# Autoencoder Implementation for Olivetti Faces Dataset

## Objective:

This project involves building an autoencoder model to compress and reconstruct images from the Olivetti faces dataset. The primary goal was to reduce the dataset's dimensionality through PCA while retaining 99% of the variance, then train an autoencoder and assess the reconstruction quality. Using k-fold cross-validation, we tuned the model’s learning rate and regularization parameter to identify optimal values that enhance the reconstruction accuracy.

## Methodology

### Data Preprocessing:

To prepare the dataset, we first applied PCA, reducing its dimensionality while retaining 99% of the variance. This step simplified the input data, reducing computational load and enhancing model efficiency.

### Autoencoder Architecture:

The model architecture included:  
Input Layer → Hidden Layer 1 → Central Encoding Layer 2 → Hidden Layer 3 → Output Layer  
  
The encoder and decoder layers each had configurations of 256 and 128 units, creating a compressed representation in the central bottleneck layer. The stacked layers allowed the model to learn a hierarchical data representation, compressing and then reconstructing it with minimal information loss.

### Hyperparameter Tuning:

Through k-fold cross-validation, we optimized the learning rate and regularization strength. The optimal parameters found were:  
Hidden Units: (256, 128)  
Learning Rate: 0.001  
Regularization: 1e-05

## Training Results

The model was trained for 50 epochs, achieving the following results:  
  
Final Loss: 0.6144  
  
This outcome marks a substantial improvement over previous attempts, where the model trained with ReLU activation and MSE loss yielded a high final loss of 14.5026. The previous settings led to significant reconstruction errors, producing distorted or less recognizable reconstructed images. However, the revised configuration with Leaky ReLU and MAE significantly enhanced the model's ability to capture and reconstruct facial features with lower error.

## Activation Function Rationale

Learning from Previous Trials with ReLU:  
  
In initial experiments, ReLU activation was used for hidden layers, intending to benefit from its computational efficiency and ability to mitigate the vanishing gradient problem. However, this setup resulted in high reconstruction error, likely due to ReLU’s zeroing of negative values, which may cause information loss, particularly in datasets with subtle pixel variations.  
  
Leaky ReLU: A More Robust Choice:  
  
Switching to Leaky ReLU allowed us to retain negative input values (with a small slope), preserving more nuanced image features and minimizing information loss. This change enabled the model to capture subtler facial details, which improved reconstruction accuracy and led to a significantly lower final loss.  
  
Linear Activation (Output Layer):  
  
A linear activation function was maintained in the output layer to enable a continuous output range suitable for grayscale pixel values. This choice allowed for flexibility in reconstructing pixel intensities without imposing a bounded range, which would limit reconstruction fidelity.

## Loss Function Rationale

Learning from MSE Limitations:  
  
MSE was initially selected as it measures the average squared difference between actual and predicted pixel values. However, it proved insufficient for this task, leading to high reconstruction error (14.5026), suggesting the autoencoder struggled to capture facial features effectively.  
  
Adopting MAE for Improved Reconstruction:  
  
Replacing MSE with MAE aligned more closely with the goal of minimizing reconstruction error, as MAE directly reduces pixel-wise absolute error. This choice led to a more interpretable loss and allowed the model to focus on the overall structural accuracy, producing clearer, more accurate image reconstructions.

## Conclusion and Recommendations

This autoencoder achieved a substantial improvement in reconstruction accuracy with the revised settings of Leaky ReLU activation and MAE loss, reducing the final loss to 0.6144. Key lessons learned include the importance of activation and loss function choices, as shown by the improved results upon switching from ReLU and MSE to Leaky ReLU and MAE.  
  
Moving forward, further exploration could involve:  
  
Architecture Enhancements: Adding layers or adjusting units per layer may yield even better feature representation.  
Alternative Loss Functions: While MAE performed well, experimenting with perceptual loss could provide improvements for tasks emphasizing visual fidelity.  
Further Activation Function Experiments: Testing ELU or other activations for encoding layers could further enhance the model’s capacity to capture fine-grained features.  
  
In summary, this project highlighted the critical impact of activation and loss function selection in autoencoder performance, particularly for high-dimensional image reconstruction tasks. The revised model’s success illustrates the effectiveness of fine-tuning and provides a foundation for continued optimization.