Synthetic Data Generation for MRI and Tabular Data

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***Abstract*— In this study, synthetic data generation methods are used in the domain of brain disorders data. Several methods are utilized on tabular and MRI data. The tabular data is used for dementia diagnosis while the MRI data is used for the study of brain tumors. In this study, the fidelity of the generated data are explored in details in order to evaluate the used models in generating realistic images and tabular data. Using the MRI data, Patch/Pixel wise model Pix2Pix in addition to Convolutional VAE and Convolutional GANs are used with the aim to generate high fidelity images. The methods are loosely compared in terms of measuring the evaluation metrics for image fidelity. The comparison is supported through studying the structural similarity index and Peak Signal to Noise Ratio of the synthetic and real images. The comparison is also supported using PCA visualizations. For the Tabular data domain, GANs and VAEs based methods are used on the tabular data which achieved the best synthetic data fidelity. There are certain limitations in this study regarding the size of the data, resolution of the images and clinical validation. A future possible direction could be through studying the utility, privacy, and data augmentations. The code, methods and results of the experiments in this report is shared on GitHub.[1]**

***Index Terms*— Synthetic, MRI, Dementia, Tabular**

I. Introduction and Background

Brain Disorders such as Dementia, Alzheimer Disease (AD) affect many people worldwide. Alzheimer is a neurodegenerative disorder that causes cognitive decline, memory loss and changes in behavior of patients. Alzheimer and Dementia disorders remain poorly understood in terms of its pathogenic mechanism [1]. Dementia and Alzheimer Disease can be studie using electroencephalogram (EEG), Magnetic Resonance Imaging (MRI) or Tabular data. In this study, the main focus will be on MRI and tabular data. Magnetic Resonance Imaging (MRI) is a useful diagnostic tool for Dementia and Alzheimer which should be used intensively by researchers to understand more about this disease pathology and develop machine learning models to help clinicians in the diagnostics.

The medical data are in general highly sensitive and private data. This introduces major limitations in developing machine learning models as these models highly depend on the availability of big data repository for training. One prominant solution for this challenge is the use of synthetic data. This way the original data can be protected and not shared while the synthetic data is used instead. Synthetic data generation has the capability to augment limited training datasets to improve model performance and provide privacy for the original data. Several approaches and variants are used in synthetic generations are mainly based on Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs) and diffusion models.

GANs can produce visually realistic MRI images but can be prone to hallucinations and mode collapse. The study [2] reports several methods for MRI and CT scans. The study [3] used Conditional-GAN by adding labels in medical image synthesis to add constraints to the models. Another study [4] used U-Net [5] based architecture combined with GANs to generate CT and MRI scans. U-Net [6] was used to generate synthetic CT images from MRI. CycleGAN [7] was applied on MRI and CT scans, however, anatomical inconsistencies were reported. Diffusion models such as DDPMs have recently outperfomed GANs in fidelity [8], [9]. Diffusion models make the data generation as the reversal of a noising process which produce robust results. These models show great promise in the medical imaging. However, This is beyond the scope of this study.

Several challenges remain open. One of the challenges is Preventing hallucinations and ensuring structural fidelity. Furthermore, rigorous Clinical evaluation is needed to evaluate the data. Furthermore, handling data leakage risks in synthetic data remain an open question in research.

Our Objectives in this study are:

- Building different Synthesizers for Dementia tabular data and comparing between the fidelity of the generated data for each of used models.
- Building different Synthesizers for MRI data on both the fine-grained patches/pixels and on large feature maps levels and comparing between the fidelity of the generated images.

The study will report results on generic MRI from brain tumor diagnosis. However, the same methods should be extended to MRI for dementia diagnosis. The tabular data is from dementia disease patients. The format of this study is as in the following: In the section II the details about the chosen data is reported aligned with the motivation of study. Section III explains the used models in this study. Here, Six different models are used in generating synthetic data. Section IV reports the main results in this study summarized and compared through figures. Section V compare and summarize the findings in this study and discuss the fidelity of generated data from all the models. Section VI concludes the study main findings with limitations and future development.

II. Used Data

In this study, two types of datasets were used. The first dataset is structured tabular dataset in which three tabular different synthetic generation models were used. The second data is unstructured medical MRI images in which three different models were used to generate synthetic data. Both the used data are publicly available for research purposes.

1) Dementia Tabular data: This data is from the the Open Access Series of Imaging Studies (OASIS) [2] from Washington University Alzheimer's Disease Research Center. OASIS project aims at making MRI data sets of the brain available to the scientific applications for future discovery and clinical uses. OASIS provides rich content with several versions of MRI and tabular data. These data is provided by [10] from OASIS and can be used for Alzheimer and Dementia diagnosis and detection. In this study, the focus on using the metadata content from MRI. This data has nondemented and demented subjects that covers a cross-sectional collection of 416 subjects aged 18 to 96. The dataset consists of both men and women.

2) MRI data: The MRI data in this study is shared by [11]. The dataset is hosted publicly on the Kaggle platform[3]. It consists of collection of brain MRI scans. The dataset is mainly for brain tumors detections. It includes labeled images with and without tumors. This

[1] https://github.com/mhmdrdwn/synthetic_MRI/

[2] https://sites.wustl.edu/oasisbrains/

[3] https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection/data

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Generator                                [1, 5]                    --
├─Sequential: 1-1                        [1, 5]                    --
│    └─Linear: 2-1                       [1, 64]                   704
│    └─ReLU: 2-2                         [1, 64]                   --
│    └─Linear: 2-3                       [1, 128]                  8,320
│    └─ReLU: 2-4                         [1, 128]                  --
│    └─Linear: 2-5                       [1, 5]                    645
==========================================================================================
Total params: 9,669
Trainable params: 9,669
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 0.01
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.04
Estimated Total Size (MB): 0.04
==========================================================================================
```

(a) Generator

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Discriminator                            [1, 1]                    --
├─Sequential: 1-1                        [1, 1]                    --
│    └─Linear: 2-1                       [1, 128]                  768
│    └─LeakyReLU: 2-2                    [1, 128]                  --
│    └─Linear: 2-3                       [1, 64]                   8,256
│    └─LeakyReLU: 2-4                    [1, 64]                   --
│    └─Linear: 2-5                       [1, 1]                    65
│    └─Sigmoid: 2-6                      [1, 1]                    --
==========================================================================================
Total params: 9,089
Trainable params: 9,089
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 0.01
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.04
Estimated Total Size (MB): 0.04
==========================================================================================
```

(b) Discriminator

Fig. 1: General GAN architecture layers

dataset has 253 subjects in the two classes of subjects. 155 subjects have tumors and 98 subjects are healthy.

III. Methodology

One of the main method used for generating synthetic data is the Generative Adversarial Network (GAN) [12]. GAN consists of two elements: Generator (G) and Discriminator (D) which are trained in an adversarial manner. The general architecture of GAN is as shown in Figure 1.

The generator aims to produce realistic samples from random noise z, while the discriminator aims to distinguish real data x from generated data $G(z)$. The general objective function consists of the discriminator loss which is:

$$\mathcal{L}_D = -\mathbb{E}_{x\sim p_{\text{data}}}\big[\log D(x)\big] - \mathbb{E}_{z\sim p_z}\big[\log(1 - D(G(z)))\big]$$

In the first term, discriminator wants to classify real data as 1. The second term, discriminator wants to classify fake data as 0. Generator wants to maximize $D(G(z))$ to fool the discriminator with the following loss:

$$\mathcal{L}_G = -\mathbb{E}_{z\sim p_z}\big[\log D(G(z))\big]$$

The other main method used for generating synthetic data is the Variational Autoencoder (VAE) [13]. VAE consists of encoder and decoder. The encoder maps input data to the latent representation and the decoder maps Maps latent representation back to reconstructed data. This is done by optimizing reconstruction Loss such as MSE between the original and reconstructed and KL Divergence loss to regularize latent space. KLD loss penalizes the encoder if it makes distributions that drift too far from the original.

A. Tabular Synthesizers

1) Conditional Tabular GAN (CTGAN): CTGAN was introduced by [14] as a GAN method designed for tabular data. This model can handle mixture of categorical and numerical features. CTGAN is simply a GAN [12] variant with several modifications. The generator outputs synthetic tabular rows where both continuous and categorical variables are generated. The Discriminator attempts to distinguish real from synthetic rows, while being conditioned on the same categorical variable used by the generator. Here, Gaussian Mixture Model (GMM) is used to transform Continuous columns to model skewed and multimodal distributions. CTGAN uses categorical variable for sampling and feed as a condition during training which outputs a synthetic row conditioned on that category. Here, CTGAN outputs valid combinations of categorical and continuous values In other words, CTGAN extends the standard GAN objective with conditional information from categorical variables.

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
VAE                                      [1, 5]                    --
├─Sequential: 1-1                        [1, 64]                   --
│    └─Linear: 2-1                       [1, 64]                   384
│    └─ReLU: 2-2                         [1, 64]                   --
├─Linear: 1-2                            [1, 5]                    325
├─Linear: 1-3                            [1, 5]                    325
├─Sequential: 1-4                        [1, 5]                    --
│    └─Linear: 2-3                       [1, 64]                   384
│    └─ReLU: 2-4                         [1, 64]                   --
│    └─Linear: 2-5                       [1, 5]                    325
│    └─Sigmoid: 2-6                      [1, 5]                    --
==========================================================================================
Total params: 1,743
Trainable params: 1,743
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 0.00
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.01
Estimated Total Size (MB): 0.01
==========================================================================================
```

Fig. 2: General VAE architecture layers. The two sequential layers are the encoder and decoder, respectively.

2) Tabular Variational Autoencoder (TVAE): TVAE was introduced by [14] as VAE method for synthesizing tabular data with a mixture of categorical and continuous features. TVAE is a variant of the VAE model [13] with extra preprocessing steps for tabular datasets. So, TVAE has encoder and decoder. Here, continuous variables are used directly while categorical variables are represented with one-hot encoding and used as a softmax layer in the decoder. The loss function is a combination of MSE for Continuous variables and Cross-entropy loss for categorical variables. This means that training objective are applied separately per feature type.

3) Deep Regret Analytic GAN (DRAGAN): DRAGAN [15] is another variant of GAN [12] with gradient penalty to help to stabilize training and reduce mode collapse. This works by training GANs and penalizing the discriminator's gradient around real data points. Gradient penalty forces the discriminator to behave smoothly around real data. In practice, This works by the adding small perturbation noise around real data points before calculating the gradient of discriminator with respect to the real data point. This penalty serves as a term in the loss function of the discriminator during training.

B. Image Synthesizers

1) Deep Convolutional Generative Adversarial Networks (DCGAN): DCGAN [3] is a class of GANs [12] that uses deep convolutional neural networks (CNN) in the generator and discriminator to be used mainly for images. Instead of full connected layers, the DCGAN generator uses a series of transposed convolutional layers with batch normalization and ReLU function. The final layer uses Tanh activations. The discriminator uses convolutional layers that classifies an input image as either real or fake. It uses convolutions, LeakyReLU activations followed by final sigmoid activation. The architecture is shown in Figure 3.

2) Pix2Pix Model: Pix2Pix [16] is an image to image translation model based on GANs. This model learns a translation mapping from an input image to an output image using the adversarial loss.

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Generator                                [1, 3, 64, 64]            --
├─Sequential: 1-1                        [1, 3, 64, 64]            --
│    └─ConvTranspose2d: 2-1              [1, 512, 4, 4]            819,200
│    └─BatchNorm2d: 2-2                  [1, 512, 4, 4]            1,024
│    └─ReLU: 2-3                         [1, 512, 4, 4]            --
│    └─ConvTranspose2d: 2-4              [1, 256, 8, 8]            2,097,152
│    └─BatchNorm2d: 2-5                  [1, 256, 8, 8]            512
│    └─ReLU: 2-6                         [1, 256, 8, 8]            --
│    └─ConvTranspose2d: 2-7              [1, 128, 16, 16]          524,288
│    └─BatchNorm2d: 2-8                  [1, 128, 16, 16]          256
│    └─ReLU: 2-9                         [1, 128, 16, 16]          --
│    └─ConvTranspose2d: 2-10             [1, 64, 32, 32]           131,072
│    └─BatchNorm2d: 2-11                 [1, 64, 32, 32]           128
│    └─ReLU: 2-12                        [1, 64, 32, 32]           --
│    └─ConvTranspose2d: 2-13             [1, 3, 64, 64]            3,072
│    └─Tanh: 2-14                        [1, 3, 64, 64]            --
==========================================================================================
Total params: 3,576,704
Trainable params: 3,576,704
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 428.35
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 2.06
Params size (MB): 14.31
Estimated Total Size (MB): 16.37
==========================================================================================
```

(a) Generator

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Discriminator                            [1, 1, 1, 1]              --
├─Sequential: 1-1                        [1, 1, 1, 1]              --
│    └─Conv2d: 2-1                       [1, 64, 32, 32]           3,072
│    └─LeakyReLU: 2-2                    [1, 64, 32, 32]           --
│    └─Conv2d: 2-3                       [1, 128, 16, 16]          131,072
│    └─BatchNorm2d: 2-4                  [1, 128, 16, 16]          256
│    └─LeakyReLU: 2-5                    [1, 128, 16, 16]          --
│    └─Conv2d: 2-6                       [1, 256, 8, 8]            524,288
│    └─BatchNorm2d: 2-7                  [1, 256, 8, 8]            512
│    └─LeakyReLU: 2-8                    [1, 256, 8, 8]            --
│    └─Conv2d: 2-9                       [1, 512, 4, 4]            2,097,152
│    └─BatchNorm2d: 2-10                 [1, 512, 4, 4]            1,024
│    └─LeakyReLU: 2-11                   [1, 512, 4, 4]            --
│    └─Conv2d: 2-12                      [1, 1, 1, 1]              8,192
│    └─Sigmoid: 2-13                     [1, 1, 1, 1]              --
==========================================================================================
Total params: 2,765,568
Trainable params: 2,765,568
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 103.82
==========================================================================================
Input size (MB): 0.05
Forward/backward pass size (MB): 1.44
Params size (MB): 11.06
Estimated Total Size (MB): 12.55
==========================================================================================
```

(b) Discriminator

Fig. 3: DCGAN architecture layers

In other words, Pix2Pix generates output image conditioned on the input image. The generator in Pix2Pix is based on U-Net [5] which is encoder-decoder structure with skip connections that allow the transfer of fine-grained spatial features from the encoder to the decoder. The discriminator does not classify the entire image as real or fake. Instead, the discriminator (PatchGAN) looks at small patches of the image (pixels wise) and outputs a prediction for each patch as real or fake. If all patches look real, the whole image is considered real. In this case, the real image is fed into the model as input and output. The architecture is shown in Figure 4.

This model is mainly used for image to image translation. This means that the model needs the original image as input in order to reconstruct it. This is a major limitation in this model as the aim should be to generate new samples in the same distribution of the input images. The workaround here is to add random gaussian noise to the input image before feeding to the model during training and inference. However, this remains a suboptimal solution.

3) Convolutional Variational Autoencoder: The architecture is based on CNN with B-VAE. B-VAE was introduced by [17] is an extension of VAE with addition of Beta weight in the KL divergence term in the loss function to help further with regularization. Convolutional Variational Autoencoder consists of encoder and decoder. The Encoder has four layers of convolution followed by ReLU layers while the Decoder has four transposed convolutional followed by ReLU layers to reconstruct the image. The architecture is shown in Figure 5.

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
UNetGenerator                            [1, 3, 64, 64]            --
├─Sequential: 1-1                        [1, 256, 8, 8]            --
│    └─Conv2d: 2-1                       [1, 64, 32, 32]           3,136
│    └─LeakyReLU: 2-2                    [1, 64, 32, 32]           --
│    └─Conv2d: 2-3                       [1, 128, 16, 16]          131,200
│    └─BatchNorm2d: 2-4                  [1, 128, 16, 16]          256
│    └─LeakyReLU: 2-5                    [1, 128, 16, 16]          --
│    └─Conv2d: 2-6                       [1, 256, 8, 8]            524,544
│    └─BatchNorm2d: 2-7                  [1, 256, 8, 8]            512
│    └─LeakyReLU: 2-8                    [1, 256, 8, 8]            --
├─Sequential: 1-2                        [1, 3, 64, 64]            --
│    └─ConvTranspose2d: 2-9              [1, 128, 16, 16]          524,416
│    └─BatchNorm2d: 2-10                 [1, 128, 16, 16]          256
│    └─ReLU: 2-11                        [1, 128, 16, 16]          --
│    └─ConvTranspose2d: 2-12             [1, 64, 32, 32]           131,136
│    └─BatchNorm2d: 2-13                 [1, 64, 32, 32]           128
│    └─ReLU: 2-14                        [1, 64, 32, 32]           --
│    └─ConvTranspose2d: 2-15             [1, 3, 64, 64]            3,075
│    └─Tanh: 2-16                        [1, 3, 64, 64]            --
==========================================================================================
Total params: 1,318,659
Trainable params: 1,318,659
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 351.50
==========================================================================================
Input size (MB): 0.05
Forward/backward pass size (MB): 2.98
Params size (MB): 5.27
Estimated Total Size (MB): 8.31
==========================================================================================
```

(a) Generator

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Discriminator                            [1, 1, 7, 7]              --
├─Sequential: 1-1                        [1, 1, 7, 7]              --
│    └─Conv2d: 2-1                       [1, 64, 32, 32]           6,208
│    └─LeakyReLU: 2-2                    [1, 64, 32, 32]           --
│    └─Conv2d: 2-3                       [1, 128, 16, 16]          131,200
│    └─BatchNorm2d: 2-4                  [1, 128, 16, 16]          256
│    └─LeakyReLU: 2-5                    [1, 128, 16, 16]          --
│    └─Conv2d: 2-6                       [1, 256, 8, 8]            524,544
│    └─BatchNorm2d: 2-7                  [1, 256, 8, 8]            512
│    └─LeakyReLU: 2-8                    [1, 256, 8, 8]            --
│    └─Conv2d: 2-9                       [1, 1, 7, 7]              4,097
│    └─Sigmoid: 2-10                     [1, 1, 7, 7]              --
==========================================================================================
Total params: 666,817
Trainable params: 666,817
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 73.72
==========================================================================================
Input size (MB): 0.10
Forward/backward pass size (MB): 1.31
Params size (MB): 2.67
Estimated Total Size (MB): 4.08
==========================================================================================
```

(b) Discriminator

Fig. 4: Pix2Pix architecture layers

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
BetaVAE                                  [1, 3, 64, 64]            --
├─Encoder: 1-1                           [1, 128]                  --
│    └─Conv2d: 2-1                       [1, 32, 32, 32]           1,568
│    └─ReLU: 2-2                         [1, 32, 32, 32]           --
│    └─Conv2d: 2-3                       [1, 64, 16, 16]           32,832
│    └─ReLU: 2-4                         [1, 64, 16, 16]           --
│    └─Conv2d: 2-5                       [1, 128, 8, 8]            131,200
│    └─ReLU: 2-6                         [1, 128, 8, 8]            --
│    └─Conv2d: 2-7                       [1, 256, 4, 4]            524,544
│    └─ReLU: 2-8                         [1, 256, 4, 4]            --
│    └─Linear: 2-9                       [1, 128]                  524,416
│    └─Linear: 2-10                      [1, 128]                  524,416
├─Decoder: 1-2                           [1, 3, 64, 64]            --
│    └─Linear: 2-11                      [1, 4096]                 528,384
│    └─ConvTranspose2d: 2-12             [1, 128, 8, 8]            524,416
│    └─ReLU: 2-13                        [1, 128, 8, 8]            --
│    └─ConvTranspose2d: 2-14             [1, 64, 16, 16]           131,136
│    └─ReLU: 2-15                        [1, 64, 16, 16]           --
│    └─ConvTranspose2d: 2-16             [1, 32, 32, 32]           32,800
│    └─ReLU: 2-17                        [1, 32, 32, 32]           --
│    └─ConvTranspose2d: 2-18             [1, 3, 64, 64]            1,539
│    └─Tanh: 2-19                        [1, 3, 64, 64]            --
==========================================================================================
Total params: 2,957,251
Trainable params: 2,957,251
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 135.40
==========================================================================================
Input size (MB): 0.05
Forward/backward pass size (MB): 1.08
Params size (MB): 11.83
Estimated Total Size (MB): 12.96
==========================================================================================
```

Fig. 5: Convolutional Beta Variational Autoencoder architecture layers

C. Evaluation Metrics

In this study, several synthetic data evaluation metrics are used to measure the similarity between real and generated data. These evaluation metrics are used to give details about the fidelity of the synthetic data. The following metrics are used:

1) Mean Square Error (MSE): This metric is the Mean Squared Error between the real R and the synthetic image S.

$$\text{MSE} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\big(R(i,j) - S(i,j)\big)^2$$

2) Peak Signal-to-Noise Ratio (PSNR): PSNR is used to measure the quality of a synthetic compared to the original image. It indicates how much noise in the synthetic image. Higher PSNR means the better quality of synthetic images. The PSNR is given by the following equation:

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right)$$

where MAX is the maximum pixel value of the image. It is usually 255 for RGB images and MSE is the Mean Squared Error between the real and the synthetic images. In practice, PSNR values that are higher than 30 dB are good quality while values less than 20 dB indicates heavy distortion in the synthetic image

3) Structural Similarity Index (SSIM): The Structural Similarity Index (SSIM) is a metric that quantifies the similarity between two images brought from classical image analysis. Given real R and synthetic S images, the SSIM is defined as:

$$\text{SSIM}(x,y) = \frac{(2\mu_R\mu_S + C_1)(2\sigma_{RS} + C_2)}{(\mu_R^2 + \mu_S^2 + C_1)(\sigma_R^2 + \sigma_S^2 + C_2)}$$

where μ_R, μ_S are the mean intensities of R and S, σ_R^2, σ_S^2 are the variances of R and S, σ_{RS} is the covariance between R and S, C_1, C_2 are small constants to stabilize the division. The values of SSIM lies between 0 and 1 where 0 indicates limited structural similarity and 1 indicates perfect structural similarity.

4) Principal Component Analysis (PCA): Principal Component Analysis (PCA) is a method for dimensionality reduction. It is used to reduce the high dimension data into lower dimensions space while preserving data features variance. PCA theoretical details are beyond the scope of this article. However, PCA is used here to study the similarity between synthetic and real data in low dimension space assuming that similar data points will share local neighborhood in the 2D space.

D. Technical Specifications

The used MRI images are already preprocessed for artifacts and cleaning. Before training, the data was resize to (64x64) pixel size. This small size is used for training the model as it is more efficient. However, bigger size can be used but this will essentially lead to long training time. The data was standardized to the scale (-1, 1). The Image synthesizers are trained for 200 epochs. Here the epoch means that the model is trained on the whole dataset 200 times. During the training, learning rates, number of layers are optimized for each model.

For the tabular data, NaN features are removed from the data in addition to the "Hand" feature which has only one value (R). The remaining features that are used for training are five. Four of those are numerical while only one is categorical. More details of experiments are shown in the GitHub repository [4]

[4] https://github.com/mhmdrdwn/synthetic_MRI/

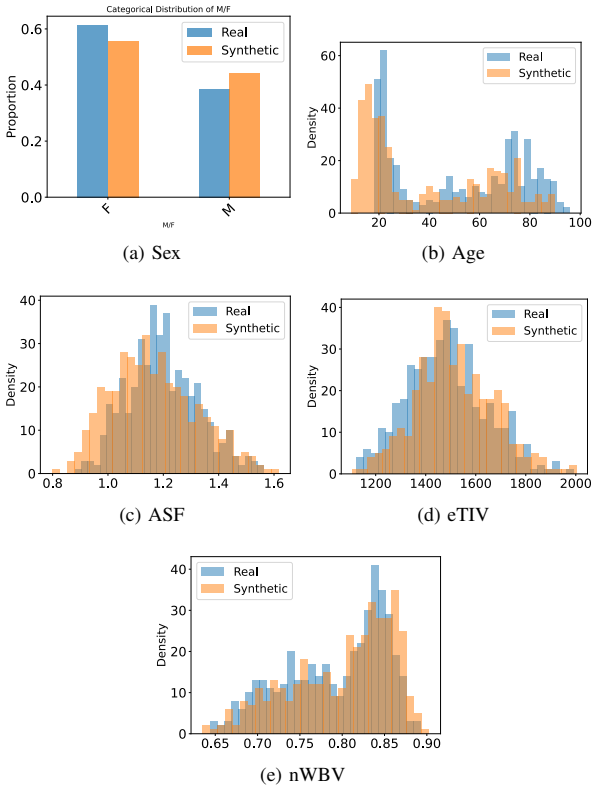


Fig. 6: Features Distribution of original vs synthetic data using CTGAN model

IV. Results

In this section, the generated synthetic data for both the used datasets are shown and studied for fidelity. The results for tabular data are shown in section IV-A and the results for image data are shown in section IV-B.

A. Tabular Synthetics

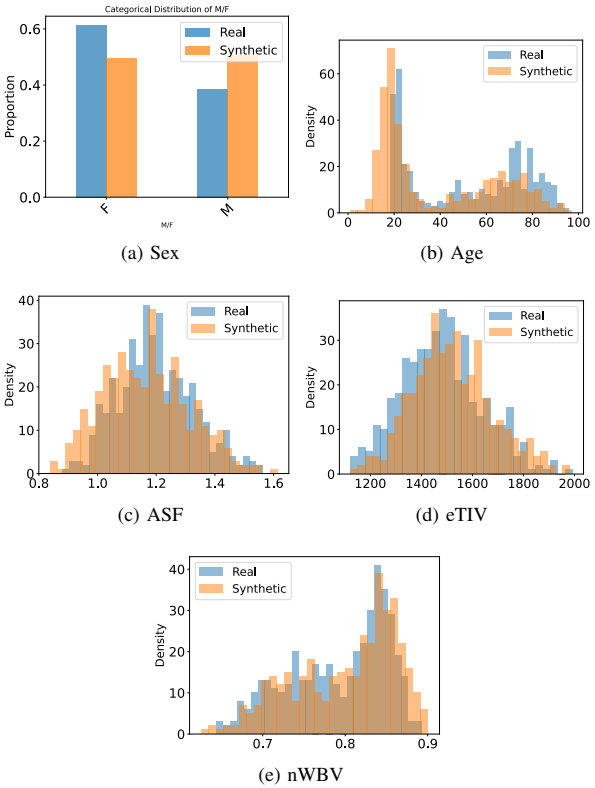
The generated synthetic in this section is generated using three different tabular models: CTGAN, TVAE and DRAGAN. In the following subsection IV-A.1, IV-A.2, IV-A.3, results are shown in terms of statistical and fidelity properties.

1) CTGAN generated tabular: After generating synthetic data using CTGAN tabular model, Figure 6 shows the distribution of the synthesized features versus the real features. In this figure, five features are shown. One categorical and four numerical. The distributions of the real and synthetic features show high overlap in general.

For the sex variable, the synthetic data is well represented for both the sexes as shown in Figure 6. Furthermore, Age, ASF, eTIV and nWBV synthetic distributions show high overlaps with the real data.

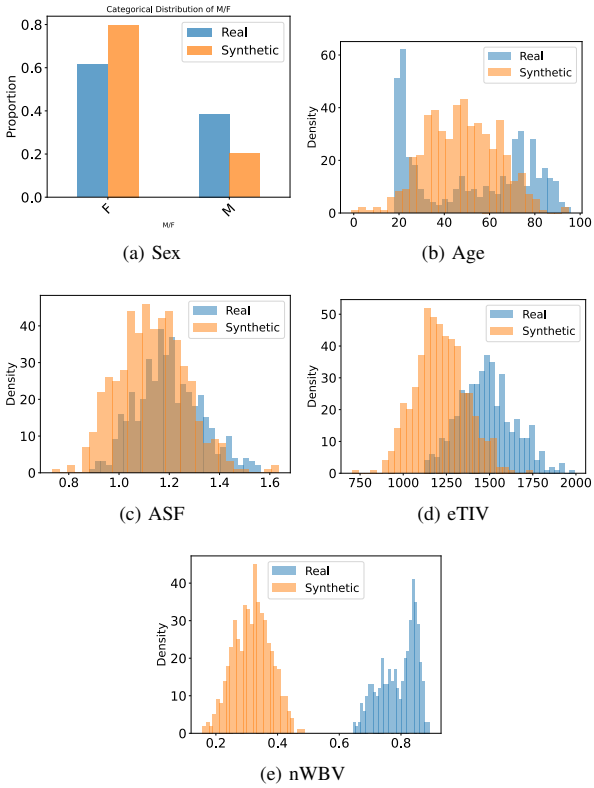
2) TVAE generated tabular: In a similar fashion to the previous figure of CTGAN, the synthetic and real features distributions are shown in Figure 8. The distributions of the real and synthetic features show high overlap in general for all the features. TVAE shows better overlap than CTGAN generated features.

3) DRAGAN generated tabular: Figure 8 shows the distributions of the real and synthetic features using the DRAGAN model. The distributions have limited overlaps. For the sex variable, the synthetic data has comparable distribution of both sex. However, for the eTIV



(a) Sex (b) Age (c) ASF (d) eTIV (e) nWBV

Fig. 7: Distribution of original vs synthetic data using TVAE model



(a) Sex (b) Age (c) ASF (d) eTIV (e) nWBV

Fig. 8: Distribution of original vs synthetic data using DRAGAN model

and nWBV features, the synthetic data generate data with ranges that are not covered in the original data.

4) Comparison: Table I reports and compares mean, standard deviation, skewness and kurtosis of the synthetic data features and the real data. The comparison is shown for the three used models on the tabular data. From the statistical analysis, the features (eTIV, mWBV, ASF), CTGAN and TVAE generate the synthetic data has comparable mean, std, Kurtosis and Skewness values. DRAGAN has the worst generated data in general except for Age feature. DRAGAN model generated data have the closest mean to the real data for the Age feature.

	Real Data				CTGAN Synthetic			
Row	mean	std	skewness	kurtosis	mean	std	skewness	kurtosis
Age	51.35	25.26	0.00	-1.59	38.3	24.6	0.53	-1.25
eTIV	1481.9	158.74	0.26	-0.15	1517.45	156.0	0.27	0.022
nWBV	0.79	0.059	-0.52	-0.88	0.8	0.06	-0.65	-0.58
ASF	1.19	0.128	0.28	-0.17	1.16	0.15	0.36	-0.382
	TVAE Synthetic				DRAGAN Synthetic			
Row	mean	std	skewness	kurtosis	mean	std	skewness	kurtosis
Age	38.12	25.36	0.592	-1.230	47.48	15.70	-0.01	-0.271
eTIV	1522.3	156.32	0.292	-0.08	1216.3	147.89	0.16	0.089
nWBV	0.80	0.062	-0.57	-0.72	0.317	0.06	-0.039	-0.39
ASF	1.16	0.14	0.26	-0.385	1.131	0.13	0.27	0.24

TABLE I: Statistical properties of the generated synthetic data for the used three models in comparison with the real data.

B. MRI Image Synthetics

Here, the generated synthetic images are shown for visual inspection and further fidelity analysis of those generated images are shown in details.

1) DCGAN generated images: Figure 9 shows randomly selected images from the synthetic data for visual inspection. Those samples are normalized between [0, 1]. However, it is hard to tell whether the images are realistic based only visual inspection specially in GAN generated images as we can not compare synthetic to real images directly. However, we argue if the GAN is working to generate realistic images, that some of generated synthetic images maybe are similar to the real images. In order to understand that, we will use PCA visualization of the real and synthetic features.

For better analysis, Figure 10 shows the distribution of raw images samples when reduced on 2D space using PCA. Here the distributions of synthetic and real images have high overlaps. This indicates that the model maybe is generating synthetic data in the same distribution of the real images.

2) Pix2Pix generated images: To study the fidelity of the generated images using Pix2Pix model, randomly selected images from the synthetic and real images are shown in Figure 11 for visual inspection. As explained earlier, the Pix2Pix expects the original images as input to the model. It is noticed from Figure 11 that the generated images are almost identical to real images even from non expert experience. This suggest that the model has learned to compress/reconstruct the input images. The images in Figure 12 are generated after adding gaussian noise to the same input real images used in Figure 11 at inference time.

Figure 13 shows the PCA reduced features visualizations of the data points from noisy real and synthetic images. The synthetic and real images showing similarity in which similar samples end up near each other which maybe suggests that some of generated images are realistic.

For further analysis, Figure 14 shows the MSE, PSNR and SSIM

Fig. 9: Samples of normalized Generated synthetic images of DC-GAN model. This batch of images has 64 MRI scans to be used for visual inspections.

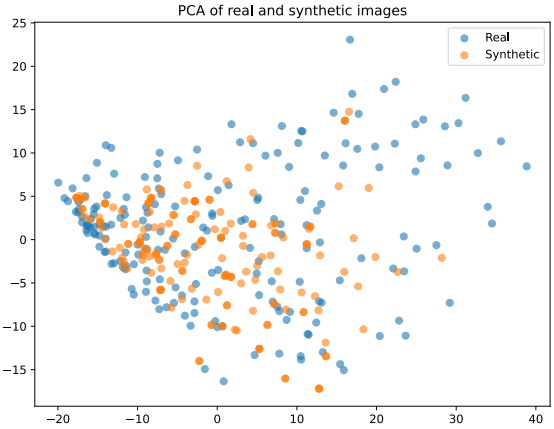
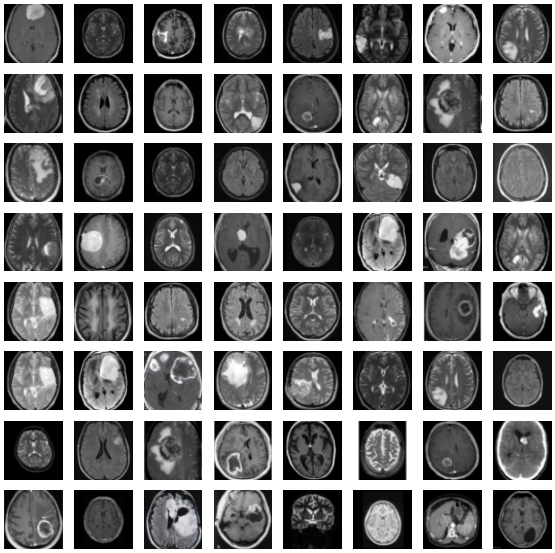
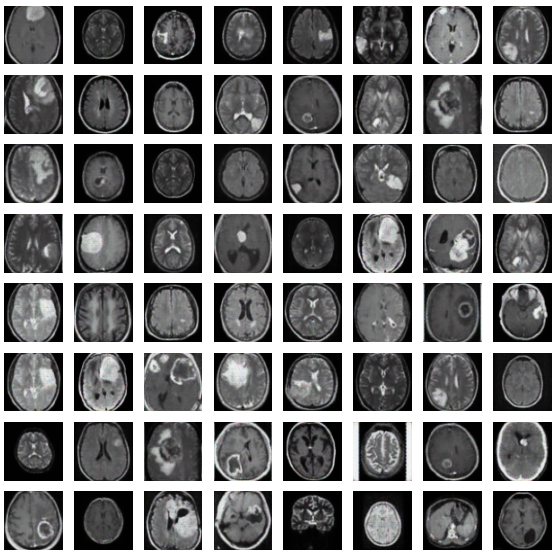


Fig. 10: PCA Distribution of real and synthetic images using DC-GAN model. In this figure, raw pixels are used.



(a) Real Data



(b) Synthetic Data

Fig. 11: Normalized real and generated synthetic images using Pix2Pix model using input images as constraint. This is used to evaluate the model ability to reconstruct images

between each of the generated and the noisy real images. Those metrics are counted over three batches of the data. This means there are comparisons between 192 synthetic and real images. The MSE values are between 0.0006 and 0.016 with mode around 0.011. The PSNR has a distribution of mode around 18 and the minimum value is 15. The SSIM has a distribution of mode around 0.5 and the minimum value is 0.3.

3) Convolutional VAE generated images: Generated images using VAE model are randomly selected and compared with real images and are shown in Figure 15. Here, the real data is the same ones used in Figure 11. It is noticed from Figure 15 that the generated images are highly similar to the real images when using the original images as input at the inference level. When using random noise as input, the Figure 16 shows the generated images from the VAE model with random sampling.

Figure 17 shows the PCA reduced features visualizations of the data points from real and synthetic images by random sampling. The synthetic and real images showing similarity in which similar samples end up near each other.

Figure 18 shows the MSE, PSNR and SSIM between each of the generated and real images. The MSE values are between 0.002 and 0.007 with mode around 0.004. The PSNR has a distribution of mode around 24 and the minimum value is 18. The SSIM has a distribution of mode around 0.8 and the minimum value is 0.4.

V. Discussion

A. Tabular synthetic Data

CTGAN and TVAE generate the synthetic data has more similar to the real data. This is supported from studying the overlapping distribution and studying of statistical analysis such as mean, std,

Fig. 12: Normalized Generated synthetic images of Pix2Pix model after adding random noise to the input data. Here, only synthetic data is shown while the real data is the same subset used in Fig 11

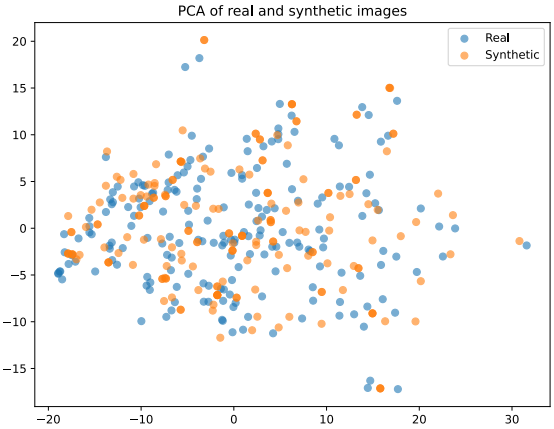


Fig. 13: PCA Distribution of real and synthetic images using Pix2Pix model after adding gaussian noise to the input image. In this figure, raw pixels are used.

Kurtosis and Skewness. This suggests that fidelity of the synthetic data generated by CTGAN and TVAE and relatively higher than DRAGAN. DRAGAN generates the worst synthetic data in terms of fidelity. In the case mWBV feature, DRAGAN generate feature values that are entirely out of distribution. It is also worth noting that the results from DRAGAN are also not numerically stable. This maybe is related to the small size of the data.

B. MRI synthetic Data

The PCA plots from DCGAN, Pix2Pix and Convolutional VAE models suggests that the synthetic data points preserve local neighborhood structure with real data. As overlapping clusters usually mean the synthetic data has learned many of the local relationships present in the real data. The synthetic data may have similar modes and variance as the real data. These are good sign of high fidelity for DCGAN, Pix2Pix and VAE.

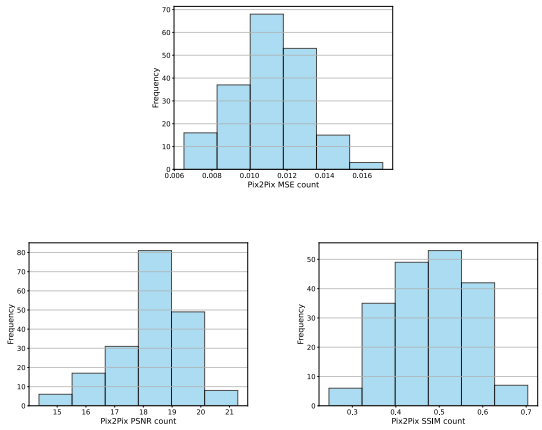


Fig. 14: Normalized Generated synthetic images of Pix2Pix model for comparison between generated images and

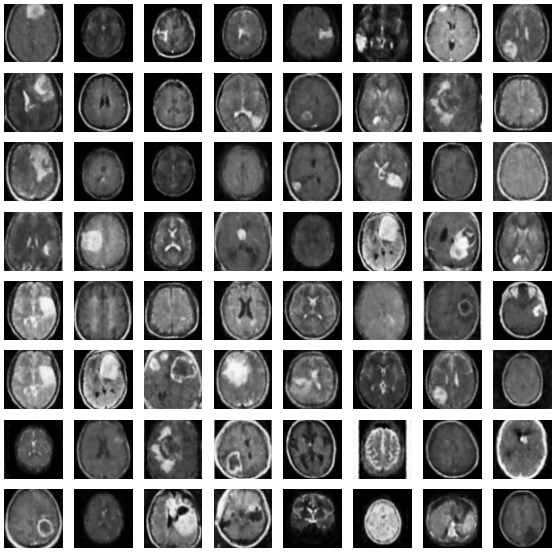


Fig. 15: Normalized Generated synthetic images of Convolutional VAE model. Here, only synthetic data is shown while the real data is the same subset used in Fig 11. Note that these generated images are using original images as input at inference. It is used here to see how well the model learned to compress/reconstruct the input images.

By comparing the three models results, It is still hard to conclude about the performances. The Convolutional VAE model achieved the strong performances in terms of generating synthetic MRI images and Applicability. As reported in Figure 15. The Convolutional VAE was able to reconstruct the original images supported by visual inspection and evaluations metrics (SSIM, MSE, PSNR). Furthermore, Figure 17 suggests that the model has learned sampling images that are close to the real distribution. VAE generated images show PSNR values between 18 and 27 which indicates that large portions of the images are of good quality. The PSNR values are in general higher for the Pix2Pix model than Convolutional VAE. This suggests that Pix2Pix generated the highest fidelity data in this study.

The main weakness of Pix2Pix is that it needs input or original images at inference as it form as a translation of images. In that case we can evaluate the model ability to reconstruct images. This

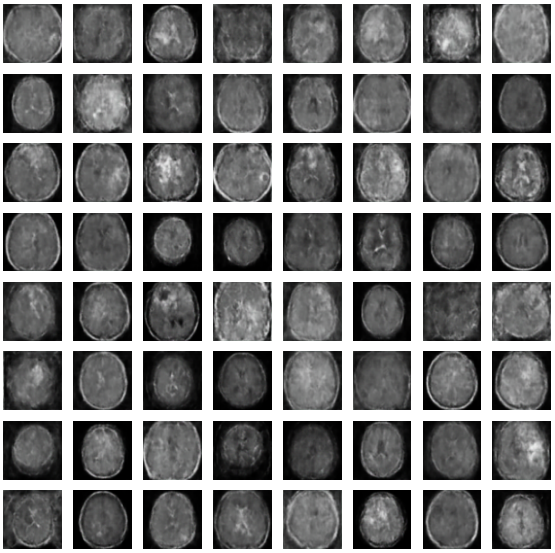


Fig. 16: Normalized Generated synthetic images of Convolutional VAE model using random sampling.

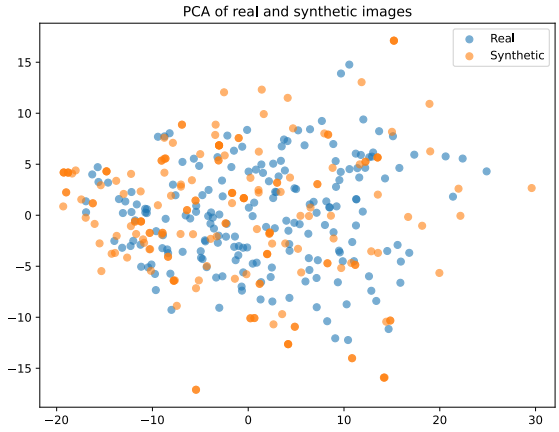


Fig. 17: PCA Distribution of real and synthetic images using Convolutional VAE model. In this figure, raw pixels are used. Note that these matrices are used when using original images as inputs instead of random sampling. Here the objective is to test the model ability in images reconstruction not synthesizing

makes this model a constructor not synthesizers. Here, the model is not similar to other models such as GANs or VAEs which takes in random noise and generate a realistic image from it at inference. The workaround this limitations is by adding noise to the input images which can be equivalent to feeding gaussian noise to the VAEs at inference. However, the model can be extended further development in order to generate new synthetic images from the distribution. But this model maybe is useful in synthetic data augmenations and images denoising.

VI. Conclusion and Future Work

In this study, the objective is building high fidelity synthetic MRI and tabular data for the goal of diagnosis of brain disorders is approached. Several models are used in the study including tabular and image based synthetic models. DCGAN and TVAE tabular models generate relatively high fidelity tabular features.

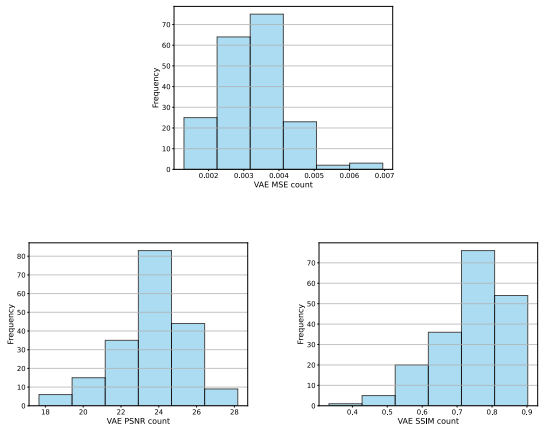


Fig. 18: Normalized Generated synthetic images of Convolutional VAE model

For the synthetic image generation, the used models generates images that are in the same distribution of the real images by looking at PCA plots. Pix2Pix can be extended further for extra applications such as image denoising, image cleaning and data augmentations which are essential for training deep learning models. This is possible direction for further development of this model.

There remain room for developments in terms of the used methods and building other methods such as Diffusion models. Diffusion models such as DDPMs have recently outperfoms GANs in data fidelity. Several recent medical imaging studies report that diffusion models generate higher quality MRI scans.

Furthermore, there are a need to training these models for longer epochs. Despite the approaching the goals of building realistic data specially in the MRI, all the models are trained for shorter time relatively due to current status the limited resources. Training for longer epochs and bigger datasets can leads to many hours and days of training the models and hyperparameters optimizations.

The image synthesizers are trained on low resolution images (64x64 images) for faster and efficient training and development. It would be beneficial to train on the models on higher resolution images in order to validate the robustness of the models.

In this study, MRI dataset with brain tumors has been used. A possible future direction is to use on actual dementia datasets. The same workflow still applies on several problems such as dementia and Alzheimer. However, applying the workflow will require further extensive work such as MRI data preprocessing and cleaning such as removing artifacts and noise before training.

This study is done with limited resources. A future direction could be use medical validation, auditing and rigorous expert review which is essential in this case. A clinical or neuroscientific insights are helpful to validate and test the generated data in order to avoid hallucinations and mistakes given the sensitivity of the tasks.

Synthetic MRI is often proposed as a solution to sensitive data privacy. However, risks of leakage of potential patient data such as membership inference still exist. Differential privacy mechanisms are highly recommended in this case.

VII. Acknowledgment

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