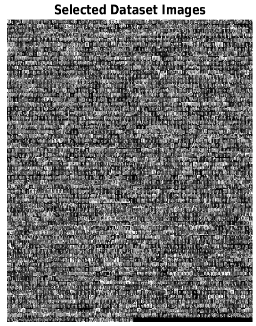
Facial Recognition Using SVD, Eigenfaces, and SVM

With HPC Integration in MATLAB

Selected Dataset Images



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1. Data Exploration

The initial phase of our project involves exploring the dataset to understand its structure, distribution, and inherent characteristics. This exploration is crucial for informed preprocessing and effective feature extraction.

To assess the distribution of images per individual in the dataset, we generate a histogram. This visualization reveals the number of images each person has, ranging from 1 to 60 images. Such an analysis helps in identifying data imbalance and determining the sufficiency of training samples for each class.

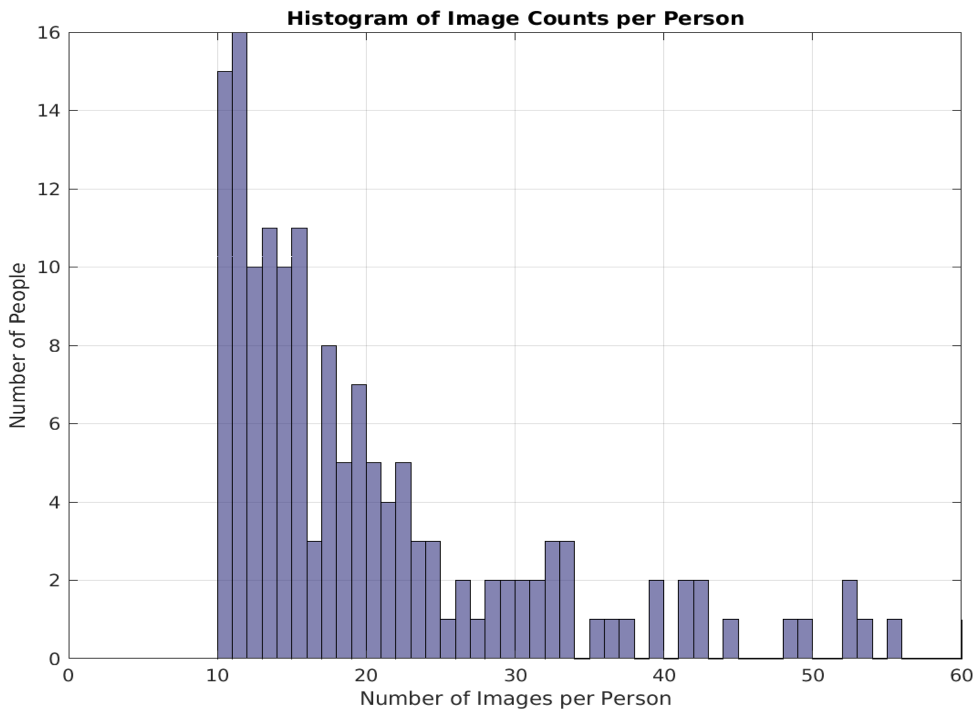

Figure 1: Histogram showing the distribution of image counts per person in the dataset.

To observe the variation in images of a single individual, we create a collage of images of Angelina Jolie. This collage showcases different expressions, angles, lighting conditions, and occlusions, illustrating the diversity within the images of one person. Such variation is critical for building a robust recognition system.

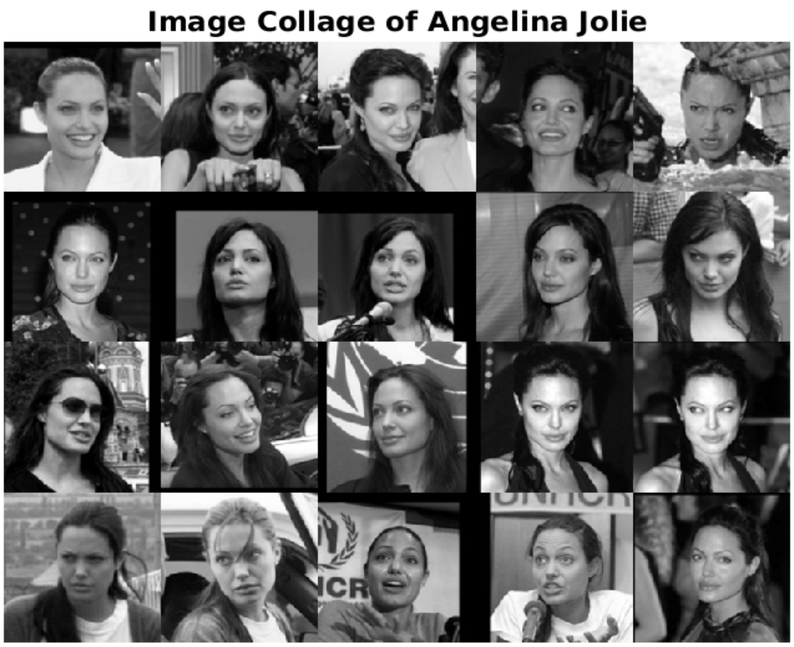

Figure 2: Image collage of Angelina Jolie showing variation across multiple images.

To understand the overall variation within the dataset, we create a collage comprising images of different individuals. This collage highlights differences in facial features, skin tones, and image conditions, providing a comprehensive view of the dataset diversity.

Figure 3: Image collage of different individuals in the dataset showcasing diversity.

2. Singular Value Decomposition and Eigenfaces

Singular Value Decomposition (SVD) is a powerful linear algebra technique that factorizes a data matrix into three components:

$$A \;=\; U\,\Sigma\,V^T$$

In the context of facial recognition, each image is first transformed into a vectorized form and stacked into a large data matrix A, where each column represents one face image. Applying SVD to A decomposes it into: U (left singular vectors) which represent the directions of maximum variance in the image space, \Sigma (singular values) which quantify the importance of each direction, and V^T (right singular vectors) which provide the coordinates of each image in the new feature space.

$$A_k \;=\; U_k\,\Sigma_k\,V_k^T$$

By retaining only the top k singular values and their corresponding vectors, we reduce the dimensionality while preserving the most significant information. The columns of U corresponding to the top k singular values are known as eigenfaces. These eigenfaces are essentially the principal components of the face space, capturing features like facial contours, eyes, noses, and mouth positions that best explain the variance in the dataset.

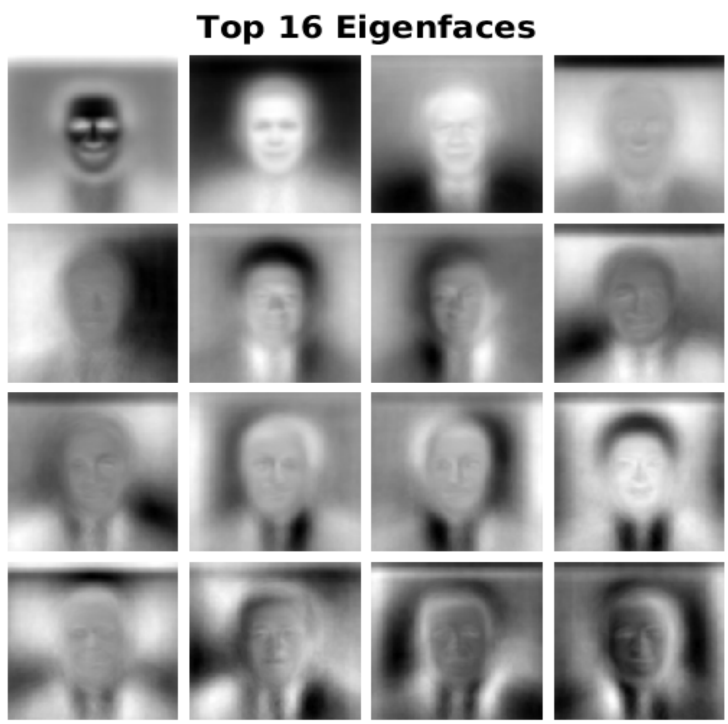

Figure 4: Top 16 extracted eigenfaces using SVD.

3. Feature Extraction and Classification with SVM

Once we have extracted the eigenfaces, each face image can be represented as a linear combination of these eigenfaces. Projecting the original images onto the reduced eigenface space yields a feature vector of significantly smaller dimension, capturing the most discriminative facial features.

These low-dimensional feature vectors form the input to a supervised classifier. In this project, we employ a Support Vector Machine (SVM) classifier. SVMs are chosen for their robustness and effectiveness in high-dimensional spaces, and when combined with a one-vs-one or Error-Correcting Output Code (ECOC) scheme, they can handle multiple classes.

The result is a facial recognition pipeline: Raw images \u2022 Preprocessing \u2022 SVD (for eigenfaces) \u2022 Feature Extraction (projecting onto eigenfaces) \u2022 SVM Classification.

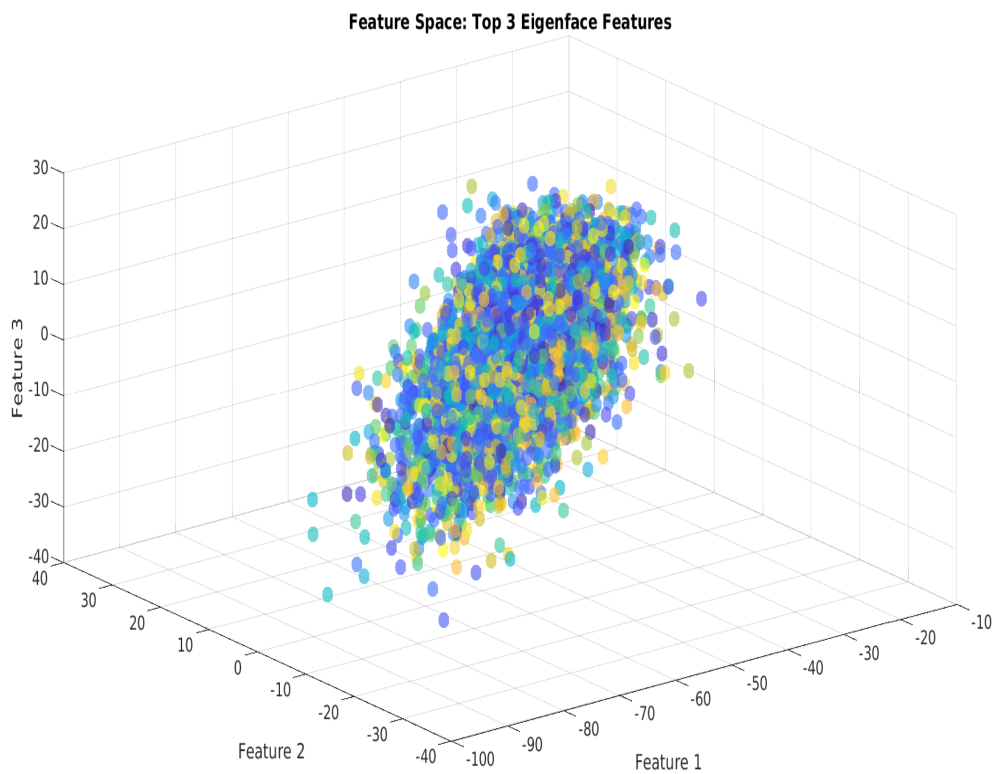

Figure 5: Visualization of the top 3 PCA/SVD-derived features of the dataset.

4. Discussion of Other Approaches and State of the Art

While Singular Value Decomposition (SVD) and Support Vector Machines (SVM) provide a robust framework for facial recognition, numerous other methodologies exist in the literature. This section explores alternative techniques and compares their advantages and limitations.

Principal Component Analysis (PCA) is a widely used dimensionality reduction technique similar to SVD. It transforms the data into a new coordinate system by identifying the principal components that maximize variance. In facial recognition, PCA is employed to extract the most significant features, known as eigenfaces, which capture the essential facial characteristics.

Linear Discriminant Analysis (LDA) focuses on finding a feature space that best separates different classes. Unlike PCA, which is unsupervised, LDA is supervised and leverages class label information to maximize inter-class variance while minimizing intra-class variance. This makes LDA particularly effective in classification tasks like facial recognition.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized facial recognition. Models like DeepFace, FaceNet, and VGG-Face learn hierarchical feature representations directly from raw pixel data, capturing intricate patterns and invariant features that outperform traditional methods. However, they require large datasets and substantial computational resources for training.

5. Results and Metrics of Face Recognition

To assess model performance, we compute a confusion matrix and ROC curves. The confusion matrix visualizes how well the classifier distinguishes among different individuals, and the ROC curve shows the trade-off between True Positive and False Positive rates. In practice, evaluating on subsets of classes helps gauge classifier effectiveness and reveals areas needing improvement.

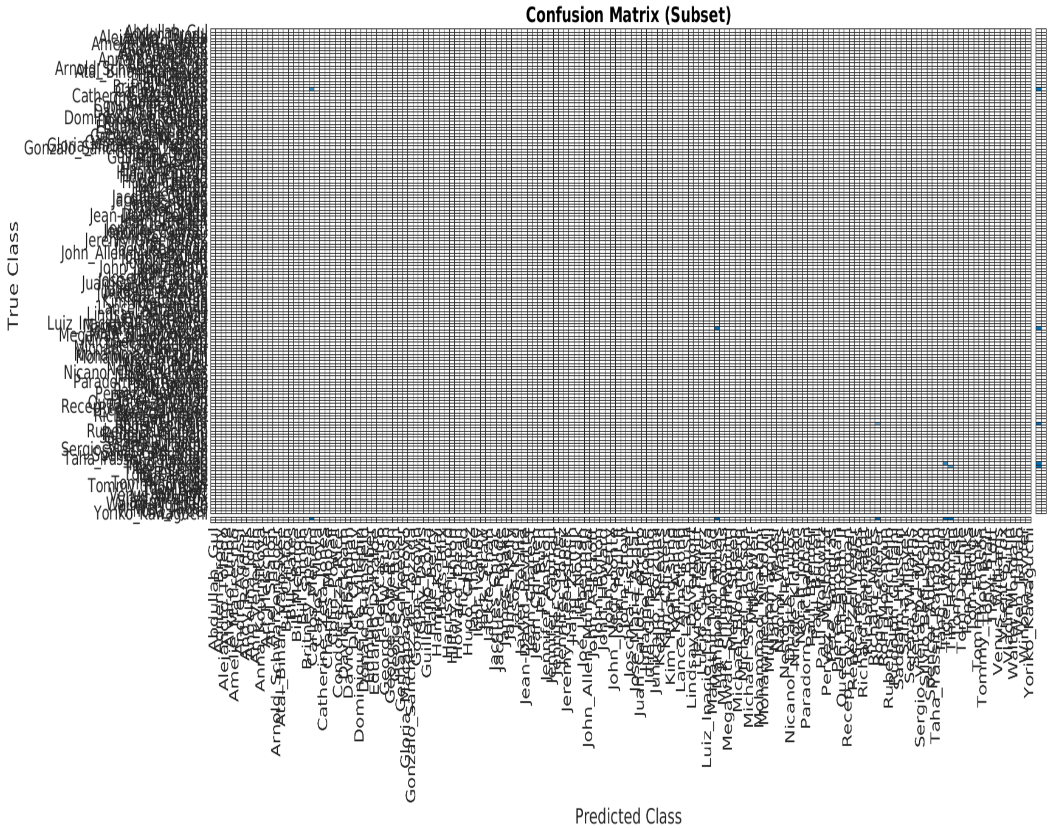

Figure 6: Confusion Matrix for a subset of 5 classes.

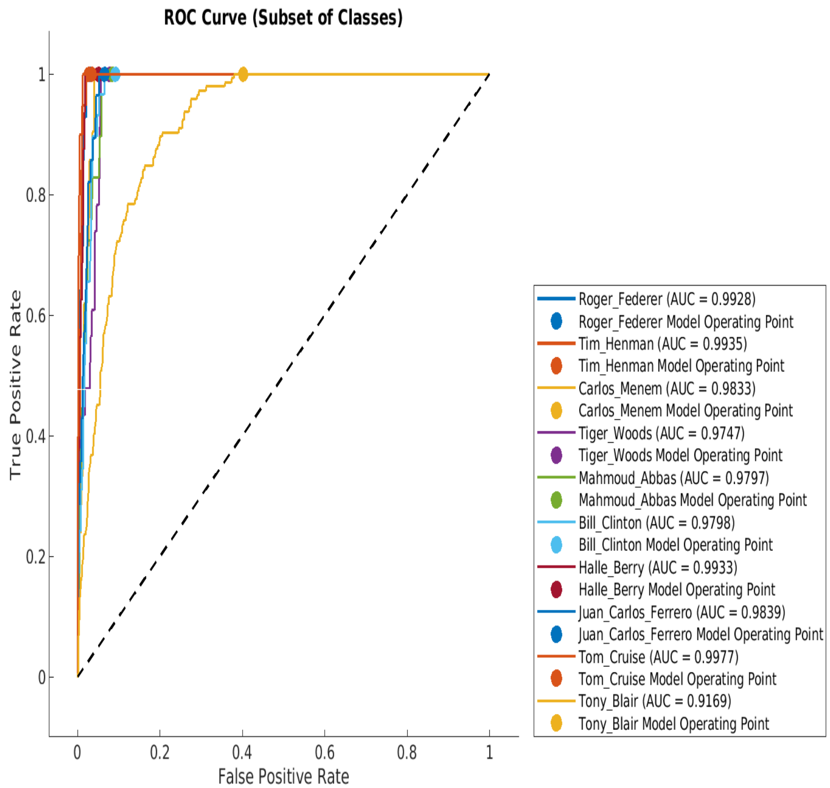

Figure 7: ROC Curve for a subset of 10 classes, illustrating classifier sensitivity and specificity.

6. Conclusion and Future Work

This project demonstrates a scalable facial recognition pipeline that leverages SVD for eigenface extraction and SVM for classification. By integrating MATLAB’s parallel computing capabilities, we ensure that the approach scales well, handling larger datasets efficiently.

Future work could explore advanced feature extraction methods, such as deep learning-based embeddings (e.g., using CNNs), and incorporate GPU acceleration for even faster computations. These enhancements can further improve both the accuracy and efficiency of the facial recognition system.

Additionally, expanding the dataset to include more diverse subjects and varying image conditions can enhance the system's robustness and generalizability. Implementing real-time recognition capabilities and deploying the system in practical applications are also promising avenues for future development.

7. HPC Integration and Scalability

High-Performance Computing (HPC) resources are pivotal in scaling facial recognition systems to handle large datasets efficiently. MATLAB's Parallel Computing Toolbox facilitates the distribution of computations across multiple cores or clusters, significantly reducing processing times.

In this project, several HPC techniques are employed:1. **Parallelized Image Preprocessing:** Utilizing parallel loops (`parfor`) to expedite image reading and resizing.2. **Distributed SVD Computation:** Leveraging parallel algorithms to perform Singular Value Decomposition on large matrices.3. **Parallel SVM Training:** Training multi-class SVM models concurrently to enhance scalability and reduce training time.