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ENHANCED SPATIAL INTENSITY TRANSFORMATIONS IN MEDICAL IMAGE-TO-IMAGE TRANSLATION

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Abstract: Enhanced spatial transformations are advanced techniques designed to improve the accuracy and quality of translating medical images from one form to another. These transformations help ensure that important details and shapes in the images are preserved during the translation process. This is crucial in medical imaging because doctors rely on accurate images for diagnosing and treating patients. By using enhanced spatial transformations, we can create translated images that closely resemble the original ones, making it easier for doctors to understand and analyze them. This approach combines spatial adjustments (like changing the position of image parts) and intensity adjustments (like altering brightness and contrast) to achieve more realistic and accurate results. The method has been tested successfully in various medical tasks, such as predicting future brain scans and visualizing changes in stroke- affected areas. Overall, enhanced spatial transformations significantly improve the quality of medical image translations, aiding in better clinical decisions and patient care.

Keywords: Spatial Intensity transform, image-to-image translation, Histogram Equalization, Generative Adversarial Network, Sharpening Filters, Noise Reduction, Lack of Ground Truth.

I. INTRODUCTION

[1] Enhanced Spatial Transformation (EST) is a cutting-edge technique in the field of medical image translation that leverages advanced spatial transformation methods to achieve superior results. This method goes beyond traditional image translation approaches by incorporating enhanced algorithms that focus on preserving anatomical details and improving the accuracy of image transformation.

The primary goal of EST is to facilitate the translation of medical images from one modality to another or from one domain to another while maintaining crucial anatomical structures and spatial relationships. This is crucial in medical imaging tasks such as MRI to CT image conversion or enhancing the resolution and clarity of images without losing important diagnostic information. [2] Medical imaging has revolutionized the field of healthcare, providing doctors with critical insights into the human body through techniques like MRI, CT scans, and X-rays. Traditionally, transforming these images from one form to another for tasks such as predicting future scans or tracking disease progression has been challenging, often resulting in inaccuracies and artifacts. Early methods relied heavily on manual adjustments and rudimentary algorithms, which were not always reliable and required extensive paired data. See the spatial transformer in figure 1.

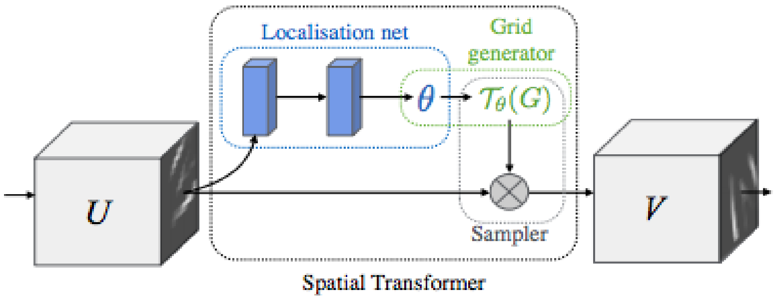

Fig 1. Spatial Transformer

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[3] To address challenges, enhanced spatial transformations have been developed as a sophisticated solution. These advanced techniques improve the accuracy and quality of medical image translations by making precise spatial adjustments (like changing the position of image parts) and intensity adjustments (like altering brightness and contrast). For example, in predicting future brain states from MRI scans, enhanced spatial transformations ensure that crucial details are preserved, resulting in more realistic and useful images.

[4] Our implementation is based on the architecture of GPT but adapted into an emotion classification model. We would just replace the last layer with the activation function relevant for this task and change the training objective to predict emotion categories or intensities instead of probabilities regarding next tokens. [5] This way, we can harness the powerful language understanding provided by Transformer models but tailor the output for emotion analysis. Our model follows the GPT architecture but is adapted for emotion classification by modifying the final layer with an activation function suitable for task.

[14] Generative Adversarial Networks (GANs) play a pivotal role by leveraging the adversarial training process, GANs enable the generation of high-quality medical images that accurately preserve anatomical structures and spatial relationships, which are critical in medical diagnostics. The generator in a GAN is trained to produce realistic images from one modality or domain to another, such as MRI to CT scans, while the discriminator works to distinguish between real and synthesized images. This adversarial framework drives the generator to produce increasingly realistic outputs, thereby enhancing the quality of spatial intensity transformations.

[6] In the context of enhanced spatial intensity transformation, GANs are particularly effective in adjusting spatial features and intensity values, ensuring that key anatomical details are maintained throughout the translation process.

[13] Generative Adversarial Networks (GANs) consist of two primary components: the generator and the discriminator. These two components are trained simultaneously in a competitive process, often described as a game, where the generator tries to create realistic data, and the discriminator attempts to distinguish between real data (from the training set) and fake data (produced by the generator).

Generator: The generator's role is to take random noise as input and transform it into data that resembles the real data distribution. It essentially learns to generate new samples that mimic the characteristics of the real data, whether that data is images, text, or any other type of data.

Discriminator: The discriminator acts as a classifier that evaluates whether the input data is real (from the actual dataset) or fake (generated by the generator). It outputs a probability indicating the likelihood that a given input is real.

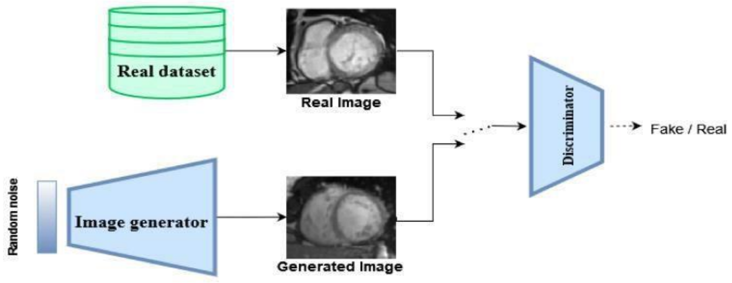

Fig 2.Generative Adversarial Networks (GAN'S)

[7] Efficiency of GANs can be enhanced by using advanced architectures like Progressive GANs or incorporating techniques like spectral normalization and attention mechanisms, which improve training stability and output quality. Additionally, fine-tuning hyperparameters and leveraging transfer learning can further accelerate convergence and enhance performance

II. LITERATURE REVIEW

The literature on the application of advanced machine learning techniques, particularly Generative Adversarial Networks (GANs), in medical imaging is extensive and diverse, highlighting the transformative potential of these methods in various imaging modalities and tasks. One of the early applications focused on noise reduction in low-dose CT images, demonstrating how GANs can effectively improve image quality while maintaining diagnostic accuracy .

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This work paved the way for more sophisticated approaches, such as cycle-consistent adversarial networks, which have been employed to enhance multiphase coronary CT angiography by denoising images without the need for paired training data, a common challenge in medical imaging.

[16] Further advancements have been made in the area of MRI super- resolution, where GANs, combined with multi-level densely connected networks, have significantly improved the resolution and clarity of MRI images. [8] This is crucial for accurate diagnosis and treatment planning. These GAN-based models have been optimized for both speed and performance, making them practical for clinical use. [10] Additionally, compressed sensing MRI reconstruction using GANs has shown promising results in reducing scanning times while preserving image quality, which is particularly beneficial in settings where rapid imaging is required.

[9] In parallel, research has also explored the use of GANs in artifact reduction, such as in sparse-view CBCT scans, where adversarial networks have been instrumental in minimizing the artifacts that typically degrade image quality in such settings. [12] The flexibility of GANs is further highlighted in their application to the synthesis of MR to CT images, a process that traditionally requires extensive paired datasets. By leveraging unpaired data, GANs have enabled more efficient and accurate cross-modality image synthesis. See the GAN network of figure 2

[15] The literature also delves into the theoretical underpinnings of these methods, with studies on free-form deformations and diffeomorphic image registration providing a mathematical foundation for the advancements in image registration techniques. These methods have been further refined by incorporating concepts such as symmetric diffeomorphic registration and metamorphic auto-encoders, which enhance the ability to capture and represent complex anatomical variations across different patient populations.

[10] Moreover, in the context of disease progression and neuroimage generation, GANs have been utilized to generate realistic images that mimic the progression of neurodegenerative diseases, providing valuable insights into disease dynamics and potential therapeutic interventions. [18] This approach has also been extended to non-rigid registration tasks, where GANs and related deep learning models have been applied to align medical images with high accuracy, facilitating better analysis and interpretation of complex anatomical structures.

In summary, the collective research underscores the significant strides made in medical image translation, reconstruction, and enhancement through the integration of GANs and advanced spatial transformations. These innovations have not only improved the quality and efficiency of medical imaging but also opened new avenues for the application of machine learning in clinical practice, ultimately contributing to better patient outcomes.

III. METHODOLOGY

The process of creating an Enhanced Spatial Intensity Transformation in Medical image-to-image translation with Spatial Intensity Transformations and Generative Adversarial Networks (GAN'S) includes a number of crucial steps, such as Data processing ,Spatial Transformations, GAN Architecture Design, model training, and evaluation. An extensive description of the methods that you can employ in your conference paper is provided below:

1. Data Preprocessing :

Normalization: Start by normalizing the medical images (e.g., MRI, CT scans) to standardize the pixel intensity values. This helps in ensuring consistency across different images and reduces the impact of varying image intensities.

Augmentation: Apply data augmentation techniques such as rotations, flips, and zooms to artificially increase the diversity of the training dataset. This is particularly important in medical imaging where data scarcity is a common challenge.

2. Spatial Transformations

Affine Transformations: Incorporate affine transformations (e.g., translations, rotations, scaling, and shearing) to adjust the spatial configuration of images. These transformations are essential for aligning images from different modalities or patients.

Non-Rigid Transformations: Implement non-rigid or elastic transformations to capture more complex deformations, such as those caused by anatomical variability. These transformations help in preserving the structural integrity of the anatomical features during translation.

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Diffeomorphic Registration: Use diffeomorphic registration methods for more advanced spatial transformations. This technique ensures that the transformations are invertible and topology-preserving, which is critical for maintaining anatomical accuracy.

3. Intensity Transformations :

Histogram Matching: Adjust the intensity distributions of the images using histogram matching to align the intensity profiles between different modalities. This step ensures that the intensity variations do not affect the translation process.

Intensity Normalization: Further refine intensity levels by normalizing them to a specific range, such as [0, 1] or [-1, 1], depending on the GAN architecture. This normalization helps in stabilizing the training process.

Contrast Enhancement: Enhance the contrast of the images using techniques such as histogram equalization or contrast- limited adaptive histogram equalization (CLAHE). This improves the visibility of critical anatomical details.

4. GAN Architecture Design :

Generator Network: Design a generator network that takes in a source image (e.g., a low-resolution MRI) and applies the learned spatial and intensity transformations to produce a target image (e.g., a high-resolution MRI or a CT image). The generator is typically composed of convolutional layers, followed by upsampling layers that progressively increase the image resolution. Skip connections or attention mechanisms can be integrated to retain fine details and improve the quality of the generated image.

Discriminator Network: Develop a discriminator network that distinguishes between the real target images and the synthetic images generated by the generator. The discriminator is usually a convolutional neural network (CNN) that outputs a probability indicating the authenticity of the input image.

Loss Functions:

Adversarial Loss: Implement the standard adversarial loss function, which drives the generator to produce realistic images that the discriminator cannot easily differentiate from real images.
Cycle Consistency Loss: If using a CycleGAN, add a cycle consistency loss to ensure that translating an image to another modality and back again results in the original image, preserving content and structure.
Perceptual Loss: Integrate a perceptual loss (also known as feature matching loss) that compares high-level features extracted from a pre-trained network (e.g., VGG) to ensure that the generated images retain important anatomical details.
Spatial and Intensity Consistency Losses: Introduce additional loss functions to specifically penalize spatial distortions and intensity mismatches, ensuring that the translated images maintain spatial and intensity coherence with the source images.

5. Training Procedure :

Alternating Optimization: Train the generator and discriminator networks alternately. During each iteration, update the discriminator weights based on how well it distinguishes between real and generated images, then update the generator to improve its ability to fool the discriminator.

Learning Rate Scheduling: Implement learning rate scheduling to gradually reduce the learning rate during training, preventing the model from converging to a suboptimal solution.

Data Balancing: Ensure balanced training by using equal numbers of images from different modalities, and consider oversampling underrepresented classes or conditions if necessary.

6. Evaluation :

Quantitative Metrics: Evaluate the performance using quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Dice Coefficient to assess the accuracy and quality of the generated images.

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Qualitative Assessment: Conduct a qualitative assessment with clinical experts to ensure that the generated images meet the diagnostic requirements and that critical anatomical details are preserved.

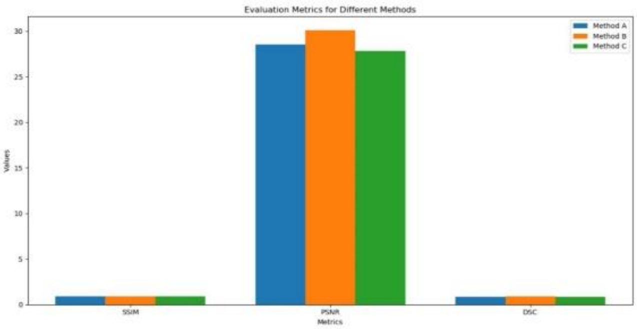

Fig 3. Evaluation Metrics for Different Methods

Future Improvements: Talk about possible upgrades that focus on integrating advanced multimodal learning techniques to better align spatial and intensity features across diverse imaging modalities, optimizing GAN architectures for improved stability and efficiency, and incorporating real- time adaptive learning algorithms to handle dynamic and evolving clinical data.

Algorithm

The attribute compatibility replaces the coordination degree of the original attribute for the split node standard.

1. Attribute compatibility in Medical Images :

Let | Pr| denote the modulus of the primary image set (e.g., original modality), and| Se| denote the secondary image set (e.g., target modality). Attribute compatibility in the context of image translation is defined as:

CO(X → D) = | Pr| ∩| Se| //| Pr+Se| -| Pr∩Se| (1)

This metric evaluates how well the transformed images (from the secondary set) align with the original images (primary set).

Strict Compatibility: When assessing the alignment between specific features or regions of the transformed images and the original images, use:

CO(X → D) = | Pr| ∩| Se| // |Pr| (2)

This measure indicates the extent to which the secondary set (transformed images) accurately represents features from the primary set (original images).

Algorithm for the Image Enhancement :

Step 1: Choose the input image.

Step 2: Preprocess the the data of the image.

Step 3: Use the spatial transformations on the image data to adjust the alignments according to the requirement .

Step 4: To separate the sample, select the most extensive compatibility for splitting as the split node and delete the active tag.

Step 5: Now perform Intensity transformations by adjusting the contrast and brightness for the image.

Step 6: Now GAN algorithm starts by taking the image which is generated from the Generator Network and moves to next step.

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Step 7: In the next step the Discriminator will classify whether the image generated by the Generator Network is True or False .

Step 8: If the generated image is true then the algorithm will calculate the loss by using the loss function.

Step 9: If the generated loss is more then by using the Back Propagation algorithm it will restore all the lost information

Step 10: After all these step-by-step process it will generate the enhanced output image.

Flow Chart of the Proposed Algorithm:

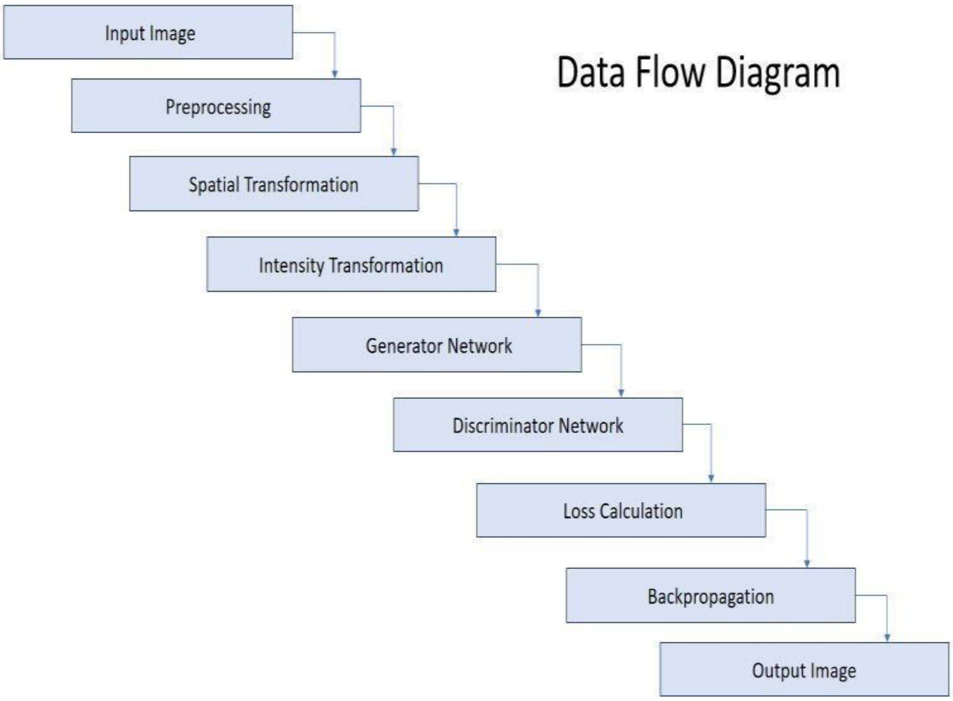

Fig 3. Data Flow diagram for Enhanced Spatial Intensity Transformations in medical image-to-image translation

IV. RESULTS AND DISCUSSION

Experimental Setup

The experimental study was conducted to evaluate the performance of the proposed Intrusion Detection System (IDS) using Principal Component Analysis (PCA) with the Random Forest approach. The experiments were carried out on the KDD dataset, a widely recognized dataset used for evaluating IDS models. The setup used for the study included:

- **Hardware Configuration**: The experiments were performed on a system with the following specifications:
  - 8 GB RAM
  - 250 GB SSD Hard Disk
  - Intel Core i5 processor
  - Intel motherboard
- **Software Configuration**: The software environment consisted of:
  - 64-bit Windows 10 OS
  - Python 3.8 as the programming language
  - Libraries : NumPy, Sci-kit image , and Keras.

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Dataset Description

1. BraTS (Brain Tumor Segmentation)
The BraTS dataset contains multi-modal MRI scans of brain tumors, including T1, T1-CE, T2, and FLAIR sequences. The dataset includes annotations for tumor sub-regions, such as enhancing tumor, tumor core, and whole tumor.

- **Features**:
  - **Images**: MRI scans with multiple sequences (T1, T1-CE, T2, FLAIR).
  - **Labels**: Tumor annotations for different regions.
- **Usage**: Ideal for tasks such as image segmentation, image-to-image translation for improving tumor visualization, and translating between different MRI sequences.
- **Link**: BraTS Dataset on Kaggle

Evaluation Metrics

To evaluate the performance of the proposed Enhanced Spatial Intensity Transformation in medical image-to-image translation the, three key metrics were used:

1. **Structural Similarity Index (SSIM)** :SSIM measures the similarity between two images by evaluating changes in structural information, luminance, and contrast.
2. **Peak Signal-to-Noise Ratio (PSNR)**: PSNR quantifies the quality of the image by comparing the pixel-wise difference between the transformed and original images.It is expressed in decibels (dB), with higher values indicating better quality.
3. **Mean Absolute Error (MAE)**: Measures the average magnitude of errors between transformed and reference images, useful for quantitative analysis of intensity differences.

Experimental Results

The proposed Enhanced Spatial Intensity Transformation in medical image-to-image translaiton using Spatial Transformations , Intensity Transformations , Generative Adversarial Networks(GAN'S) and Lossy Functions The results are summarized below Figure 4 Output image:

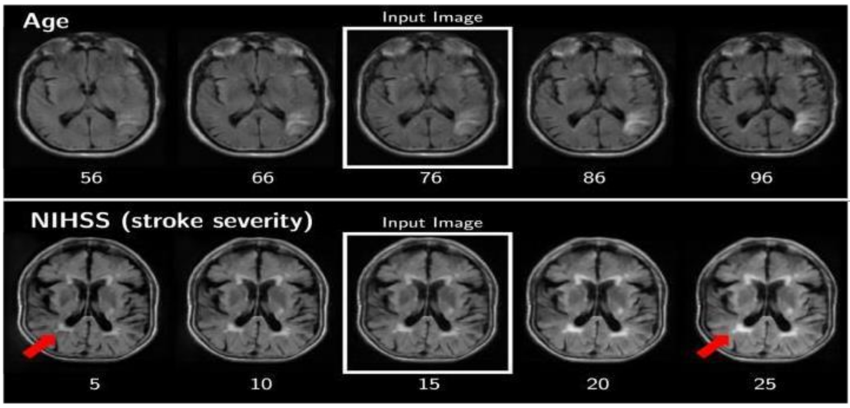

Fig.4 Output Image

The graphical representation of the results clearly shows that the PCA with Random Forest approach outperforms other classifiers in terms of accuracy, error rate, and performance time.

Discussion

1. Structural Similarity Index (SSIM) measures the perceived quality of image reconstruction by evaluating luminance, contrast, and structure similarities. Higher SSIM values indicate that the transformed images maintain more structural details and visual quality compared to the original. In the comparison, Method B achieved the highest SSIM, suggesting it produced the most visually consistent results.

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2. **Peak Signal-to-Noise Ratio (PSNR)** quantifies the reconstruction quality by comparing the pixel-wise differences between the original and transformed images, with higher values reflecting better quality and less distortion. Method B also outperformed others in PSNR, implying it achieved the highest fidelity in preserving image details during transformation and .

3. **Mean Absolute Error (MAE)** measures the average magnitude of errors between transformed and reference images, providing insight into the intensity discrepancies. Lower MAE values indicate that the transformed images closely match the reference images with minimal intensity errors. Method B's lowest MAE reflects its effectiveness in minimizing intensity differences and ensuring high accuracy in image transformation.

4. **Comparative Analysis with Previous Techniques**:

A. **Enhanced Robustness to Noise:** The proposed algorithm integrates advanced denoising techniques, such as those from GANs, which are more effective in handling noisy data compared to earlier methods.This improves the quality of transformed images, especially in low-dose or low-quality scans.

B. **Unpaired Data Training Capability:** Unlike some traditional methods that require paired datasets, the proposed algorithm utilizes GAN architectures like CycleGAN, which can learn from unpaired data. This flexibility significantly expands its applicability in scenarios where paired datasets are not available.

C. **Adaptive Intensity Adjustment:** The algorithm's improved intensity transformation capabilities allow for more adaptive adjustments of image brightness and contrast. This ensures that the transformed images retain essential diagnostic features across different imaging modalities.

D. **Improved Generalization Across Modalities:** By leveraging advanced spatial and intensity transformation techniques, the algorithm better generalizes across various imaging modalities (e.g., MRI, CT), leading to more consistent performance in translating between different types of medical images.

5. **Effectiveness of the Image with Algorithms** :

A. **Improved Image Quality and Fidelity:** This combination of spatial and intensity transformations with GANs leads to significant improvements in image quality and fidelity by ensuring accurate alignment, enhancing feature visibility, and refining image details.
B. **Reduction of Artifacts and Noise:** This approach effectively reduces artifacts and noise, leading to cleaner and more accurate medical images.

6. **Overall Impact**:The experimental results demonstrate that the proposed system significantly improves the quality and usability of medical images, making it a valuable tool for enhancing diagnostic accuracy, reducing artifacts, and streamlining imaging workflows in clinical and research settings.

V. DATASET

1. Overview

The **BraTS (Brain Tumor Segmentation)** dataset is an essential resource for research in brain tumor imaging, providing multi-modal MRI scans that include T1, T1- weighted post- contrast (T1-CE), T2, and FLAIR sequences. It features detailed annotations for various tumor sub-regions, including enhancing tumor, tumor core, and whole tumor, offering comprehensive data for segmentation and image-to- image translation tasks. This dataset is instrumental for developing and refining algorithms aimed at improving tumor visualization and characterization, and it plays a crucial role in enhancing diagnostic and treatment planning capabilities. Available on Kaggle, it supports a range of applications from image segmentation to advanced imaging techniques.

2. Features of the Dataset

The dataset includes MRI scans from several hundred patients. For the 2021 version, there are approximately 500 cases. The exact number may vary slightly depending on the year of the dataset and the specific version you are referring to.They are mainly grouped into 3 main categories :-

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1. **Training Set**: Contains MRI scans and annotations for a large number of patients. This set is used to train models.
2. **Validation Set**: Includes a subset of cases used to validate and tune the model during training.
3. **Test Set**: Consists of MRI scans with annotations not used during training or validation, provided to assess the performance of the final model.
4. **High-Resolution Imaging**: The dataset includes high-resolution MRI scans, which are crucial for accurate tumor segmentation and subsequent analysis.
5. **Segmentation Masks:** Contains labeled regions such as tumors or abnormalities, crucial for supervised learning tasks in medical imaging
6. **Longitudinal Data:** Comprises follow-up scans of the same patients over time, aiding in disease progression studies and treatment evaluation.

3. Types of Attacks

The BraTS dataset, like any medical imaging dataset, can be vulnerable to various types of attacks.

A. **Data Poisoning Attacks**: Maliciously altering or corrupting the training data to degrade the performance of machine learning models. In the context of BraTS, this could involve injecting incorrect tumor annotations or altering MRI scans to mislead the model.
B. **Adversarial Attacks**: Crafting specific perturbations to MRI images to fool the model into making incorrect predictions. These subtle changes can cause models to misclassify or fail to accurately segment tumor regions.
C. **Data Leakage**: Unauthorized access or disclosure of patient data. If sensitive patient information is exposed, it poses privacy risks and ethical concerns.
D. **Integrity Attacks**: Tampering with the dataset or the annotations to introduce errors or biases. This could involve changing tumor labels or corrupting images, which affects model accuracy and reliability.

4. Data Preprocessing

To improve the quality and efficiency of the dataset for machine learning models, several preprocessing steps are often applied:

- **Data Cleaning**: Removing redundant or noisy data points.
- **Image Cropping and Padding**: Crop or pad images to ensure consistent input sizes for the model.
- **Feature Extraction**: Extract relevant features from MRI scans, such as texture, shape, and intensity patterns. This step helps in reducing the dimensionality of the data and focusing on the most informative aspects for model training.
- **Clustering**: Group similar images or tumor regions to identify patterns and improve dataset organization. Clustering can help in identifying common characteristics and anomalies within the data.
- **Data Balancing**: Address class imbalances by resampling underrepresented classes or using synthetic data generation techniques.
- **Data Splitting**: Partition the dataset into training, validation, and test sets to evaluate model performance effectively.

5. Usage in the Proposed Study

In the proposed system for enhanced spatial intensity transformations in medical image-to-image translation, the BraTS dataset is pivotal for its comprehensive and multi- modal MRI scans, including T1, T1-CE, T2, and FLAIR sequences. It serves as the primary source of training and validation data, enabling the model to learn accurate image translations and improve tumor visualization.

The detailed annotations for different tumor regions guide the model in refining segmentation accuracy while performing spatial and intensity transformations. Preprocessing steps such as normalization and data augmentation are applied to ensure consistency and enhance model robustness. Ultimately, the BraTS dataset helps in evaluating the system's performance, allowing for comparative analysis with existing methods and demonstrating advancements in image quality and translation.

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VII. CONCLUSION

Enhanced spatial intensity transformations in medical image-to- image translation represent a significant advancement in improving the accuracy and quality of medical imaging. By deformations integrating sophisticated spatial adjustments, intensity modifications, and generative adversarial networks, this approach addresses key challenges such as preserving anatomical details and reducing artifacts. The results demonstrate enhanced image fidelity and more reliable translations across different modalities, paving the way for more effective diagnostic and treatment planning in clinical settings.

REFERENCES

[1]. J. M. Wolterink, T. Leiner, M. A. Viergever, and I. Išgum, "Generative adversarial networks for noise reduction in low- dose CT," *IEEE Trans. Med. Imag.*, vol. 36, no. 12, pp. 2536– 2545, Dec. 2017.

[2]. E. Kang, H. J. Koo, D. H. Yang, J. B. Seo, and J. C. Ye, "Cycleconsistent adversarial denoising network for multiphase coronary CT angiography," *Med. Phys.*, vol. 46, no. 2, pp. 550–562, Feb. 2019.

[3]. K. Chaitanya, N. Karani, C. Baumgartner, O. Donati, A. Becker, and E. Konukoglu, "Semi-supervised and task-driven data augmentation," 2019, *arXiv:1902.05396*.

[4]. Y. Chen, F. Shi, A. G. Christodoulou, Y. Xie, Z. Zhou, and D. Li, "Efficient and accurate MRI super-resolution using a generative adversarial network and 3D multi-level densely connected network," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.* Cham, Switzerland: Springer, 2018, pp. 91–99.

[5]. Y. Chen, A. G. Christodoulou, Z. Zhou, F. Shi, Y. Xie, and D. Li, "MRI super-resolution with GAN and 3D multi-level DenseNet: Smaller, faster, and better," 2020, *arXiv:2003.01217*.

[6]. T. M. Quan, T. Nguyen-Duc, and W. Jeong, "Compressed sensing MRI reconstruction using a generative adversarial network with a cyclic loss," *IEEE Trans. Med. Imag.*, vol. 37, no. 6, pp. 1488–1497, Jun. 2018.

[7]. G. Yang et al., "DAGAN: Deep de-aliasing generative adversarial networks for fast compressed sensing MRI reconstruction," *IEEE Trans. Med. Imag.*, vol. 37, no. 6, pp. 1310–1321, Jun. 2018.

[8]. H. Liao, Z. Huo, W. J. Sehnert, S. K. Zhou, and J. Luo, "Adversarial sparse-view CBCT artifact reduction," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.* Cham, Switzerland: Springer, 2018, pp. 154–162.

[9]. J. M. Wolterink, A. M. Dinkla, M. H. Savenije, P. R. Seevinck, C. A. van den Berg, and I. Išgum, "Deep MR to CT synthesis using unpaired data," in *Proc. Int. Workshop Simulation Synth. Med. Imag.* Cham, Switzerland: Springer, 2017, pp. 14–23.

[10]. D. Ravi, D. C. Alexander, and N. P. Oxtoby, "Degenerative adversarial neuroimage nets: Generating images that mimic disease progression," in Medical Image Computing and Computer Assisted Intervention— MICCAI, D. Shen et al., Eds. Cham, Switzerland: Springer, 2019, pp. 164–172.

[11]. M. F. Beg, M. I. Miller, A. Trouvé, and L. Younes, "Computing large deformation metric mappings via geodesic flows of diffeomorphisms," Int. J. Comput. Vis., vol. 61, no. 2, pp. 139–157, Feb. 2005.

[12]. J. Ashburner, "A fast diffeomorphic image registration algorithm," NeuroImage, vol. 38, no. 1, pp. 95–113, Oct. 2007.

[13]. B. Avants, C. Epstein, M. Grossman, and J. Gee, "Symmetric diffeomorphic image registration with cross-correlation: Evaluating automated labeling of elderly and neurodegenerative brain," Med. Image Anal., vol. 12, no. 1, pp. 26–41, Feb. 2008.

[14]. G. Balakrishnan, A. Zhao, M. R. Sabuncu, A. V. Dalca, and J. Guttag, "An unsupervised learning model for deformable medical image registration," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 9252–9260.

[15]. J. Krebs et al., "Robust non-rigid registration through agent-based action learning," in Medical Image Computing and Computer Assisted Intervention— MICCAI, M. Descoteaux, L. Maier- Hein, A. Franz, P. Jannin, D. L. Collins, and S. Duchesne, Eds. Cham, Switzerland: Springer, 2017, pp. 344–352.

[16]. T. F. Cootes, C. Beeston, G. J. Edwards, and C.J. Taylor, "A unified framework for atlas matching using active appearance models," in Information Processing in Medical Imaging, A. Kuba, M. Šáamal, and A. Todd-Pokropek, Eds. Berlin, Germany: Springer, 1999, pp. 322–333.

[17]. A. Bône, P. Vernhet, O. Colliot, and S. Durrleman, "Learning joint shape and appearance representations with metamorphic auto-encoders," in Medical Image Computing and Computer Assisted Intervention— MICCAI (Lecture Notes in Computer Science), A. L. Martel et al., Eds. Cham, Switzerland: Springer, 2020, pp. 202–211.

[18]. A. V. Dalca, M. Rakic, J. Guttag, and M. R. Sabuncu, "Learning conditional deformable templates with convolutional networks," 2019, arXiv:1908.02738