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A Retrospective Study on Brain Tumor Image Generation using various GAN Architectures

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***Abstract*—Brain tumors can have a lethal impact on humans. An estimate of 24,000 people lose their lives per year due to this abnormality. Several research papers were studied to gather valuable insights on the working of multiple combinations of GAN frameworks, which yielded a deeper understanding of the mechanism. U-Net architecture is one of the most commonly implemented frameworks of CNN particularly for medical images. Different approaches of testing on datasets were carried out to yield the respective results. This research is a cumulative study of various techniques on GAN models.**

***Index Terms*—Generative adversarial networks, Generator, Discriminator, Brain Tumor.**

I. INTRODUCTION

The brain is one of the most essential organs of the human body. It consists of over a hundred billion nerves to perform complex functions of the body. Any abnormal growth in the brain cells leads to the formation of brain tumors. Brain tumors account for 85% to 90% of all primary central nervous system tumors. In 2020, it is anticipated that 3,08,102 individuals would receive a primary brain or spinal cord tumor diagnosis worldwide.[1] Brain tumors can be of different types, but are broadly classified into malignant, which is cancerous and benign, which is known to be harmless. These tumors can start in any part of the brain and spread to various regions, which could increase the risk, therefore an early detection is necessary. MRI and CT scans are predominantly used in identification of brain tumors. Acquisition of these images is challenging since they are highly confidential and violate the privacy of the patients. In order to train a deep neural network model, humongous data is required to obtain favorable results. Generative Adversarial Networks can be implemented to resolve this conflict. The main aim and objectives which have been studied from various research papers are; to study the techniques for enhancing the image resolution, to investigate the methods used to achieve privacy protection, interpreting the images synthesized by GAN model, to scrutinize several GAN architecture combinations for production of realistic images. Analysing different testing strategies and performance evaluation and to comprehend the architectures implementing multiple generators and discriminators to improve the sensitivity of image synthesis. GANs are commonly used for generation of images from texts, converting a monochrome image into colour, and predicting video frames.

GAN is an unsupervised deep learning architecture used to create synthetic images. There are two main components in the model namely generator and discriminator. The generator is a neural network model that synthesizes an image starting from noise data and the discriminator is a classifier which classifies the generated image as real or fake based on the pre-trained CNN model. The term adversarial implies a competition between two networks contesting a zero sum game where a gain by one agent results in a loss by another and visa versa. The generator begins to extract features based on the discriminator's outcome and improves itself with each iteration, until the discriminator is unable to distinguish among the two images. Certain conditions can be applied to the Generative adversarial network to promote the production of specified user required output which can focus on particular regions of an image. The generated images can be used to populate the dataset which can be beneficial in training a model and achieve better performance and accuracy. In this study numerous GAN architectures' implementations regarding the structure, number of generators and discriminators, internal CNN frameworks, number of input images to train a discriminator.

This review is structured as follows, Section 2 contains Literature Survey, Section 3 consists Results and discussion lastly Section 4 includes Conclusion.

II. LITERATURE SURVEY

Dorin Doncenco et al. [2] implies the working of conditional GAN for the use of image to image translation to initiate and generate a series of synthetic brain MRI images of multiple sequences with real data of randomic features such as the tissue of the brain and cancerous tissues using generative adversarial networks.The model was trained and tested using the Brain Tumor Segmentation Challenge 2020 dataset, the training was done with a certain set of labeled gliomas due to which the model was able to synthesize the visible tumors. The evaluation of data was done using DeepMedic which is an image segmented CNN. Although the finer structure of the brain was slightly blurry, The synthetic tumors produced by C-GAN could be easily distinguished from the healthy tissue. Since the synthesized data did not show signs of improvement while training the segmentation models therefore the generated data can not be used for clinical decision-making procedures which proves that the network requires fine tuning.

Jiayi Ma et al.[3] discusses a Conditional Generative Adversarial along with dual discriminators for fusing a series of visible images and infrared images with different resolutions.For the procedure of fusion, this model does not need ground truth fused images and can fuse images of various resolutions without thermal radiation resulting in lesser texture loss. A publicly available TNO Human Factors dataset was made use of to train and test the model; during the testing phase the generator was solely trained to generate the fused images, with a predefined resolution ratio input images of varied sizes can be used since there does not exist any fully connected layers.The proposed DDcGAN is applied to fuse MRI and PET images which can be better performed with other deep learning algorithms.

Yushi Chang et al.[3] used a machine learning based method to developed to create 4D skeletal textures with multiple contrasts;For more accurate imaging simulations, the extended cardiac-torso (XCAT) phantom has been used. A dual discriminator with Generative adversarial network is used to organ mappings that correlate to anatomical textures. Computational human phantoms are used as virtual patients in this work to examine imaging technology. Both CT and CBCT textures are created in the chest region difficulties. The XCAT phantom's capacity to recreate accurate patient-quality imaging data is significantly improved by the use of anatomical texturing. The application of anatomical texturing considerably enhances the ability of the XCAT phantom to reproduce precise patient-quality imaging data. This opens up new opportunities by allowing the phantom to assess image quality in a more realistic manner.

Baiying Lei et al. [4] used a novel and effective GAN model for segmenting skin lesions from dermoscopy images is proposed. Dual discrimination (DD) and deep encoder-decoder segmentation (UNet-SCDC) are its two modules.The DD module aims to improve the decision-making process by enhancing discriminative model with two independent but complimentary discriminators.The The proposed GAN is evaluated using the 2017 and 2018 Skin Lesion Challenge Datasets from the International Skin Imaging Collaboration (ISIC).A convolutional neural network called U-Net was created for the segmentation of biological images,To obtain discriminative feature representations and maintain more precise information for precise segmentation, the UNet SCDC module is used.

Lalith Kumar Shiyam Sundar et al. [5] aimed to develop a motion-correction system that would enable precise, data-driven recognition of involuntary subject motion during dynamic 18F-FDG brain research using conditional generative adversarial networks (cGAN).This study involved ten healthy participants, five men and 5 women; 70% of the total datasets were used to train the cGAN using MR navigators to adjust for motion;In order to create artificially manufactured low-noise images from early high-noise PET frames, the cGAN mappings that were developed were then applied to the test dataset.The result indicated that the motion-corrected IDIF and the AIF yielded AUCs that were 1.2% and 0.9% apart, respectively. These 2 input functions produced gray matter CMRGlc values that varied by less than 5% (2.4% and 1.7%, respectively).

Mina Rezaei et al.[6] This research is based on the evaluation of brain tumor segmentation and the prediction of survival of a patient on being diagnosed with a tumor.the segmentation of images has been achieved by Conditional generative adversarial network which is trainable based on the user necessities and conditions applied to the model. CNN model has been put to use to determine and predict the survival day, this models tends to be an automated trainable parallel CNN. The architecture implemented in the generator is said to be U-NET which is a CNN model used mainly in the biomedical field for image segmentation. A DICE score has been achieved for the validated data. The network learns a loss that is relevant in unknown data since it is tailored to the task and the data at hand. The future scope proposed by the author implies to develop and implement RNN within the Encoder-Decoder to improve the working of the generative network.

Xiaoqin Wei et al.[7] introduced a for automatically segmenting liver in CT images using generative adversarial networks and Masked region-based CNN. The k-clustering algorithm was used to improve the segmentation results by extracting important anchors and the noisy features present in liver images were handled using GANs in the model. The authors were successful in producing good results with effectiveness and robustness in segmenting liver in CT images. Hristina Uzunova et al. [8] implemented a model for translating 3D medical images between different domains where images of high resolution are utilized . Firstly, the authors generated a set of images with low resolutions and then continuously generated pieces of images by enhancing the resolution by utilizing LR GANs and HR GANs respectively . The experiments performed were based on domain translation scenarios and the model was successful in generation of high-quality images of high resolution as a result of the multi-scale scheme being implemented.

Maayan Frid-Adar et al. [9] established methods for enhancing the performance of convolutional neural networks for classification of medical images of liver lesions using generative adversarial networks. The authors performed the classification of the dataset using CNN architecture and GANs were utilised for generation of synthetic realistic looking images and specifically DCGAN and ACGAN were used. The authors suggest that by utilising the unlabeled data, the quality of lesion samples generated can be improved.

Jun Huang et al. [10] introduced a novel end-to-end model named MGMDcGAN that enables the fusion of multimodal medical images where the images of different resolutions can be used. The first cGAN's generator was used to produce a real like fused image and the second cGAN with mask was used to improve dense structure information in images indicating functional information. The authors were successful in the process of fusion of images indicating structural information and the images indicating functional information without any information loss. The experiments resulted in better visual effects and in preserving maximum amount of information in the source images.

Donghai Zhai et al. [11] developed a model named ASS-GAN used for segmentation of breast ultrasound images. The authors have implemented the learning approach which uses both labeled and unlabeled data to train the network. The model implemented was able to generate reliable segmentation predicted masks without any labels. The model successfully achieved good results in terms of dice coefficient. The authors were successful in improving segmentation performance by utilising unlabeled data in the absence of labeled data.

Quingyun Li et al. [12] developed a model named tumorGAN which is a new data augmentation method that can be implemented for segmentation of brain tumor images.It is a generative adversarial network that can generate synthetic images of brain tumors from existing data to expand the training dataset.The authors evaluated the performance of the model based on BraTS 2018 dataset which demonstrated the effectiveness of the model and utilized multi modal data for the process of segmentation of tumor images.Focus was on extracting the tumor areas from the images so that more combinations could be developed between the tumors and healthy tissue and expand the dataset. The model is powerful and performed well compared to Pix2pix which indicated that it can be help in the generation of more realistic images that will help in the segmentation task. The outcome from the experiments indicated that the model can help in enhancing tumour segmentation in multi-modal as well as single-modality datasets.

Kaleb Smith et al. [13] explains the difficulties faced due to lack of data which leads to low performance of models. There are many real world data which are represented with respect to time which are difficult to acquire. The authors propose Time Series GAN which contains two GANs which provide data within stipulated time limit.

Dena Nadir George et al. [14] have proposed a model which uses decision tree and multi layer perceptron layer algorithm. These two classifiers help in classifying the type of brain tumor. The model provides precision of 95%. Each step in the process is in detail considering the different shapes and sizes of the tumour for providing accurate results. Classification of MRI images is easier as all the complexities are taken care of.

M.Krithika et al. [15] have used Generative Adversarial Networks on multimodal datasets. To improve the quality of the images, different architectures are implemented. The model is used to predict neurodegenerative diseases.

In Ho Lee et al. [16] have used Super Resolution and Style Transformation GAN on IR UAV Dataset. In the paper, STSRGAN model is used for improving the resolution of images. Infrared Unmanned Aerial Vehicle with small target dataset is produced, this method gives better performance over traditional STSRGAN methods through experiment.

Baoqiang Ma et al. [17] implemented da-GAN by introducing an additional discriminator D2 to yield an increase in the training weight in the intricate areas of the hippocampal region. The experiment resulted in the generation of higher quality MRI scan images which not only pertained to the hippocampal area but also the entire scanned brain image. The usage of two segmentation models heavily impacted the segmentation accuracy of the trained model.

Euijin Jung et al. [18] advanced a proposition of utilising conditional GAN for the synthesis of MRI images with 2D discriminator and 2D generator. The authors were able to successfully generate MRI images in terms of quality of the image, efficiency and condition based generation and claimed to be compatible with numerous 2D generator models. The trained model resulted in accurate prediction of an ailment which is beneficial for early detection and identification of the Alzhemer’s disease progression in a given area.

Imran Ul Haq et al. [19] developed a model name BTS-GAN for breast tumour segmentation and initiated the task to produce tumour masks close to the ground truth masks by appending a PDC module in the generator model and utilising an altered objective function to yield an IoU of 77% and average DSC score of 85%.

Stephanie L. Hyland et al. [20] aimed at generating synthetic datasets for the major purpose of avoiding privacy breach of the patients. The authors considered real valued data with labels and generated more sample images with the associated label. The evaluation method consisted of training the model on the synthetic images and testing is carried out on the real images and were able to achieve comparable results when tested against real images.

Yuqin Li et al. [21] framed a model to increase the quality of a denoised image using conditional GAN. The model is trained conditionally on the noise image with the associated gradient image. The authors were able to improve the quality while maintaining the structure with the lossless images.

Lanyu Song et al. [22] devised a model named CapGAN which is a combination of attention mechanism, RNN and CNN to generate a report on the medical diagnosis using conditional GAN and reinforcement learning. The feedback is acquired through the combination of the discriminator and the language style evaluator to extract the accurate diagnosis report.

Hanxi Sun et al. [23] establishes the significance of data acquisition and acknowledges concerns regarding protection of sensitive information of the patients. The authors suggest generation of synthetic images and analyse a GAN based model and evaluate on the sample diversity, image fidelity and dataset privacy. The authors were successful in handling different parameters and denoising the images.

Shweta Tyagi et al. [24] aimed at providing a second medical opinion to detect lung cancer at an early stage. The authors have added excitation blocks and concurrent squeeze in the generator network and channel excitation block and spatial squeeze for the discriminator framework. The training and validation of the model was performed on a publicly available dataset and testing was implemented on a local dataset and arrived at the conclusion that amongst various combinations of the network, CSE-GAN performed the best. The trained model was able to generalise and identify the intricate details such as variations in thickness and cancer population in the CT images.

Changhee Han et al [26] have implemented 3D multi-conditional GAN on a database of lung images. Sensitivity and be attained and it can be used as a training tool by the medical students to produce fake images with required conditions.

Lianli Gao et al [27] have proposed LD-CGAN which converts texts to images. In original GAN the output is undetermined as the input is taken from noise data whereas in CGAN the output images can be controlled by implementing certain conditions o the model. The authors have tried to reduce the complexity in the process of text to image conversion.

Table 1: Comparison of GAN Architectures

Criteria	Vanilla GAN	C-GAN	DC-GAN	Cycle-GAN	SR-GAN
Network Architecture	Multilayer Perceptron	Multilayer Perceptron	Transposed CNN layer	CNN with constraints	Sub-pixel CNN
Gradient Updates	One step for G and K steps for D	One step for G and K steps for D	G and D use Adam Optimizer	G and D use Adam Optimizer	G and D use Adam Optimizer
Methodology	Maximize value function for D and minimize G	Maximize value function for D for conditioned information extraction	Maximize value function for D and minimize G	Two G and D	Residual network for G and maximize value function for D
Loss function	Min-max GAN loss	Wasserstein GAN loss	L1 and L2 loss	MSE and MAE	Weighted sum of content loss and adversarial loss
Performance metrics	Log- likelihood	Log-likelihood	Accuracy and error rate	PSNR, SSIM and MOS	PSNR, SSIM and MOS

III. RESULTS AND DISCUSSIONS

In Table 1, prominent GAN architectures are compared against the parameters of gradient updates, implementation strategery, loss function, architecture and evaluation metrics.

Vanilla GAN is a supervised GAN model which was an elementary model consisting of an multilayer neural network which uses the stochastic gradient descent to minimize the loss. Conditional GAN is majorly applied to medical dataset to extract the nuances by conditioning specific requirement as a label. Deep Convolutional GAN was proposed to solve the issue of mode collapse related to the bias formed with generating only a specific set of sample images. Cycle GAN is an architecture designed specifically to perform image to image translation on unpaired sets of images. Super Resolution GAN is primarily used to boost and maintain the picture quality to recapture the finer textures. A thorough analysis and comparison of GAN architectures is integrated into Table 1. The derived prognosis from this research concludes CGAN is a suitable model for medical related data.

IV. CONCLUSION

The Generative adversarial network helps to produce ample amount of data in the form of images which have a definite resolution and composition as the real input images, this aids in forming numerous images which can be used as the dataset for building models projects due to which the violation of privacy of an institution or an individual can be avoided since GAN aims in producing realistic synthetic images which in return is a cost efficient method of gathering data The image resolution can be improved due to the continuous cyclic regenerating process of fine tuning the produced image by the generator which upholds the resolution quality. The research field requires an immense amount of data to validate the applied methodologies, therefore multiple images can be synthesized by GAN to facilitate the accuracy of prediction. One of the use cases is administration of these models by conditioning the generator to produce any specific requirement. An amalgamation of numerous approaches could prove beneficial for both experimental and definitive outcome.

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