**Assignment 5: Autoencoders**

**Analysis Report**

In this assignment, we applied unsupervised learning techniques, specifically PCA and Autoencoder, to the Olivetti faces dataset. First, we retrieved and loaded the dataset, which contains 400 images of faces (64x64 pixels) and 40 unique targets, as confirmed by the dataset details output. The dataset was then split into training, validation, and test sets using stratified sampling to ensure balanced representation.

A collage of a person's face

Description automatically generated

Principal Component Analysis (PCA) was performed to reduce dimensionality while retaining 99% of the variance with 176 components, and the data was transformed accordingly.

A graph with a curve

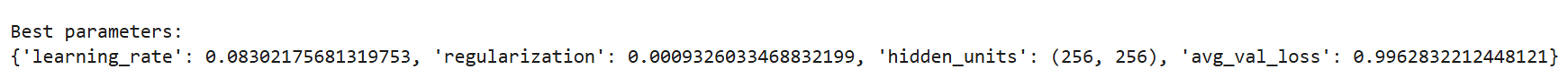
Description automatically generated

A generalized autoencoder was built with **ReLU activation functions** in the hidden layers to avoid the vanishing gradient problem (gradients become very small during backpropagation, causing the network to learn very slowly or stop learning altogether) and ensure efficient training (i.e. ReLU is chosen for the encoding and decoding layers to introduce non-linearity, allowing the autoencoder to learn more complex representations)

Also, sigmoid activation function was used in the output layer to constrain the output values between 0 and 1, matching the normalized input data range.

ReLU only activates neurons with positive inputs, which helps maintain larger gradients and avoids the vanishing gradient problem, simplifying the decision-making process by either passing the positive value through or setting it to zero. In contrast, sigmoid and tanh functions consider the entire range of input values, which can make the decision to activate a neuron more complex. This complexity can lead to smaller gradients and slower learning, especially in deeper networks. **Mean Squared Error (MSE) was chosen as the loss function** to measure reconstruction quality by penalizing larger deviations between original and reconstructed images and **Adam optimizer** for faster and more efficient training.

Hyperparameter ranges were defined, and combinations were sampled for random search, followed by K-fold cross-validation to evaluate different hyperparameter combinations. The best parameters were identified based on average validation loss, with the output showing the optimal learning rate, regularization, and hidden units.



The best model was then rebuilt and trained on the full training data, achieving a **test loss of 0.7298**. Finally, the model predicted and displayed reconstructed images, which, while decent in distinguishing faces, tended to replicate similar faces for different individuals.

A collage of a person's face

Description automatically generated

Figure . Original vs Reconstructed images from the Autoencoder model