Analysis Report – Autoencoders

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1. The autoencoder was defined as following:

A screenshot of a computer program

Description automatically generated

1. Fine tune hyperparameters include:

* hidden\_units\_1\_values = [128, 256]
* hidden\_units\_2\_values = [64, 128]
* hidden\_units\_3\_values = [32, 64]
* learning\_rates = [0.001, 0.01]
* l2\_regs = [0.0001, 0.001]

1. Best Parameters: (256, 64, 64, 0.01, 0.0001)
2. Test Loss: 0.3390536308288574.

This suggests that the autoencoder is performing reasonably well in reconstructing the images, but there may still be room for improvement.

1. The original image and the reconstructed image:

A collage of a person's face

Description automatically generated

1. Rationale with respect to the activation functions and loss function used:
2. ReLU was used in the encoder layer of the autoencoder – ReLU allows the model to learn complex patterns in the data and is essential for capturing complex features of the images. ReLU’s output zero for negative input leads to a sparse representation, which helps reduce overfitting and improve model generalization. Lastly, ReLU is computationally efficient compared to other activation functions.
3. Sigmoid was used in the output layer of the autoencoder – its output (0,1) is suitable for pixel values and ensures the reconstructed images maintain a similar scale to the input images.
4. The Mean Squared Error (MSE) was used for training the autoencoder – MSE measures the average squared differences between the actual pixel values and predicted pixel values, which evaluates the quality of the reconstruction. Moreover, it is beneficial for gradient-based optimization (Adam) and helps in achieving better convergence during training.