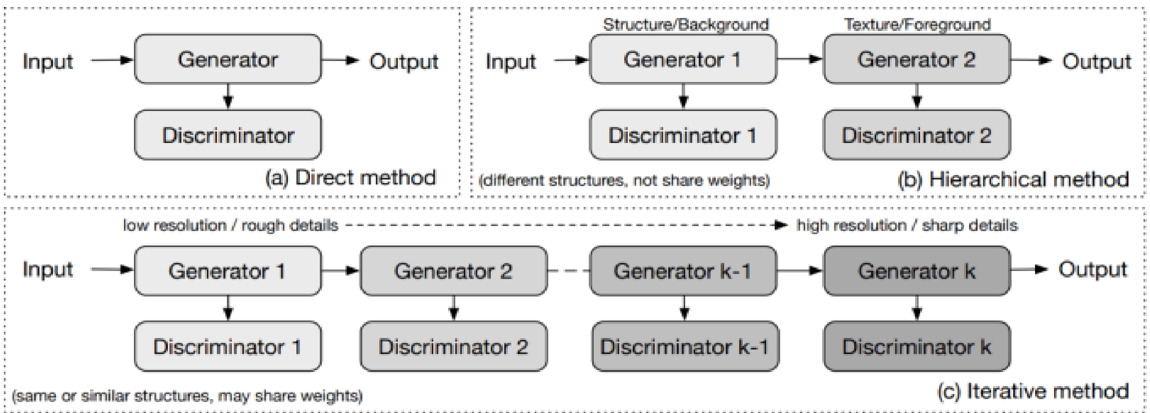


Fig 1 Three approaches of image synthesis using Generative Adversarial Networks

2.1 APPROACHES OF IMAGE SYNTHESIS WITH GAN:
To create false pictures, GANs typically employ three techniques: hierarchical approaches, iterative methods, and direct methods. The number of generators and discriminator networks accounts for the majority of the variation. The other two techniques gain from employing numerous generators and discriminators however the Direct Method simply uses one generator and one discriminator. Algorithms under the Hierarchical Method, like SS-GAN, use two networks for the generator and discriminator, in contrast to the Direct Method. These techniques, such as "styles & structure" and "foreground & background," divide a picture into two halves. Sequencing or parallel connections are used to link the generators. On the other hand, the Iterative Methods create pictures from coarse to fine by using comparable numerous generators. Generator in this model improves upon the output of generator. Moreover, weight-sharing across the generators is a benefit of iterative methods.

3.BRAIN IMAGE SYNTHESIS WITH GAN:

This section provides an overview of the many uses of GAN for brain image synthesis, such as MRI-CT, CT-PET.

3.1. MRI-CT:

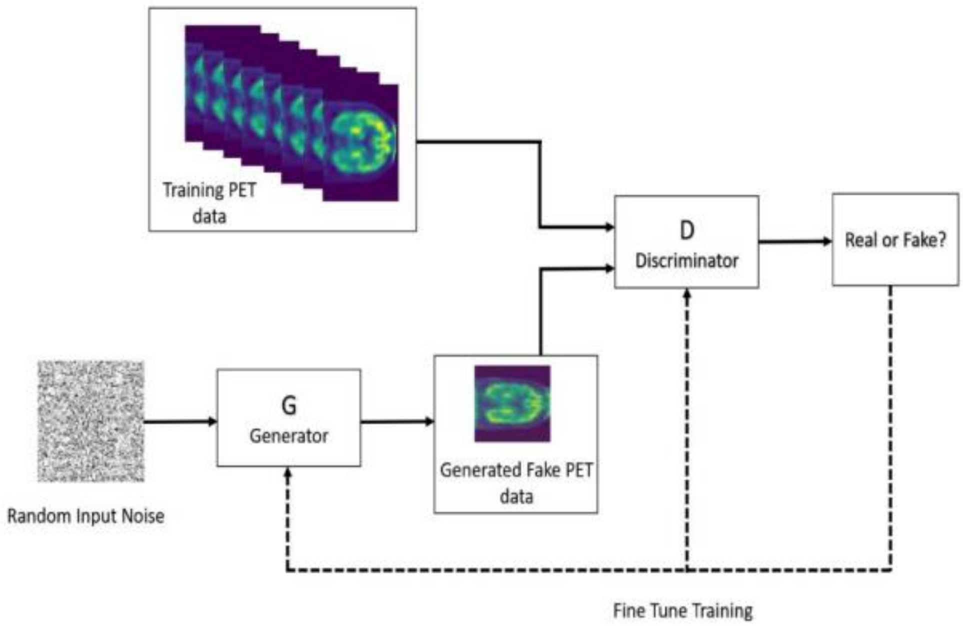
Magnetic Resonance Imaging (MRI):

- Principle: Based on the magnetic characteristics of various tissues, magnetic resonance imaging (MRI) creates comprehensive pictures of interior structures by applying intense magnetic fields and radiofrequency pulses.
- Contrast: Magnetic resonance imaging (MRI) is a great tool for soft tissue imaging because it can clearly distinguish between various soft tissues, including ligaments, muscles, organs, and the brain.
- Benefits: Since it doesn't use ionizing radiation, repeated imaging is safer. It works well for neurological, musculoskeletal, and soft tissue exams and offers good soft tissue contrast.
- Limitations: MRI scans can take a long time, and certain patients who have metallic implants or claustrophobia may not be good candidates for this procedure.

Computed Tomography (CT):

- Principles: CT produces cross-sectional pictures of the body by using X-rays. The subject is rotated around by the X-ray source, and various angles of detection are used to quantify the radiation that enters the body.
- Contrast: Bones and dense structures can be best seen with CT. It effectively detects anomalies in the chest, abdomen, and bones and has high spatial resolution.
- Benefits: CT scans are quick and accessible. They work effectively in emergency scenarios and are frequently applied to trauma evaluations.
- Limitations: Ionizing radiation is a part of CT, and it can be dangerous, particularly when done repeatedly. Compared to MRI, it does not offer as much soft tissue contrast.

Large soft-tissue signal intensity differences make MR image generation from CT images a difficult process. In this part, we examine the approaches to this problem that have been recently published suggested using a cyclic GAN in conjunction with a fully CNN to create CT images from MR pictures while lowering radiation exposure for patients. They successfully generated CT images from MR images after conducting 315 photos from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. To calculate the model consistency loss, two metrics were used: mean absolute error (MAE) and mean squared error (MSE). The generator loss is now almost equivalent to the discriminator loss after the model has been trained. They used encoder-decoder architecture to map available imaging modalities of glioma into a common feature space by the encoder to generate target missing imaging modalities by the decoder. Two different models: early-fusion-CoCa-GAN (eCoCa-GAN) and intermediate-fusion-CoCa-GAN (iCoCa-GAN), were compared to accommodate the common feature space; in their experiment, iCoCa-GAN outperformed eCoCa-GAN and finally recommended to develop the common feature space. Additionally, they performed segmented photographs of the tumors to highlight specific tumor locations and improve synthesis processes. Given the input rough segmentation mask, the segmentation tasks shared the same common feature space as the synthesis tasks, which enabled the synthesis loss function to reflect the particular tumor information by concentrating more on mass areas. This made the representation for image synthesis as comparable to the look of the tumor. The findings showed that iCoCa-GAN performs better than other models for image synthesis in terms of quality and enhances tumor segmentation, particularly in situations when the number of accessible modalities is constrained. presented a CNN model based on deep learning and ResNet50 to categorize Alzheimer's disease using brain MRI. In addition, they used a CycleGAN model to produce MR images of the brain in order to expand the data set. They examined a dataset consisting of 476 samples classified as Alzheimer's disease (AD) and 705 samples classified as normal cognition (NC). The NC samples from AD pictures and the AD samples from the NC real images were produced by the CycleGAN model with two generators. Subsequently, the discriminator assessed the GAN loss function by contrasting the synthetic pictures with the actual ones. They made encouraging strides in data synthesis and effectively increased the



classification accuracy for Alzheimer's disease.

Fig1.1 An example of synthetic brain PET image generator.

created a switchable version of CycleGAN and compared it to the original to enhance cross-contrast MRI pictures. Switchable CycleGAN employed a switchable generator to synthesize pictures with multiple styles, whereas Original CycleGAN used two independent image generators (forward and backward generators) for the training phase, which required more time and parameters. 1,517 patients' T1- and T2-weighted brain MR images were gathered using the extensive collection of accessible brain MR images known as accessible Adolescent Brain Cognitive Development (ABCD). A total of 30,340 slices were collected, with 10 slices from each picture. Of these, 70% were utilized for training, 10% for testing, and 20% for testing. Switchable CycleGAN fared better than the original Cycle GAN, according to a quantitative comparison of the two models using peak signal-to-noise ratio (PSNR) and the structural similarity index measure (SSIM). In the qualitative assessment, switchable CycleGAN produced more consistent results with the target pictures with less artifacts and greater features of brain tissue when comparing the visualization results of each model. Additionally, it was discovered that switchable CycleGAN performed better than the original CycleGAN on small datasets with shorter training times. produced a unique end-to-end hierarchical GAN architecture by analyzing 3,538 brain MR and 9,276 thoracic CT scans to enhance high-resolution 3D pictures.

Due of the limited memory of Graphical Processing Units (GPUs), the majority of AI models are trained on low-resolution pictures that contain artifacts. A memory-efficient approach that concurrently creates a low-resolution version of the photos and a randomly chosen sub-volume of the high-resolution images is used to depict the hierarchical structure. The encoder that was integrated allowed for the extraction of clinically significant features from high-resolution sub-volume pictures, guaranteeing anatomical consistency and producing high-resolution images that required less memory for training.

The model's performance was investigated using both qualitative and quantitative methods.

When phony images resembled genuine ones, Frechet Inception Distance (FID), Maximum Mean Discrepancy (MMD), and Inception Score (IS) were used to objectively evaluate the image quality. Compared to the baseline model, the hierarchical GAN model produced more realistic pictures and performed better in qualitative and quantitative analyses used pix2pix to improve CT pictures from contrast-enhanced MR images using a 3D GAN model architecture. The goal of their investigation was to produce CT images for use in radiation treatment planning. Additionally, the model is made to enhance the sharpness and clarity of the CT pictures that are produced. They trained their model using 26 pairs of CT and MRI images, and then utilized the remaining 5 pairs as a testing set. Using quantized image similarity algorithms such as cosine angle distance, Euclidean distance, mean square error, PSNR, and SSIM, the produced scan's resemblance to real pictures was assessed. Radiologists assessed their degree of satisfaction with spatial geometry and noise level as great, with contrast and artifacts as acceptable, and with anatomical and structural features as fair used a GAN-based model to produce an MRI from a CT scan in order to identify individuals who may have had an acute ischemic stroke.

3.2. MRI-PET:

Combining Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) through the use of Generative Adversarial Networks (GANs) has gained attention in medical imaging research. This integration aims to leverage the strengths of both modalities, providing complementary anatomical and functional information for a more comprehensive understanding of the underlying physiological process.

Data Fusion with GANs:

- Goal: Using matched MRI data, GANs may be used to create synthetic PET scans, and vice versa. This procedure is useful because it makes it possible to create paired datasets even in situations where getting simultaneous MRI-PET images could be difficult or costly.
- Benefits: GANs make it possible to create bigger and more diversified datasets for training and assessment by synthesizing one modality from the other. When linked MRI-PET pictures are scarce, this is very helpful.

Cross-Modality Image Translation:

- Concept: MRI pictures may be converted into artificial PET-like images and vice versa using cross-modality image translation taught on GANs. This makes it easier to integrate functional and anatomical data.
- Application: To improve the structural context of PET pictures and facilitate more precise localization and interpretation of functional problems, anatomical features from MRIs can be converted to PETs.

Enhancing Resolution and Image Quality:

- Objective: By utilizing high-resolution data from MRI scans during the synthesis phase, GANs can help to enhance the quality and resolution of PET pictures.
- Benefits: Improved picture quality can result in a more precise and trustworthy measurement of metabolic activity in PET scans, which is essential for cancer, neurology, and cardiology applications.

Artifact correction and noise reduction:

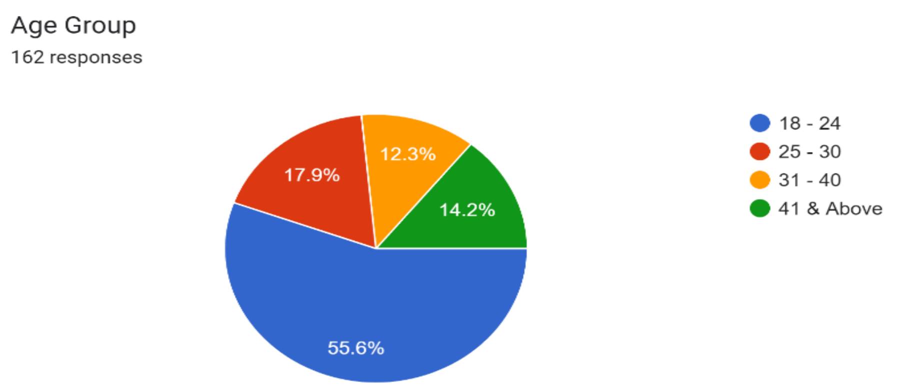
- Concept: By using information from related high-quality MRI pictures, GANs may be taught to mimic and repair noise and artifacts in PET scans.
- Application: Improving the robustness of PET images is especially important since noise and artifact removal leads to evaluations that are more precise and pertinent to clinical settings.

Numerous disorders can be diagnosed using Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). Due to its high cost and elevated danger of radiation exposure, PET imaging is not available in the majority of medical facilities worldwide. A 3D self-attention conditional GAN called SC-GAN was proposed by extending a 2D conditional GAN into a 3D conditional GAN and adding a 3D self-attention module to it in order to generate PET synthetic images from MRI scans. PET synthesis from MRI multi-modal images has become a popular method that can reduce the cost and patient's radiant dose caused by PET imaging. To minimize blurriness and enhance the quality of produced pictures, a self-attention module simulates the interaction between widely separated image voxels. This approach enhanced the accuracy of picture synthesis by utilizing exhaustive loss functions such as brain area RMS error (RMSE), feature matching loss, and spectral normalization. The Alzheimer's Disease Neuroimaging Initiative 3 provided the dataset utilized in this study (ADNI-3) PET scans picked from amyloid PET served as the goal, while MRI scans chosen from T1-weighted (T1w) and fluid-attenuated inversion-recovery (FLAIR) structures served as the input. A total of 265 people were chosen, 207 of whom were employed for testing and 58 for training. Next, the model was assessed by contrasting its NRMSE, PSNR, and SSIM metrics with those of other studies.

centered on the usage of globally and locally aware image to image translation GAN (GLA-GAN) with a multi-path architecture for the cross-modality synthesis of PET scans from MRI images for the diagnosis of Alzheimer's disease (AD). It was thought that the quality of synthetic PET scans may be enhanced by utilizing both local and global settings. To enhance the quality of the synthetic images, SSIM (MS-SSIM) was employed as an extra objective function in this study. For the training process, 402 input and target samples with pre-existing FDG-PET and MRI modalities were chosen from the ADNI dataset. Finally, utilizing SSIM, PSNR, and MAE metrics to compare with previous efforts, the quality of the synthesized pictures and the model accuracy for AD diagnosis were assessed. suggested a novel technique called GANBERT to produce PET pictures with a broad intensity range from MRI scans. The design is made up of a 3D generator that resembles a U-Net and uses MRI scan data to create PET pictures. Additionally, it contains two Bidirectional Encoder Representations from Transformers (BERT) that function as a GAN discriminator by using their next sentence prediction (NSP) to forecast both synthetic and real PET pictures. The suggested model was trained and tested using the ADNI dataset.

5. CT-PET:

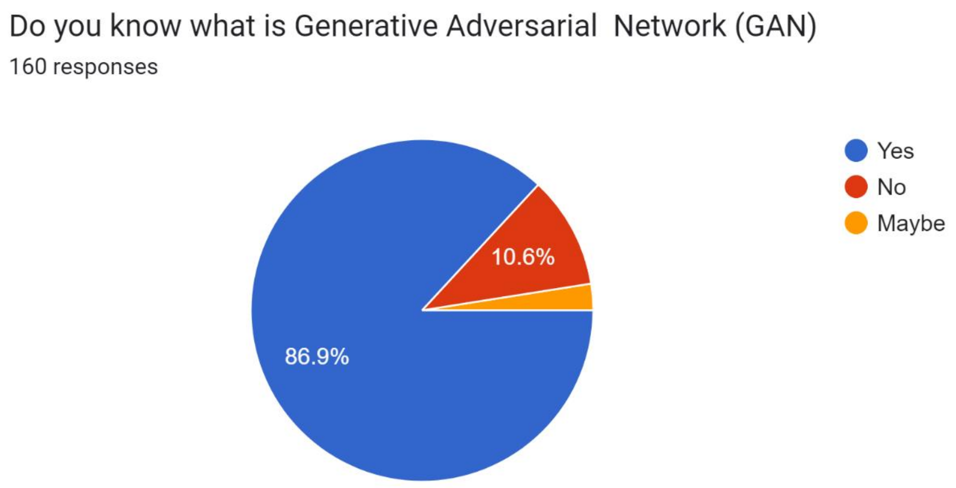
PET stands for Positron Emission Tomography, a nuclear medicine imaging method that makes use of a little quantity of radioactive substance called a radiotracer or radiopharmaceutical. The patient receives an injection of this material, which releases positively charged particles known as positrons. Gamma rays are created when positrons and electrons in the body destroy one another. These gamma rays are picked up by detectors in the PET scanner, and a computer uses the radiotracer's distribution to create pictures that depict regions of elevated or lowered metabolic activity. CT, or computed tomography, is a radiography imaging method that produces finely detailed cross-sectional pictures, or slices, of the body using X-rays. Anatomical details included in these photos enable the imaging of things including bones, organs, and tissues. With a single imaging session, CT-PET offers a more complete image of the body by combining PET and CT scans. The comprehensive anatomical pictures generated from CT are layered with the functional information from PET, which indicates regions of elevated metabolic activity. More precise localization of abnormalities is made possible by this integration, which also aids in the diagnosis and staging of a number of disorders, including cancer. In oncology, CT-PET is often used for cancer staging, diagnosis, and therapy monitoring. It is also used to evaluate brain and heart function in neurology and cardiology, respectively. The integration of functional and anatomical data increases the precision of diagnosis and the capacity to develop effective treatment plans. Positron emission tomography-computed tomography, or CT-PET, is a medical imaging method that combines computed tomography (CT) with positron emission tomography (PET), two cutting-edge imaging modalities. In a single examination, this hybrid imaging method offers both functional and anatomical information. Because PET scans have less resolution and precise information than CT images, it might be difficult to synthesize CT from PET images. Several research managed to get results with low average errors in spite of these difficulties. The scattered advantages of many translation techniques, including ResNets, pix2pix, PAN, and Fila-sGAN, are combined with a new high-capacity generator architecture in a newly suggested GAN framework called MedGAN. With a focus on PET-CT translation, this system aims to enhance technical post-processing activities that demand globally consistent picture attributes. They also included non-adversarial losses into the framework, such as the perceptual, stylistic, and content losses. A dataset of 46 patients from the brain area obtained using a combined PET/CT scanner was utilized to evaluate this architecture. The structures in the CT pictures generated by the suggested framework were homogenous and realistic, closely matching the CT images obtained using ground truth. This suggested architecture is modified in a different research, which assesses the MedGAN framework solely using non-attenuation corrected PET data (NAC PET) for autonomous attenuation correction of brain fluorine-18-fluorodeoxyglucose (FFDG) PET images. For training purposes in this work, a dataset of 50 patients' CT and NAC PET data was utilized, and 40 patients' data were used for technical and clinical validation. The findings demonstrate that, using the suggested framework, independent attenuation correction of brain F-FDG PET is possible and can be done with high accuracy. suggested a method for gathering attenuation data in a clinical PET scanner that is delayed so that extra CT images are not required. In order to do this, a GAN-based image synthesis network is created, which creates a pseudo-CT picture from the PET back projection (BP) and NAC PET images. To acquire the transformation field between the two scans, a non-rigid registration is then conducted between the pseudo-CT picture and the CT image from the first scan. By applying the transformation field to the CT images from the first scan, the final estimated CT image for the delayed PET picture is produced. This study evaluates the efficacy of the suggested approach using the Generative Adversarial Networks (GAN) technology through the use of experiments with clinical datasets.



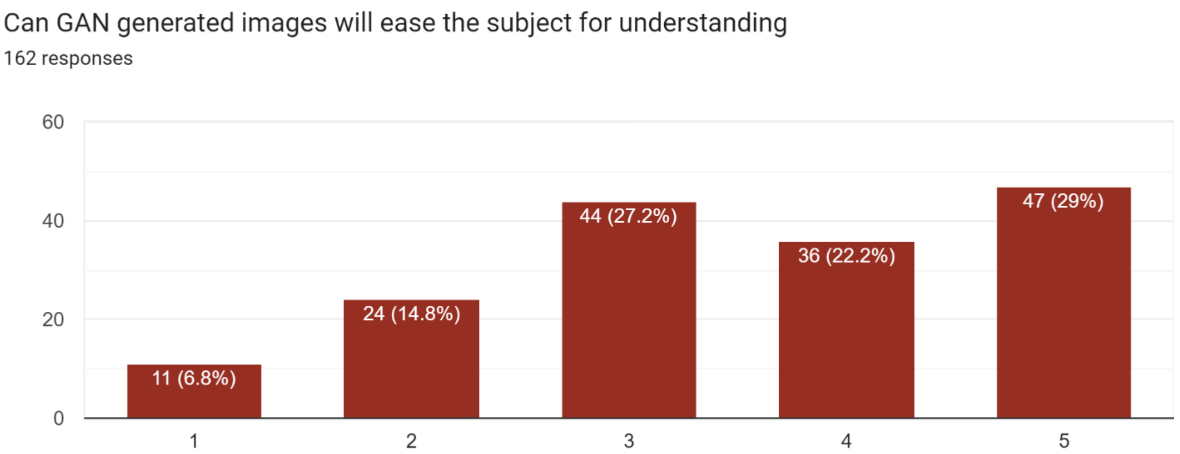
SURVEY REPORT:

1. **Age Group**

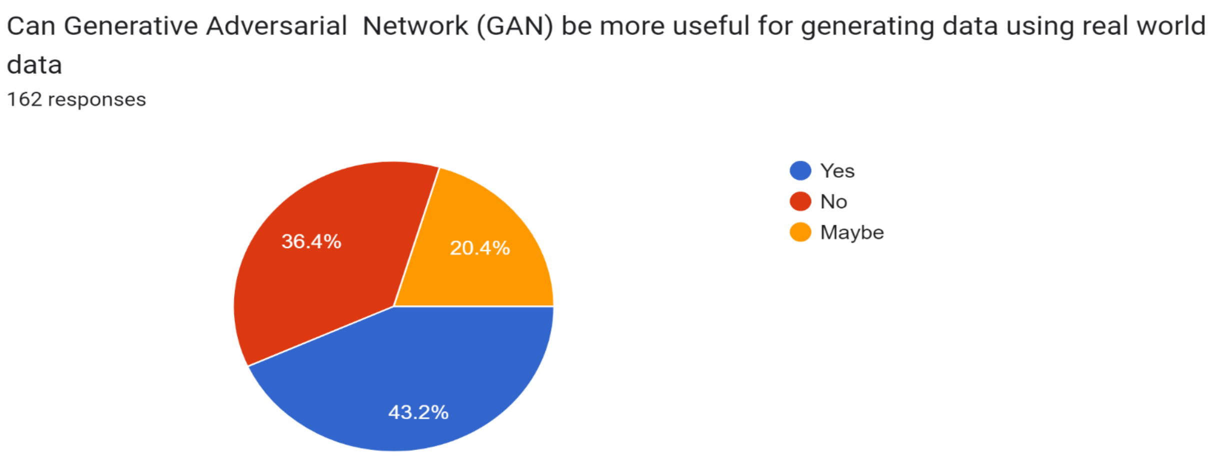
2. Do you know what is Generative Adversarial Network(GAN)?



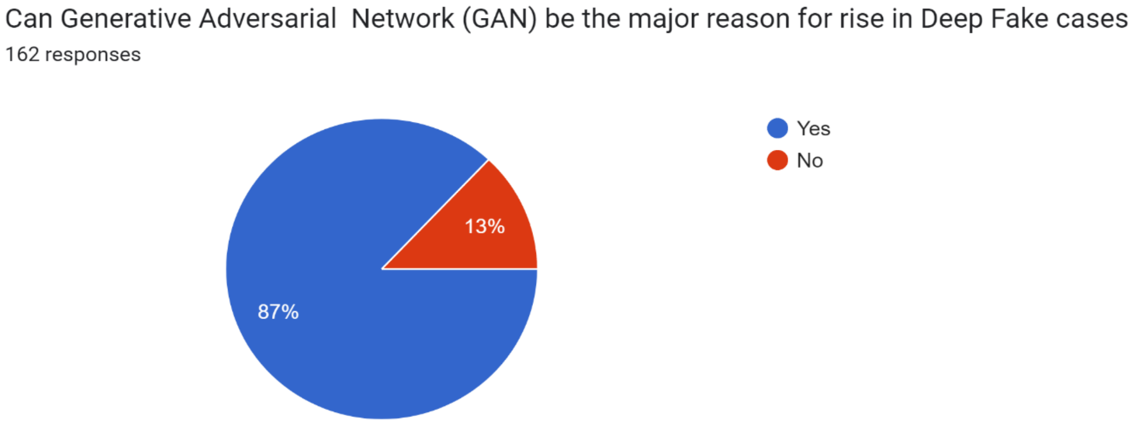
3. Can GAN generated images will ease the subject for understanding?



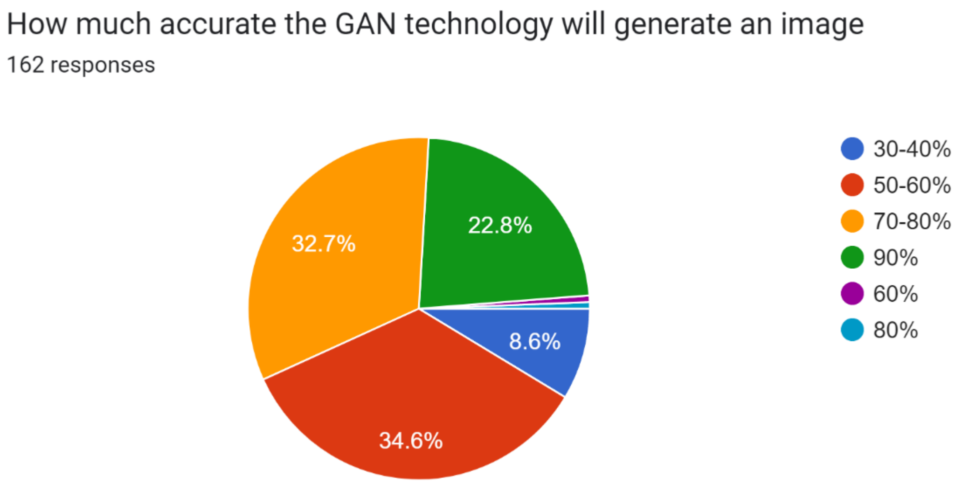
4. Can Generative Adversarial Network (GAN) be more useful for generating data using real world data?



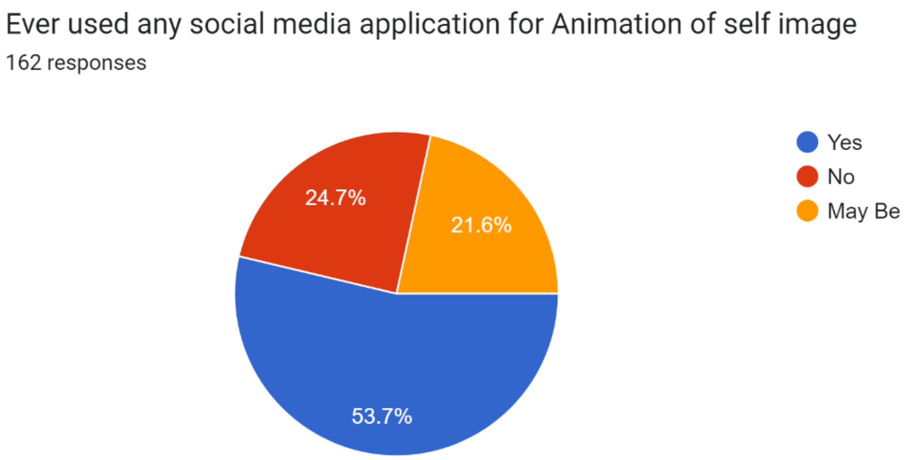
5. Can Generative Adversarial Network (GAN) be the major reason for rise in Deep Fake cases



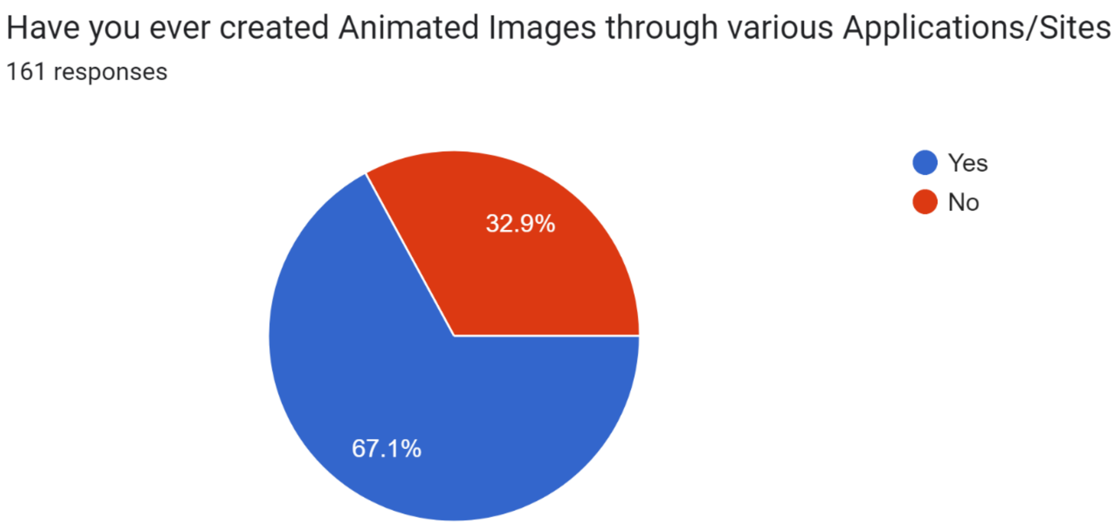
6. How much accurate the Gan technology will generate an image?



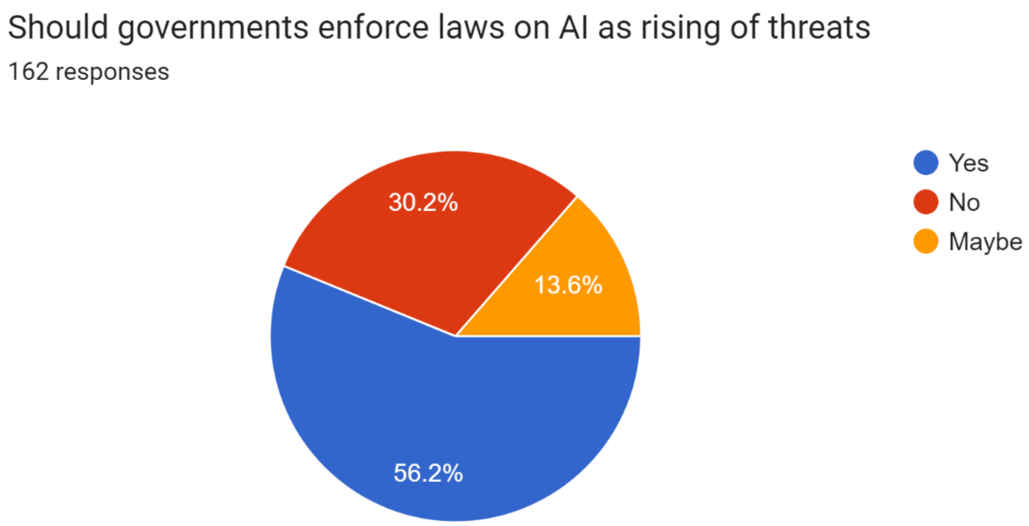
7. Ever used any social media application for Animation of self image?



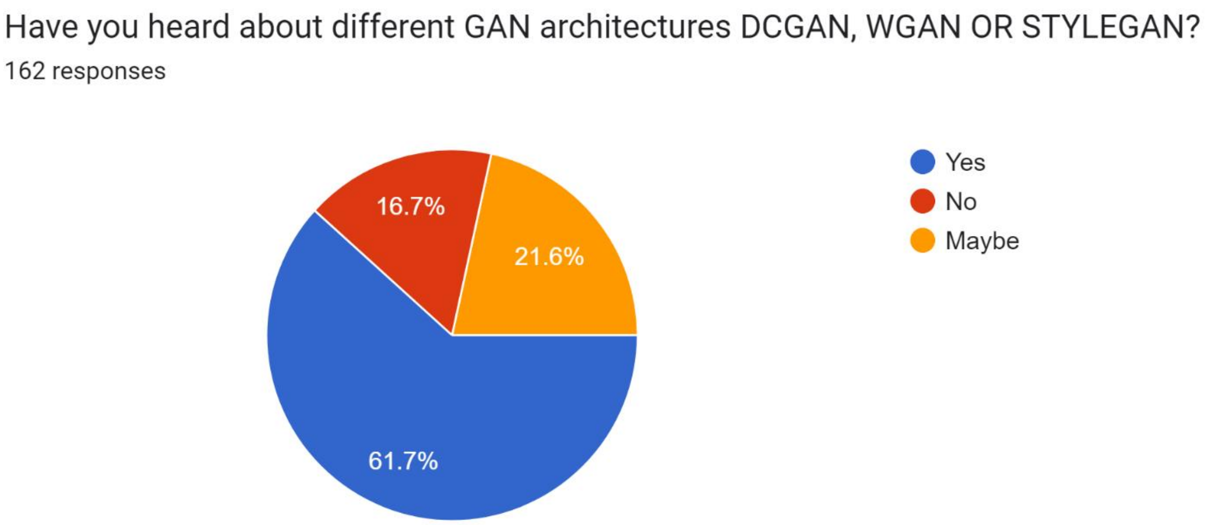
8. Have you ever created Animated images through various Applications/Sites?



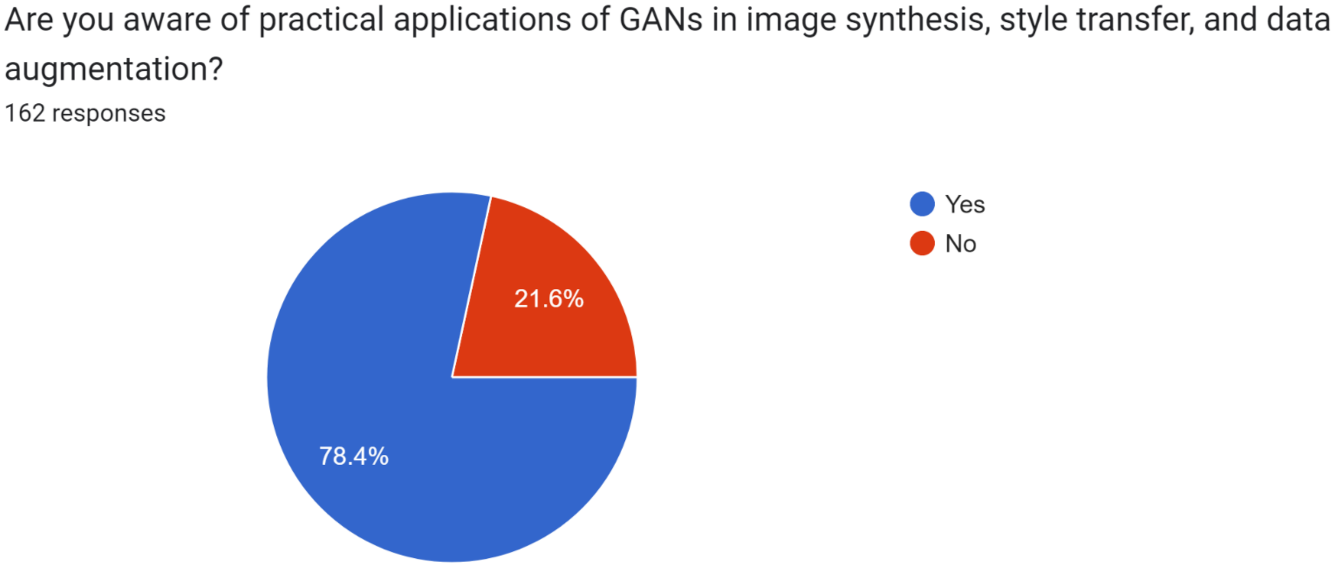
9. Should governments enforce laws on AI as rising of threats?



10. Have you heard about different GAN architecture DCGAN, WGAN OR STYLEGAN?



11. **Are you aware of practical applications of GANs in image synthesis, style transfer and data augmentation?**



DESCRIPTIVE STATISTICS:

1. **Do you know what is Generative Adversarial Network (GAN)**

Do you k2w what is Generative Adversarial Network (GAN)	
Mean	1.15625
Standard Error	0.033817484
Median	1
Mode	1
Standard Deviation	0.427761101
Sample Variance	0.18297956
Kurtosis	7.656270892
Skewness	2.82775072
Range	2
Minimum	1
Maximum	3
Sum	185
Count	160

2. Have you ever created Animated Images through various Applications/Sites

Have you ever created Animated Images through various Applications/Sites	
Mean	1.327044025
Standard Error	0.037322256
Median	1
Mode	1
Standard Deviation	0.470615747
Sample Variance	0.221479182
Kurtosis	-1.464475379
Skewness	0.744383233
Range	1
Minimum	1
Maximum	2
Sum	211
Count	159

3. Can GAN generated images will ease the subject for understanding

Can GAN generated images will ease the subject for understanding	
Mean	3.5125
Standard Error	0.09872915
Median	4
Mode	5
Standard Deviation	1.248835936
Sample Variance	1.559591195
Kurtosis	-0.911981465
Skewness	-0.342695421
Range	4
Minimum	1
Maximum	5
Sum	562
Count	160

4. Ever used any social media application for Animation of self image

Ever used any social media application for Animation of self image	
Mean	1.68125
Standard Error	0.06416608
Median	1
Mode	1
Standard Deviation	0.81164384
Sample Variance	0.658765723
Kurtosis	-1.17949342
Skewness	0.647309553
Range	2
Minimum	1
Maximum	3
Sum	269
Count	160

5. Should governments enforce laws on AI as rising of threats

6. Have you heard about different GAN architectures DCGAN, WGAN OR STYLEGAN?

Have you heard about different GAN architectures DCGAN, WGAN OR STYLEGAN?	
Mean	1.60625
Standard Error	0.065214254
Median	1
Mode	1
Standard Deviation	0.824902319
Sample Variance	0.680463836
Kurtosis	-0.998661387
Skewness	0.846116327
Range	2
Minimum	1
Maximum	3
Sum	257
Count	160

Mode	1
Standard Deviation	0.722939492
Sample Variance	0.522641509
Kurtosis	-0.615735088
Skewness	0.846771688
Range	2
Minimum	1
Maximum	3
Sum	252
Count	160

7. Can Generative Adversarial Network (GAN) be the major reason for rise in Deep Fake cases

Can Generative Adversarial Network (GAN) be the major reason for rise in Deep Fake cases	
Mean	1.13125
Standard Error	0.026779256
Median	1
Mode	1
Standard Deviation	0.338733769
Sample Variance	0.114740566
Kurtosis	2.897140805
Skewness	2.204785918
Range	1
Minimum	1
Maximum	2
Sum	181
Count	160

8. Are you aware of practical applications of GANs in image synthesis, style transfer, and data augmentation?

Are you aware of practical applications of GANs in image synthesis, style transfer, and data augmentation?	
Mean	1.21875
Standard Error	0.032784645
Median	1
Mode	1
Standard Deviation	0.4146966
Sample Variance	0.17197327
Kurtosis	-0.114862533
Skewness	1.373583127
Range	1
Minimum	1
Maximum	2
Sum	195
Count	160

9. Can Generative Adversarial Network (GAN) be more useful for generating data using real world data

Can Generative Adversarial Network (GAN) be more useful for generating data using real world data	
Mean	1.775
Standard Error	0.060753911
Median	2
Mode	1
Standard Deviatio	0.768482946
Sample Variance	0.590566038
Kurtosis	-1.196931364
Skewness	0.409845603
Range	2
Minimum	1
Maximum	3
Sum	284
Count	160

STRENGTH:

To the best of our knowledge, this is the first review on the use of GANs in brain MRI images, despite the fact that other studies have been published on their use in medical imaging. This review is the most thorough on the subject because it covers every study that employed GANs for brain MRI. This review aids readers in understanding the potential of GANs for brain MRI data synthesis and how they could enhance brain tumor identification and segmentation in brain MRI.

LIMITATIONS:

We incorporated research from five significant databases into our study. Therefore, if certain research were not included in the databases that were included, they may have been overlooked. Additionally, the review only includes works that have been published in English owing to practical constraints. Therefore, it's possible that pertinent research written in other languages was overlooked. The research on significant applications, including synthesis, segmentation, diagnostics, super-resolution, and noise reduction, is enumerated in this study. Some applications' definitions may partially overlap with those of others.

CONCLUSION:

We examined the generative adversarial network and its uses in the synthesis of brain images in this research. We also provided an overview of the direct, hierarchical, and iterative approaches for creating fake pictures that GANs employ. Generic generative and discriminative networks, which make up GANs, are two types of sophisticated deep learning-based models that are used to produce and synthesis medical pictures. Next, we divided the uses of GANs for brain image synthesis into three groups, reviewing each technique independently: CT-MRI, MRI-PET, and CT-PET.

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