Research a method that determines how good your z features are. You may start with the correlation example:
https://colab.research.google.com/drive/1NNH6QBIVZ4SzeLr-hDPYVEoMJ8BnAJYk
Answer the following question: For this particular task, how did you measure how good your configuration for latent space dimensionality is? Make sure your answer follows the following criteria:

- Objectively sound (computationally proven)
- Explainable

The mean square error (MSE) observed during training is a computationally proven metric used in machine learning. It measures the average difference between the original input data and its reconstruction in the autoencoder model. MSE loss directly reflects the fidelity of the reconstruction process and provides a reliable measure of how well the autoencoder reconstructs material from the latent space representation. Lower values of MSE indicate a good relationship between the original and reconstructed data. This means that the reconstruction is better and thus can represent the latent space.

Loss values observed during training, such as those listed below, provide information about the autoencoder's evolution over executiontime. A decrease in the MSE value indicates that the reconstruction accuracy is gradually increasing, while a small decrease means reconstruction. This prediction shows the value of MSE loss as a measure of the latent space that represents the hiding of important information from the input data. This also means that the z-score effectively captures important features of the input. As autoencoders reduce MSE loss, the latent space representation between the structure of the object and the preservation of the underlying structure is increased. MSE loss therefore provides a statistical measure of evidence and means how well the z value captures the data of interest,ultimately determining the effectiveness of the latent space represented in the model autoencoder.

MSE Loss Results:

```
Folder 25, Epoch [1/50], Loss: 0.0731
Folder 25, Epoch [6/50], Loss: 0.0809
Folder 25, Epoch [11/50], Loss: 0.0666
Folder 25, Epoch [16/50], Loss: 0.0704
Folder 25, Epoch [21/50], Loss: 0.0489
Folder 25, Epoch [26/50], Loss: 0.0489
Folder 25, Epoch [31/50], Loss: 0.0389
Folder 25, Epoch [36/50], Loss: 0.0316
Folder 25, Epoch [41/50], Loss: 0.0245
Folder 25, Epoch [46/50], Loss: 0.0179
Average PSNR on test dataset: 13.1283 dB
Folder 50, Epoch [1/50], Loss: 0.0807
Folder 50, Epoch [6/50], Loss: 0.0956
Folder 50, Epoch [11/50], Loss: 0.0800
```

```
Folder 50, Epoch [16/50], Loss: 0.0606
Folder 50, Epoch [21/50], Loss: 0.0551
Folder 50, Epoch [26/50], Loss: 0.0441
Folder 50, Epoch [31/50], Loss: 0.0398
Folder 50, Epoch [36/50], Loss: 0.0398
Folder 50, Epoch [41/50], Loss: 0.0381
Folder 50, Epoch [46/50], Loss: 0.0336
Average PSNR on test dataset: 10.9314 dB
Folder 75, Epoch [1/50], Loss: 0.1380
Folder 75, Epoch [6/50], Loss: 0.1128
Folder 75, Epoch [11/50], Loss: 0.0862
Folder 75, Epoch [16/50], Loss: 0.0701
Folder 75, Epoch [21/50], Loss: 0.0529
Folder 75, Epoch [26/50], Loss: 0.0419
Folder 75, Epoch [31/50], Loss: 0.0399
Folder 75, Epoch [36/50], Loss: 0.0335
Folder 75, Epoch [41/50], Loss: 0.0346
Folder 75, Epoch [46/50], Loss: 0.0367
Average PSNR on test dataset: 9.6461 dB
```