# Synthetic Brain MRI Image Generation with VQ-VAE (COMP3710)

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## **Project Overview**

#### The Algorithm and the Problem

The algorithm implemented in this project is a VQ-VAE (Vector Quantised - Variational Auto-Encoder) model, which is an architecture that aims to encode data into a compressed format (embedding higher dimensional data into a lower dimensional subspace) and then decode this compressed format to recreate the original image as closely as possible. For this project, we will be training the model on the OASIS brain MRI image datset so that we can use it to generate novel and realistic synthetic brain MRI images.

#### **How it Works**

It works by transforming the image into a set of encoding vectors, using a CNN (convolutional neural network) encoder network, which are then quantised to fit the codebook vectors of the model. These quantised encodings are then passed to the decoder network which is made up of a transposed convolution (deconvolution) layers, which generated a synthetic reconstruction that is very similar to the original input image. This model is then trained until the VQVAE is very accurate at encoding the images into a condensed format while preserving the information held within.

In addition to being able to reconstruct images, we also might want to generate novel brain images, so to do this we can also train a separate CNN, using the PixelCNN architechure that can generate brain images directly from samples of codebook vectors.

#### Goals

The performance goals for this project are, generally, for the model to produce a "reasonably clear image" and also, more concretely, for the model to achieve an average structured similarity index (SSIM) of over 0.6.

## **Usage Guide**

#### Installation

- 1. Install Anaconda
- 2. Create a clean conda environment and activate it
- 3. Install all of the required packages (see dependancy list below)
- 4. Download the OASIS dataset from this link

#### **Usage**

- Run python train.py to train the model
- Run python predict.py to test out the trained model

#### **Dependancies**

The following dependancies were used in the project:

- tensorflow (version 2.9.2)
- tensorflow\_probability (version 0.17.0)
- numpy (version 1.23.3)
- matplotlib (version 3.5.1)
- PIL / pillow (version 9.1.0)
- imageio (version 2.22.1)
- skimage (version 0.19.3)

#### **Methods**

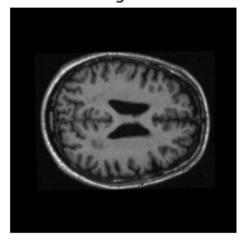
The training, validation and testing splits of the data were used as provided in the original dataset, with these partitions taking up 85%, 10%, and 5% respectively (total 11,328 images in dataset), in line with good standard practice for dataset partitioning. The data pixel values of the images were normalise to be within -1 to 1 by dividing by 255 and subtracting 1 to avoid data biases.

# **Results**

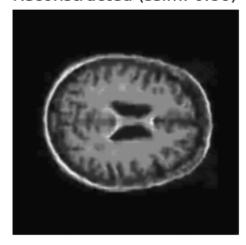
## **Example Generations**

Below are some examples of the generations made by the VQ VAE model after 20 epochs of training over the full OASIS training dataset. These generations were produced by putting real MRI image examples from the test set into the model and then getting the reconstructed output from the model.

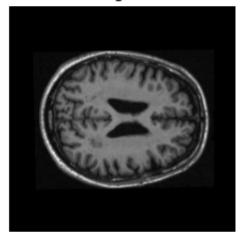
Original



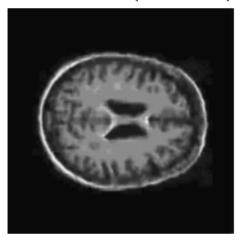
Reconstructed (ssim: 0.86)



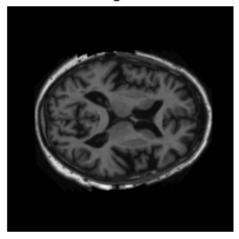
Original



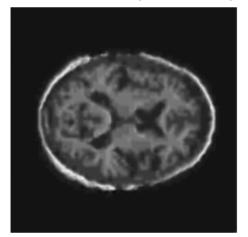
Reconstructed (ssim: 0.86)



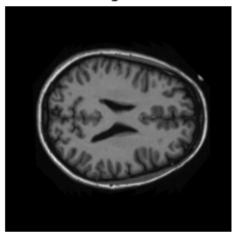
Original



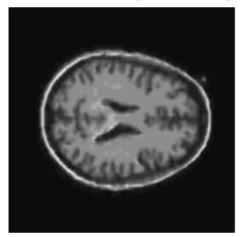
Reconstructed (ssim: 0.89)



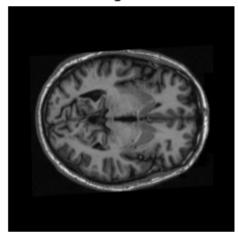
Original



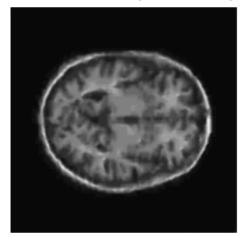
Reconstructed (ssim: 0.87)



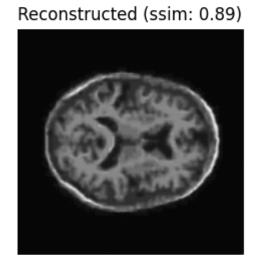
Original



Reconstructed (ssim: 0.86)

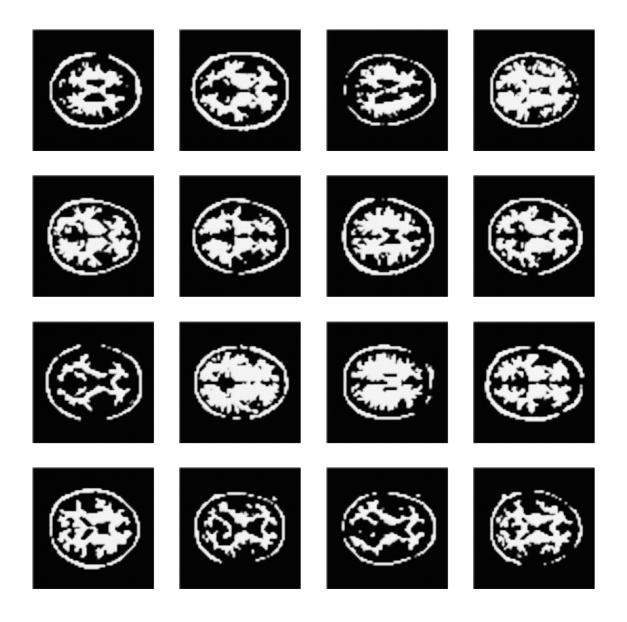


Original



# **Generation Quality Over Time**

Below is an animation of the progression of the quality of the model's generations over the course of training.

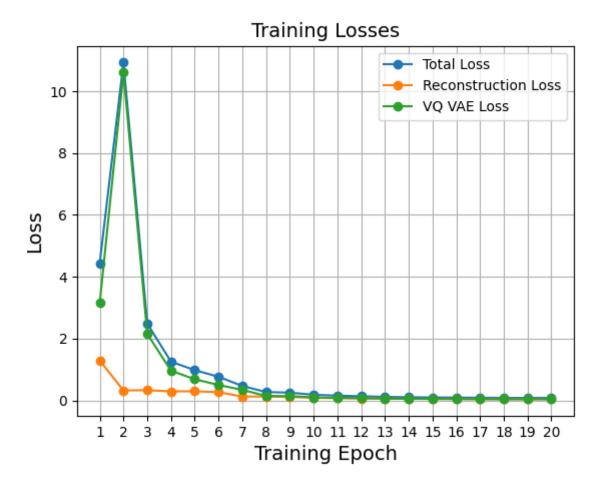


## **Training Metrics**

The various loss metrics of the model were recorded throughout training to track its performance over time, these include:

- Total Loss: What does the total loss represent???
- Reconstruction Loss: What does the reconstruction loss represent???
- VQ VAE Loss: What does the VQ VAE loss represent???

These losses are plotted over the course of the models training in both standard and log scales below:



Model Log Loss Progress Throughout Training:



In addition to statistical losses, a more real world metric to track the quality of our generations over time is to compare the similarity of the reconstructed output images it produces with the original input image they are created from. This similarity can be measured by the SSIM (Structured Similarity Index). At the end of each epoch, the SSIM was computed for 10 randomly selected images from the test dataset, and the average was recorded. This average SSIM can be seen plotted over time below:

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