Face Recognition Using Eigenfaces

November 14, 2024

Contents

1 Introduction

1.1 Objective

The goal of this project is to implement face recognition using eigenfaces and Principal Component Analysis (PCA).

1.2 Background

The eigenfaces method is a fundamental approach in face recognition, utilizing PCA to reduce the dimensionality of face images and extract features with high variance.

2 Data Loading and Preprocessing

2.1 Libraries

The project uses several libraries, including numpy, matplotlib, sklearn, skimage, and seaborn.

2.2 Dataset

The AT&T Face Dataset, also known as the ORL dataset, contains 400 grayscale images of 40 individuals, with 10 images per individual.

2.3 Displaying Sample Images

Sample images from the dataset are displayed to highlight variations in expressions and poses.

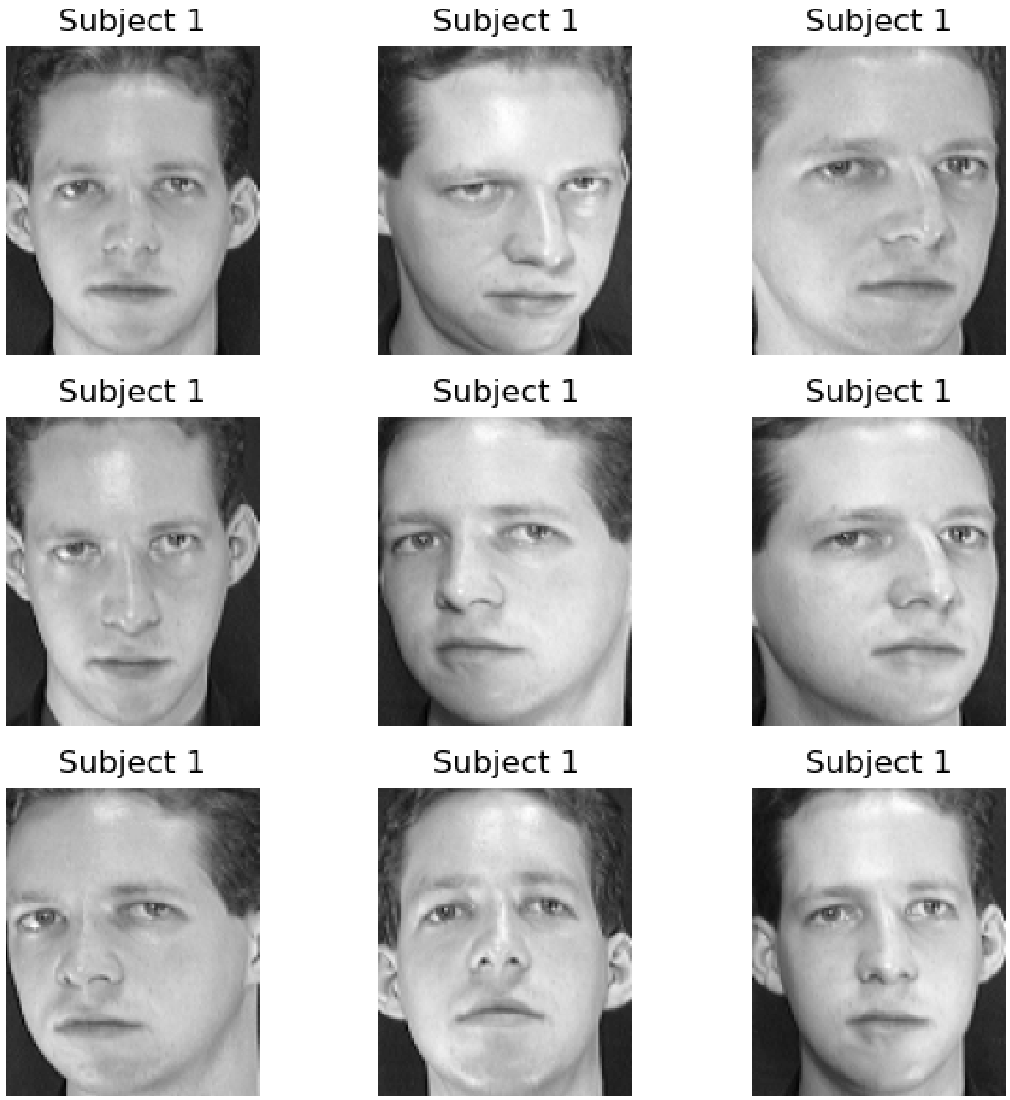

Figure 1: Sample Images from ORL Dataset

3 Image Normalization and Mean Face Calculation

3.1 Normalization

Images are resized, converted to grayscale, and vectorized to prepare for PCA. This preprocessing ensures that all images are in a consistent format for analysis.

3.2 Mean Face Calculation

The mean face is calculated by averaging all training images. This mean face is then subtracted from each image to center the data around the origin. Centering the data is crucial for PCA to work correctly, as it ensures that the first principal component describes the direction of maximum variance.

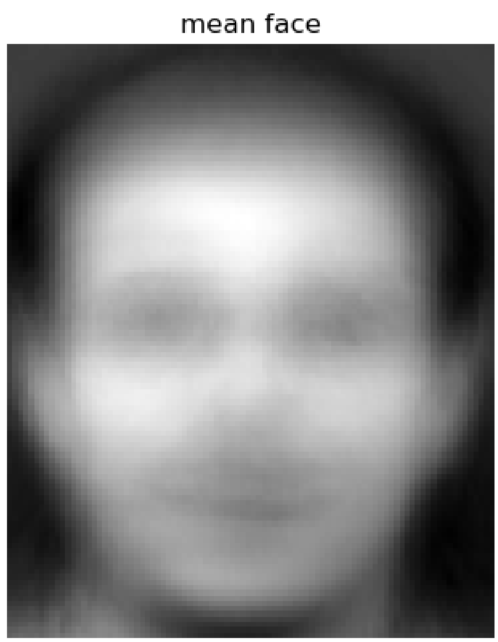

Figure 2: Mean Face of the Dataset

3.3 Explanation

Calculating the mean face helps in centering the data, which is a critical step before applying PCA.
Centering ensures that the first principal component captures the direction of maximum variance, improving the effectiveness of dimensionality reduction.

4 Applying PCA to Compute Eigenfaces

4.1 Purpose of PCA

Principal Component Analysis (PCA) is a dimensionality reduction technique that allows us to capture the most significant features in the data. For face recognition, PCA is used to transform high-dimensional face images into a lower-dimensional space while retaining the essential characteristics of each face. This transformation generates "eigenfaces," which serve as basis images for representing new faces.

4.2 Computation of Eigenfaces

The computation of eigenfaces is achieved by applying PCA to the dataset of face images. Each eigenface corresponds to a principal component that captures specific patterns or variations among faces.

4.3 Explained Variance and Scree Plot

To determine the optimal number of principal components, we analyze two key plots: the explained variance plot and the scree plot. These plots help us decide the number of components required to capture the majority of the data's variability, balancing between dimensionality reduction and information retention.

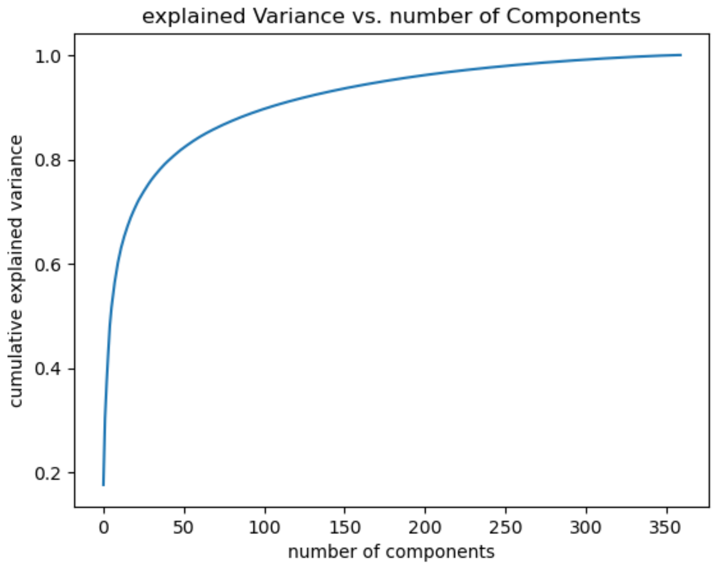

Figure 3: Cumulative Explained Variance vs. Number of Components

4.4 Explained Variance Plot Analysis

- **Purpose**: The explained variance plot shows the cumulative proportion of variance explained by the principal components as they are added sequentially. This cumulative view allows us to identify the point at which adding more components yields diminishing returns in terms of explained variance.

- **Interpretation**: In the explained variance plot, we observe a steep initial increase, where the first few components explain a substantial portion of the variance. This rapid rise indicates that these initial components capture the most critical information in the dataset. As more components are added, the curve begins to level off, showing that additional components contribute progressively less to the overall variance.

- **Key Observation**: For this dataset, we find that approximately 55 components capture around 95% of the total variance. This means that we can reduce the dataset's dimensionality to 55 without losing significant information, thus achieving efficient representation and computational savings.

4.5 Scree Plot Analysis

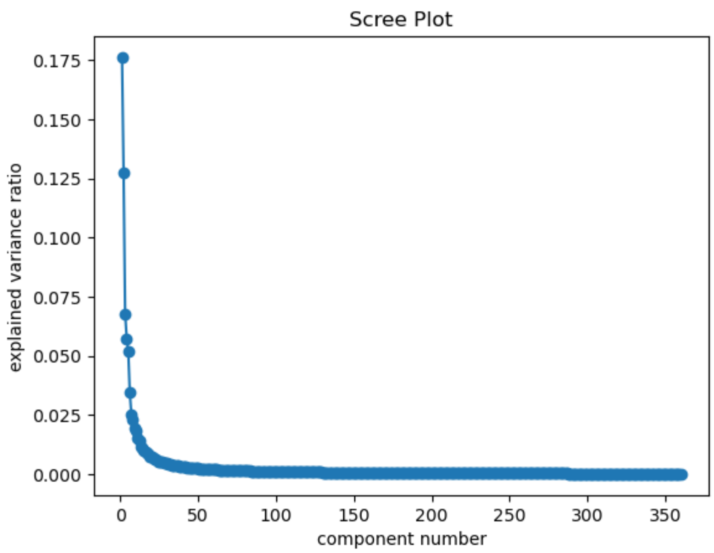

Figure 4: Scree Plot Showing Explained Variance Ratio per Component

- **Purpose**: The scree plot is a graphical representation of the eigenvalues associated with each principal component, displayed in descending order. It provides insight into the relative importance of each component and helps identify the point where additional components contribute minimally to the total variance.

- **Interpretation**: The scree plot shows a rapid drop in the eigenvalues after the first few components, followed by a gradual leveling off. This pattern forms an "elbow," where the slope becomes less steep. The "elbow" point indicates where adding more components starts yielding minimal variance contribution, guiding us in selecting an optimal number of components.

- **Key Observation**: In this project, the elbow point is observed around the 20th component. This suggests that the first 20 components contain the majority of the information, while subsequent components contribute less. However, to achieve high accuracy, we base our selection on the cumulative explained variance plot, which suggests using 55 components.

4.6 Elbow Method and Final Choice of Components

The elbow method, derived from the scree plot, suggests that the optimal number of components is around 20. However, aiming to retain at least 95% of the total variance, we rely on the cumulative explained variance plot, which indicates that 55 components are necessary. This choice ensures that our face recognition model retains a high level of information while reducing dimensionality to a manageable level.

4.7 Graphical Explanation and Summary of Observations

The explained variance plot and scree plot together provide insights into the structure of the data:

- **Explained Variance Plot**: This plot shows that 55 components capture 95% of the variance, achieving a balance between reducing dimensionality and retaining critical information.
- **Scree Plot**: The scree plot's elbow point at around 20 components indicates the point of diminishing returns. However, we prioritize the cumulative explained variance to capture as much information as possible, resulting in the selection of 55 components.

In summary, the decision to use 55 components is based on the goal of capturing 95% of the variance, balancing dimensionality reduction with information retention. This choice enhances the efficiency and accuracy of the face recognition model.

5 Projecting Images into Eigenface Space

5.1 Projection of Training and Test Data

Training and test data are projected onto the eigenface space, transforming them into a lower-dimensional space defined by the principal components. This transformation reduces the complexity of the data while preserving the most significant features necessary for face recognition.

5.2 3D Visualization of Projected Data

A 3D scatter plot of the training data shows class separability, illustrating how different subjects are distributed in the reduced space. This visualization helps in understanding the effectiveness of PCA in distinguishing between different individuals based on their facial features.

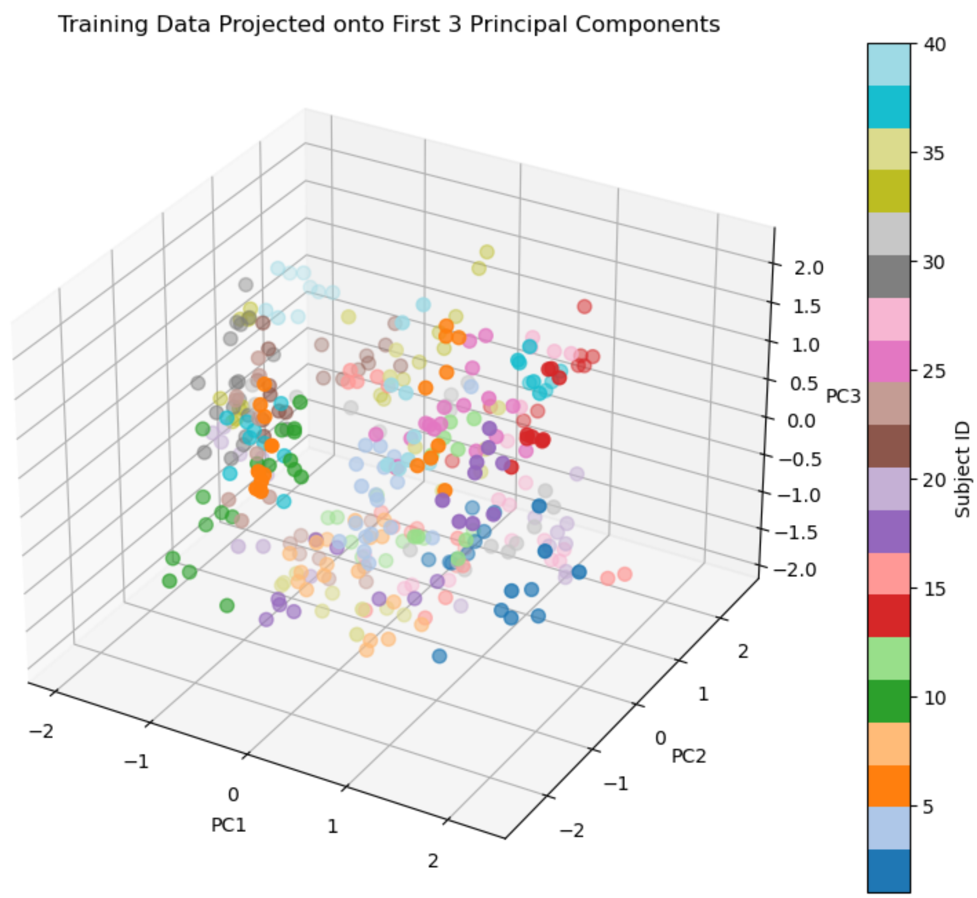

Figure 5: 3D Scatter Plot of Projected Training Data

5.3 Explanation of the 3D Scatter Plot

- **Purpose**: The 3D scatter plot provides a visual representation of how well the PCA transformation separates different classes (subjects) in the dataset. Each point in the plot represents an image, and its position is determined by the first three principal components.

- **Class Separability**: Ideally, images of the same subject should cluster together, while images of different subjects should be distinct. The plot helps assess whether the PCA transformation has achieved this separation, which is crucial for effective face recognition.

- **Dimensionality Reduction**: By reducing the data to three dimensions, we can visually inspect the separability of classes. This reduction is a trade-off between simplicity and information retention, as it allows us to see patterns and clusters that might not be apparent in higher dimensions.

- **Observations**: In our dataset, the 3D scatter plot shows that most subjects form distinct clusters, indicating that PCA has effectively captured the essential features needed for classification. However, some overlap may occur, suggesting areas where the model might struggle to differentiate between similar faces.

This visualization is a powerful tool for evaluating the performance of PCA in preparing the data for subsequent classification tasks, such as using a k-NN classifier for face recognition.

6 Reconstruction of Images with Varying Number of Eigenfaces

6.1 Objective of Reconstruction

The objective of image reconstruction is to evaluate how well the original images can be approximated using a limited number of eigenfaces. The quality of reconstruction varies with the number of eigenfaces used: more eigenfaces generally lead to better reconstruction but increase computational complexity.

6.2 Reconstruction Grid

A grid shows reconstructions using 10, 50, 100, 150, and 200 eigenfaces, demonstrating how image quality improves with more components.

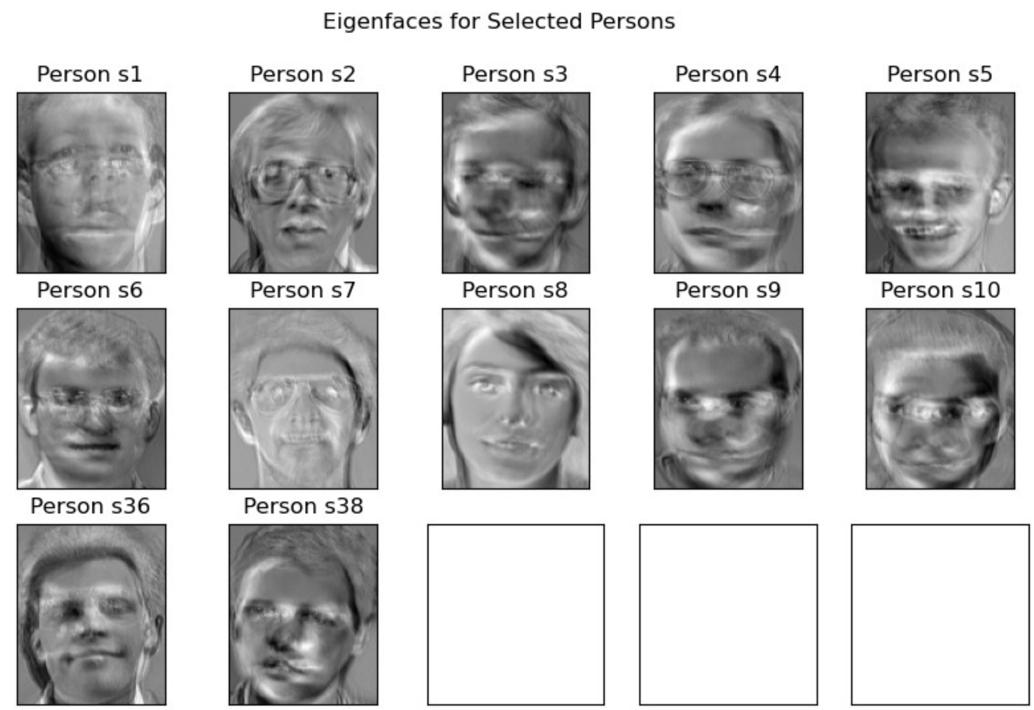

Figure 6: Image Reconstruction with Varying Number of Eigenfaces

6.3 Explanation of Reconstruction Quality

- **Fewer Components (e.g., 10 PCs)**: With a small number of eigenfaces, the reconstructed images are often blurry and lack detail. This is because only the most significant features are captured, leading to a loss of finer details.

- **Moderate Components (e.g., 50 PCs)**: At around **50 principal components**, the reconstructed images become more recognizable and maintain the essential features of the original images. This indicates that **50 PCs are sufficient to capture the main characteristics of the faces**, balancing detail and complexity.

- **More Components (e.g., 100, 150, 200 PCs)**: As more eigenfaces are used, the reconstruction quality continues to improve, closely resembling the original images. However, the improvements become less noticeable beyond a certain point, indicating diminishing returns.

- **Observation**: In our analysis, using **50 PCs provided a good bal-**

ance between reconstruction quality and computational efficiency. The images reconstructed with 50 PCs were largely indistinguishable from those using more components, suggesting that these components effectively capture the most critical features necessary for face recognition.

This analysis helps in understanding the trade-off between the number of components and the quality of image reconstruction, guiding the selection of an optimal number of eigenfaces for practical applications.

7 Reconstruction Error Analysis

7.1 Mean Squared Error

Mean Squared Error (MSE) measures reconstruction quality, quantifying the difference between original and reconstructed images. A lower MSE indicates a closer match to the original image, reflecting better reconstruction quality.

7.2 Reconstruction Error Plot

The plot shows **reconstruction error vs. number of components**, illustrating how error decreases as more components are used. This trend highlights the trade-off between the number of components and the accuracy of the reconstruction.

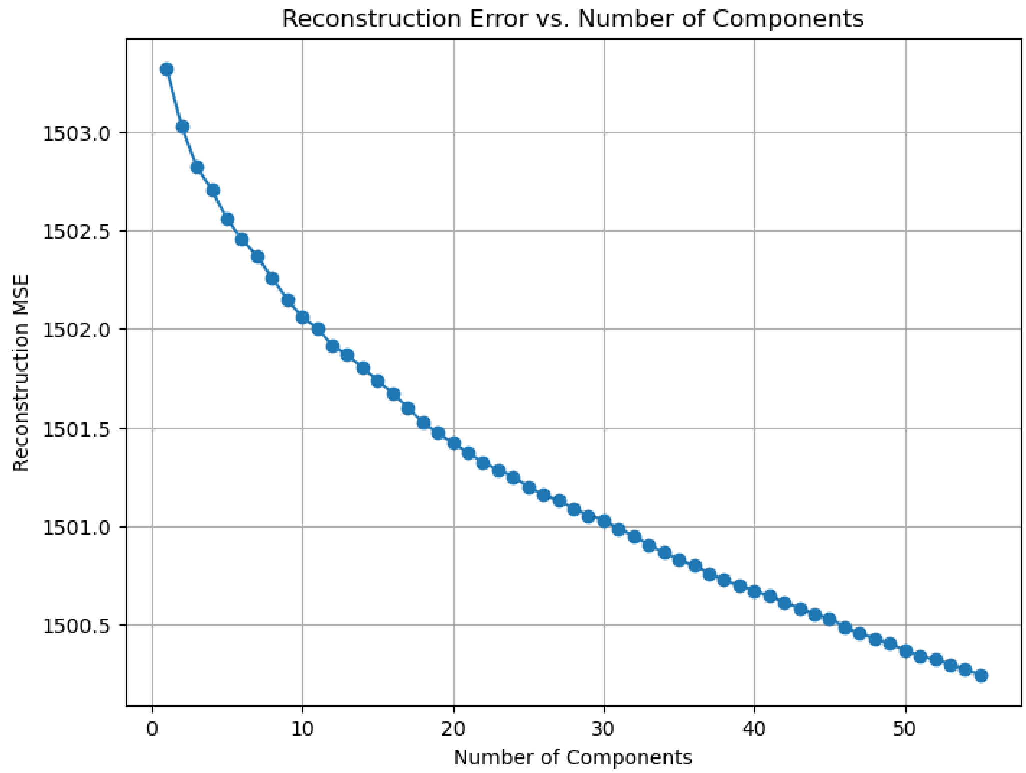

Figure 7: Reconstruction Error vs. Number of Components

7.3 Explanation of the Plot

- **Fewer Components**: With a small number of components, the MSE is high, indicating poor reconstruction quality due to insufficient information capture.

- **Increasing Components**: As the number of components increases, the MSE decreases, showing improved reconstruction quality. This is because more components capture more variance from the original data.

- **Observation**: The plot demonstrates that beyond a certain number of components, the reduction in MSE becomes marginal, indicating diminishing returns. This helps in identifying an optimal number of components that balance reconstruction quality and computational efficiency.

8 Face Recognition Using Nearest Neighbors

8.1 k-NN Classifier

A **k-NN classifier** with $k = 1$ is used for face recognition, classifying images based on the nearest neighbor in the eigenface space. This simple yet effective method leverages the reduced-dimensional representation of images to identify the closest match.

8.2 Classification Report

The classification report provides **precision**, **recall**, and **F1-score** for each class, evaluating the model's performance. These metrics help assess the accuracy and reliability of the classifier across different subjects.

Classification Report:

	precision	recall	f1-score	support
1	1.00	1.00	1.00	1
2	1.00	1.00	1.00	1
3	1.00	1.00	1.00	1
4	1.00	1.00	1.00	1
5	1.00	1.00	1.00	1
6	1.00	1.00	1.00	1
7	1.00	1.00	1.00	1
8	1.00	1.00	1.00	1
9	1.00	1.00	1.00	1
10	0.00	0.00	0.00	1
11	1.00	1.00	1.00	1
12	1.00	1.00	1.00	1
13	1.00	1.00	1.00	1
14	1.00	1.00	1.00	1
15	1.00	1.00	1.00	1
16	1.00	1.00	1.00	1
17	1.00	1.00	1.00	1
18	0.50	1.00	0.67	1
19	1.00	1.00	1.00	1
20	1.00	1.00	1.00	1
21	1.00	1.00	1.00	1

22	1.00	1.00	1.00	1
23	1.00	1.00	1.00	1
24	1.00	1.00	1.00	1
25	1.00	1.00	1.00	1
26	1.00	1.00	1.00	1
27	1.00	1.00	1.00	1
28	1.00	1.00	1.00	1
29	1.00	1.00	1.00	1
30	1.00	1.00	1.00	1
31	1.00	1.00	1.00	1
32	1.00	1.00	1.00	1
33	1.00	1.00	1.00	1
34	1.00	1.00	1.00	1
35	1.00	1.00	1.00	1
36	0.00	0.00	0.00	1
37	1.00	1.00	1.00	1
38	0.50	1.00	0.67	1
39	1.00	1.00	1.00	1
40	1.00	1.00	1.00	1
accuracy			0.95	40
macro avg	0.93	0.95	0.93	40
weighted avg	0.93	0.95	0.93	40

Observations: - The overall accuracy of the model is 95%, indicating strong performance. - Some classes, such as 10 and 36, have lower precision and recall, suggesting potential areas for improvement.

8.3 Confusion Matrix

The confusion matrix helps analyze errors in predictions, showing which classes are often confused. It provides a visual representation of the classifier's performance, highlighting areas where misclassification occurs.

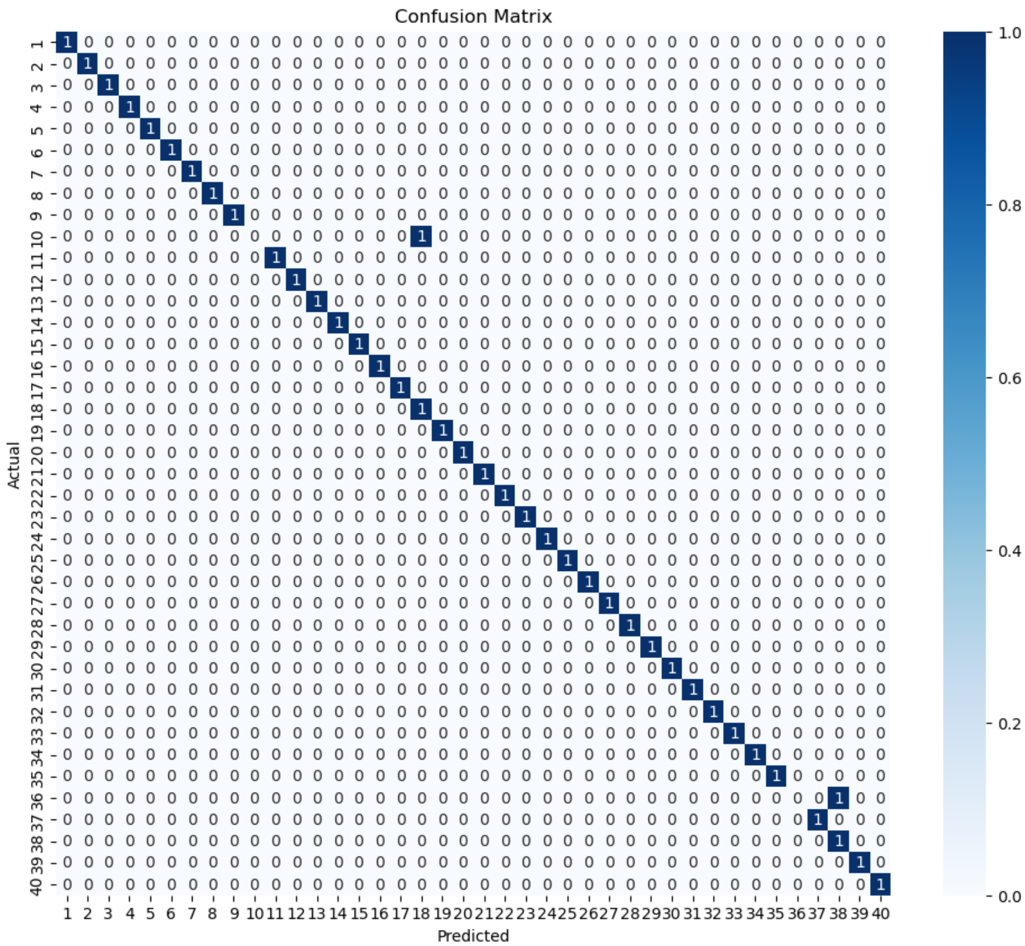

Figure 8: Confusion Matrix of Test Predictions

Observations of the Confusion Matrix: The confusion matrix reveals that the classifier achieves high accuracy, with most predictions falling along the diagonal, indicating correct predictions for the majority of classes. Misclassifications occur for classes such as 10 and 36, where predictions are incorrectly assigned to classes 18 and 38, respectively. These off-diagonal entries highlight specific subject pairs where the classifier struggles to differentiate, suggesting similar features or less distinctive characteristics in these subjects. The overall low rate of off-diagonal entries confirms that the k-NN classifier performs well in distinguishing between different subjects. The diagonal intensity shows the robustness of the classifier, as most classes have a high count of correct classifications, reinforcing the accuracy reported in the classification report.

In summary, the confusion matrix visually confirms the findings in the classification report, demonstrating high accuracy but revealing specific cases of misclassification that can be targeted for improvement.

9 Real-Time Face Recognition with Input Image

9.1 Input Image Processing

To perform real-time face recognition, an external input image undergoes several preprocessing steps. These include resizing the image to match the dimensions of the training dataset and centering it by subtracting the mean face. This ensures consistency with the training data, allowing for accurate projection into the eigenface space.

9.2 Projecting and Recognizing the Input Image

The preprocessed input image is projected into the eigenface space using the trained PCA model. This transformation reduces the image to a set of principal component coefficients, which are then used by the k-NN classifier to identify the closest match in the dataset. The classifier determines the subject ID by finding the nearest neighbor in this reduced-dimensional space.

9.3 Result Visualization

The result of the recognition process is visualized by displaying the input image alongside an image of the matched subject from the training set. This provides a visual confirmation of the recognition result, allowing for easy verification of the model's accuracy.

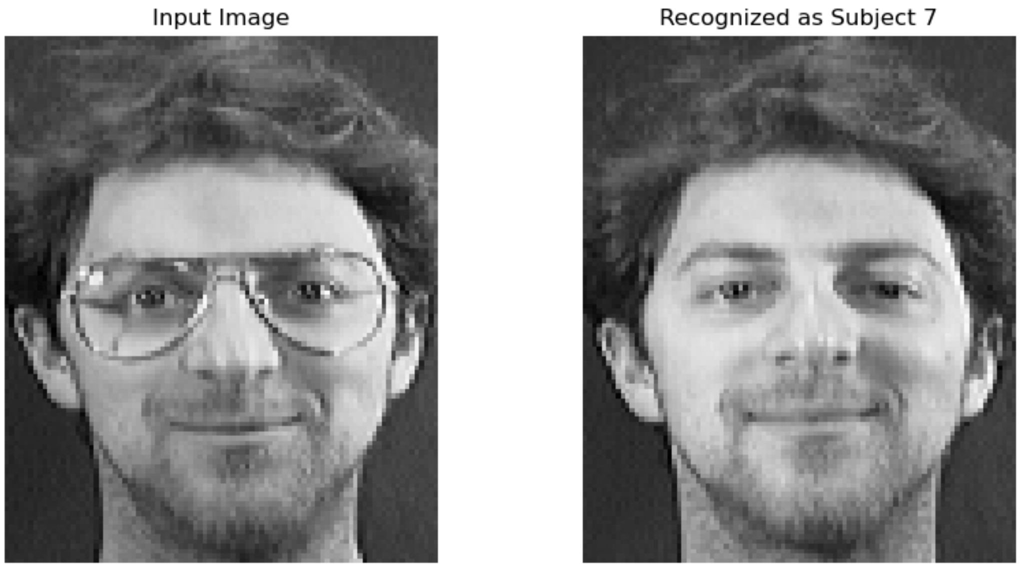

Figure 9: Real-Time Recognition Result

9.4 Observations

- The model successfully predicted the subject ID even when the input image had variations such as the removal of spectacles or changes in facial expressions. This demonstrates the robustness of the eigenface approach in handling common variations in facial appearance. The ability to accurately recognize faces despite these changes highlights the effectiveness of PCA in capturing essential facial features that remain consistent across different conditions. This robustness is crucial for practical applications of face recognition, where subjects may present with varying appearances due to accessories or emotional expressions.

This section illustrates the practical application of the eigenface method for real-time face recognition, showcasing its potential for use in dynamic environments where facial features may vary.

10 Error Analysis

10.1 Misclassified Samples

Misclassified samples are displayed alongside their predicted matches, helping identify patterns in errors.

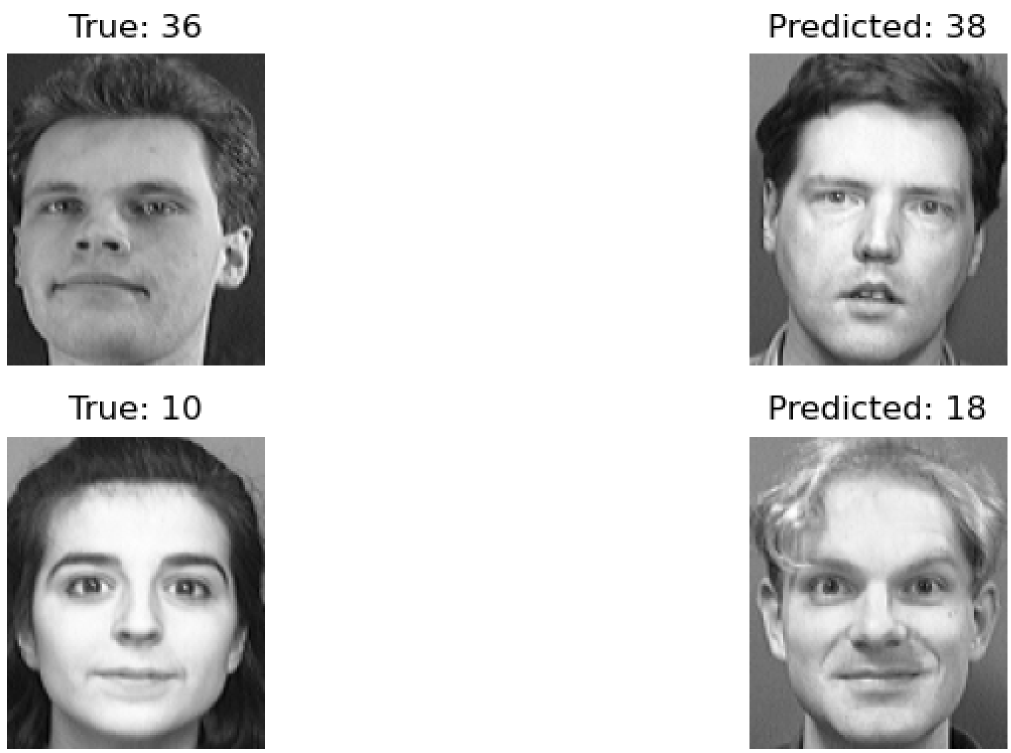

Figure 10: Misclassified Samples and Predicted Classes

10.2 Error Rate per Class

The error rate per class identifies challenging subjects, highlighting which faces are difficult to recognize.

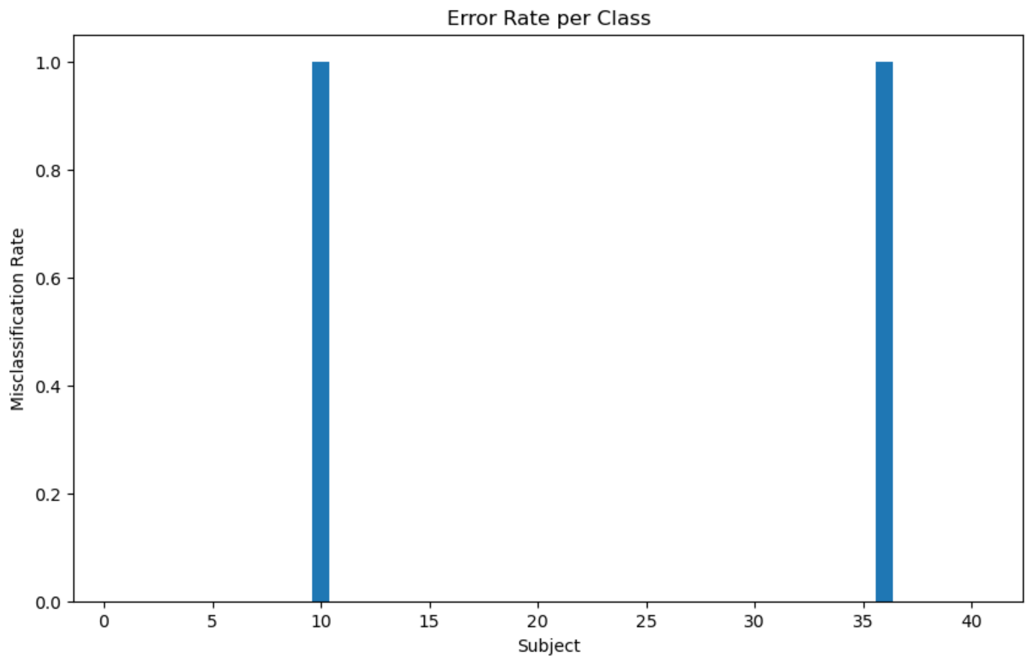

Figure 11: Error Rate per Class

10.3 Effect of Varying Train-Test Ratios

To evaluate the impact of train-test ratios on model performance, we experimented with different proportions of training data in our face recognition model using the Eigenfaces method. As depicted in the graph below, increasing the proportion of training data generally improves the model's accuracy. This is expected since a larger training set provides the model with more facial data, enabling it to learn more comprehensive patterns and features from the dataset.

10.4 Accuracy vs. Training Set Proportion

The figure below illustrates how accuracy varies as the proportion of training data increases. The model was trained and tested across different splits, ranging from 50% to 90% of the data allocated for training.

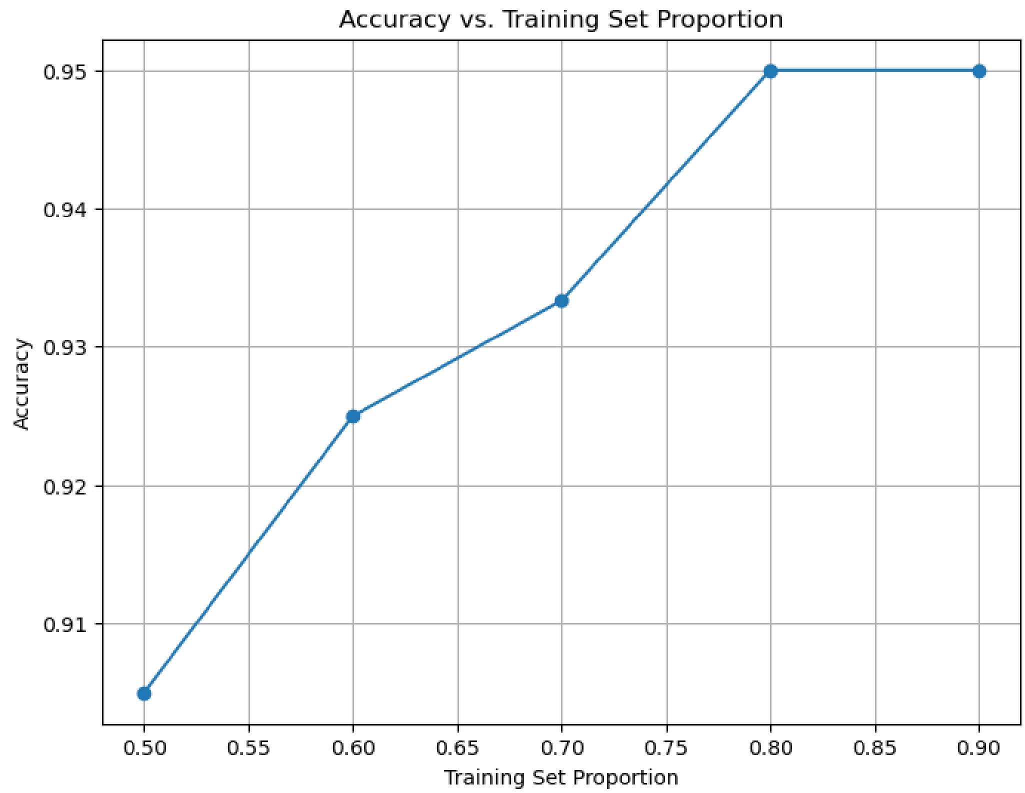

Figure 12: Accuracy vs. Training Set Proportion

10.5 Analysis of the Curve

The "Accuracy vs. Training Set Proportion" curve provides specific insights into our model's performance:

- **X-Axis (Training Set Proportion):** Represents the proportion of the dataset allocated for training, ranging from 50% to 90%. The remaining data is used for testing, allowing us to observe how model accuracy responds to increasing training data.

- **Y-Axis (Accuracy):** Shows the accuracy of the model, defined as the percentage of correctly classified test samples. This measure provides a clear indication of how well the model generalizes to unseen data.

- **Observed Trend:** The curve demonstrates a positive correlation between training set proportion and accuracy. Starting from a training set proportion of 50%, the accuracy is around 91% and increases steadily as more data is added. At around 80% training data, the accuracy reaches approximately 95%, and further increases in training data yield minimal gains.

- **Plateau Effect:** Beyond an 80% training proportion, the model's accuracy begins to plateau near the 95% level, indicating diminishing returns from additional training data. This suggests that the model has captured most of the variability and features needed for effective recognition and that adding more data beyond this point yields limited benefit.

- **Implications for Model Optimization:** This analysis highlights the importance of balancing training data size with model performance. While increasing the training set proportion improves accuracy, the plateau suggests that using around 80% of the data for training is a reasonable choice, as it offers a high level of accuracy while leaving sufficient data for testing.

This subtopic emphasizes the trade-off between training set size and accuracy, providing a basis for selecting an optimal train-test ratio in our face recognition application.

11 Conclusion

11.1 Summary of Findings

In this project, we implemented a face recognition system using Principal Component Analysis (PCA) combined with the k-Nearest Neighbors (k-NN) classifier. The application of PCA effectively reduced the high dimensionality of facial image data by extracting the most significant features that capture the essential variance among different faces. This dimensionality reduction not only streamlined the computational process but also enhanced the efficiency of the recognition system. The k-NN classifier leveraged these extracted features to classify faces accurately based on their proximity in the feature space. Our results demonstrate that the integration of PCA and k-NN provides an effective balance between dimensionality reduction and classification accuracy, making it a viable approach for face recognition tasks.

11.2 Limitations

Despite the overall success of the system, we identified several limitations that affect recognition accuracy. One significant limitation is the system's difficulty in distinguishing between faces with very similar features. When individuals share close facial characteristics, the PCA may not capture enough distinct features to differentiate between them, leading to potential misclassifications. Additionally, the system is sensitive to variations in lighting conditions. Changes in illumination can alter the appearance of facial features, and since PCA primarily captures the most prominent variance, it may not account for these inconsistencies, thereby reducing the robustness of the recognition process under different lighting scenarios.

11.3 Future Directions

To overcome the identified limitations and enhance the performance and robustness of the face recognition system, future work could involve the incorporation of deep learning techniques or the development of more advanced algorithms. Implementing convolutional neural networks (CNNs) could enable the system to learn more complex and hierarchical features from facial images, improving its ability to distinguish between similar faces and handle variations in lighting, pose, and expression. Additionally, exploring advanced dimensionality reduction methods or combining PCA with other feature extraction techniques could further improve the system's accuracy. Integrating preprocessing steps to normalize lighting conditions and employing data augmentation strategies to expand the training dataset might also contribute to more robust recognition performance.

12 References

- Turk, M., & Pentland, A. (1991). Face recognition using eigenfaces. *Proceedings. 1991 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 586-591.
- AT&T Laboratories Cambridge. The ORL Database of Faces.