**Overview and Inspiration**

* **The significance of medical imaging**: CT and MRI are both commonly used and have distinct advantages.
  + **MRI**: Time-consuming and costly, but excellent for soft tissue contrast.
  + **CT**: Quick and reasonably priced, but it uses dangerous ionizing radiation.
* **Problem**: MRI is expensive and scarce compared to CT, which is widely available.
* **Objective**: Convert CT scans into MRI-like images by combining the diagnostic depth of MRI with CT accessibility.
* **Gap**: There was not much previous research on translating CT to MRI; however, GANs (Pix2Pix, UNIT, and CycleGAN) worked well for translating other medical texts.
* Because CycleGAN can handle unpaired datasets (i.e., no exact CT–MRI pairs), it was chosen as the model.

**Dataset**

* **Source**: Brain cross-sections, open-source Kaggle repository.
* **Domains**:
  + **Domain A**: CT scans.
  + **Domain B**: MRI scans.
* **Preparation**:
  + scaled to [-1, 1] (for tanh) and resized to 256 x 256 pixels.
  + 500 CT and 500 MRI pictures (out of about 1700 total) were chosen for training.
  + Because of the small dataset, augmentation is used to lessen overfitting.

**Methodology**

1. **Why Are GANs Used?**

* GANs are useful for translating contrast, textures, and anatomy in medical imaging because they can model complex transformations.
* **Challenge**: Unpaired CT and MRI scans → resolved with Cycle GAN.

1. **Architecture of Cycle GAN**

* **Generators**
  + Transformer (6 residual blocks) → Decoder → Encoder.
  + CT (256 x 256 x 3) input, synthetic MRI output.
* **Discriminators**:
  + PatchGAN is used to classify local patches as real or fake rather than the entire image.
  + Consistency of Cycles:Synthetic MRI → CT → reconstructed CT (should match original).maintains anatomical precision.

1. **Functions of Loss**

* **Adversarial Loss**: Promotes outputs that resemble real MRIs.
* **Cycle Consistency Loss**: Guarantees the ability to reconstruct translated images.
* Adversarial + Cycle Consistency = Total Loss.

**Experiments**

* **Framework**: Keras, TensorFlow 2.6.5, and Python 3.8.
* **Hardware**: RTX A6000 GPU from Nvidia (CUDA 11.3).
* **Instruction**:
  + 500 periods.
  + 500 is the batch size.
  + Fifty thousand times.
* **Metrics for Evaluation**:
  + MAE (Mean Absolute Error) → similarity in pixel values.
  + MSE (Mean Squared Error) → error magnitude.
  + PSNR (Peak Signal-to-Noise Ratio) → image quality & fidelity.

**Results**

* **Produced Pictures**:
* Realistic anatomical features and MRI-like images were generated by CycleGAN.
* For instance, the gray matter, white matter, CSF, and vessels were all clearly visible in the T1-weighted brain MRI obtained from the CT scan.
* **Quantitative Comparison (CNN vs. CycleGAN):**

|  |  |  |
| --- | --- | --- |
| **Metric** | **CNN** | **CycleGAN** |
| MAE | 70.44 | **0.5309** |
| MSE | 60.867 | **0.3790** |
| PSNR | 9.457 | **52.344** |

* **CycleGAN** performs significantly better than the CNN baseline.
* **Training Loss Trends**: Consistent decline across cycle and adversarial losses → model convergence verified.

**Conclusion**

* Success of CycleGAN:
* CT → MRI accurately translated without paired data.
* produced MRI-like, high-fidelity images with a high PSNR and minimal error.
* **Clinical Significance**:
  + lessens reliance on expensive MRI equipment.
  + prevents further radiation exposure.
  + decreases patient wait times and improves diagnostic capabilities.
  + When compared to CNN, CycleGAN performs noticeably better on unpaired medical datasets.

**Future Work**

* **Improvements**:
  + Sharper, higher-resolution MRI images can be obtained by integrating Super-Resolution GAN (SRGAN).
  + For more realism and detail, investigate hybrid CycleGAN + SRGAN.
  + For robustness, compare with Pix2Pix, UNIT, and UNet.
* **Objective**: Create MRI-like scans that are clinically dependable for wider diagnostic use.