NATIONAL ECONOMICS UNIVERSITY

FACULTY OF MATHEMATICAL ECONOMICS

Business Analysis

Spring 2024

FACIAL RECOGNITION

DSEB 63 - GROUP 06

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I. Introduction

Today, we stand on the brink of a new era in technology where Machine Learning isn't just a buzzword but a cornerstone in developing intelligent systems that can learn, adapt, and make decisions. Among the myriad of applications this technology has empowered, face recognition systems stand prominently, carving a niche that spans security, personal identification, and beyond.

In our journey, we will delve into the fascinating world of face recognition systems, driven by the advancements in Machine Learning. Additionally, we will uncover the layers behind the scenes - the feature extraction and classification processes that serve as the backbone of this system.

As we navigate through the intricacies of building a custom face detection and recognition feature, we'll gain insights into the practical aspects and the potential applications that this technology harbors for the future.

Our expedition will also touch upon the role of Machine Learning-based face verification systems as it is our main goal to enhance security measures through 3D liveness detection, painting a picture of a future where technology and security converge seamlessly.

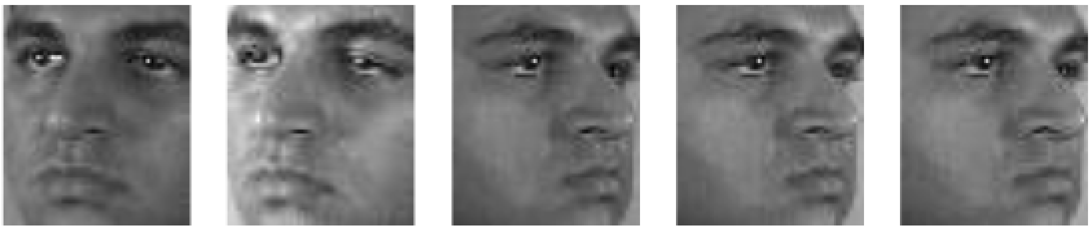
AT&T Dataset

Additionally to the AT&T dataset which was provided and requested by our professor advisor, we have accumulated 4 more datasets through various sources in order to expand on the variety of the features, such as the like of ‘face expressions, diff head poses, and light angles”. We believe this will help with the accuracy of the training process and greatly improve the functionality of our system.

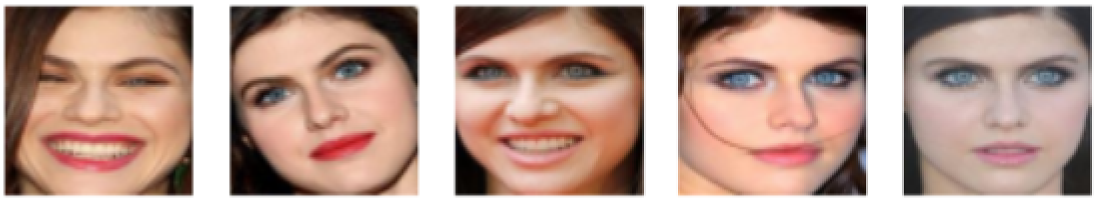
Dataset	Total observes	Number of people	Images per folder	Image size	Differences		
					Light angles	Head poses	Facial expressions
Set 1 (ATT)	400	40	10	112x92		✓	✓
Set 2	5430	30	181	60x51	✓	✓	
Set 3 (Celeb faces)	1519	31	49	160x160	✓	✓	✓
Set 4 (Faces94)	2400	120	20	70x70			✓
Set 5 (US Pres)	~4000	5	~800	200x180	✓	✓	✓

Examples from each additional Datasets used:

- Dataset 1:



- Dataset 2:



- Dataset 2 (gray scaled):

- Dataset 3:

- Dataset 4:

II. Literature review

The study of face recognition has been conducted widely for a long time. Generally, It has 3 steps: face detection, feature extraction then face recognition.
Face detection is detecting whether the provided images contain faces.

1. Feature extraction

Facial recognition relies on the analysis of key structural elements: size, shape, and overall configuration. Several techniques achieve this, broadly categorized into three conceptual approaches: holistic, local, and hybrid.

Local appearance-based methods concentrate on extracting detailed information from crucial facial landmarks such as the eyes, nose, and mouth. In contrast, holistic approaches process the entire face as a single unit. Finally, hybrid methods leverage the strengths of both, combining detailed landmark analysis with holistic processing.

In our work, we adopted a holistic approach. These methods typically represent facial images as a pixel matrix, which is then often transformed into feature vectors for efficient processing. Subsequently, these feature vectors are employed within a low-dimensional space, achieved through dimensionality reduction techniques. Data can encompass a multitude of features, but their significance varies. Reducing dimensionality can aid in the accurate visualization of data structure. Consider the act of throwing a paper airplane; in reality, this occurs in a three-dimensional space. However, as you may recall from high school physics, depicting this scene on a blackboard (a two-dimensional plane) suffices for the necessary calculations. This exemplifies the core principle of dimensionality reduction, which ultimately serves to optimize processing efficiency.

Within our project, we specifically employed techniques such as Linear Local Embedding (LLE), Principal Component Analysis (PCA) and its kernel variant (KPCA), and Independent Principal Component Analysis (IPCA).

PCA: Project data on the directions of maximum variance (Meaning important information still remained)

LLE: Reconstructs each data point using a linear combination of its k-nearest neighbors

2. Face recognition

The last step involves comparing the similarity of the target face to other known faces stored in the database. You can using Distance measurements such as euclidean, manhattan or cosine formula or using clustering algorithm like SVM,

a. Distances

- The Euclidean distance, also known as the Pythagorean distance, is the length of a line segment between two points in Euclidean space, calculated using their Cartesian coordinates.

$$d(\boldsymbol{X}, \boldsymbol{Y}) = L_{p=2}(\boldsymbol{X}, \boldsymbol{Y}) = \|\boldsymbol{X} - \boldsymbol{Y}\| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2};$$

- Manhattan distance is a metric that measures the absolute differences between two points' Cartesian coordinates, essentially calculating the total difference between their x and y coordinates.

$$d(\boldsymbol{X}, \boldsymbol{Y}) = L_{p=1}(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{i=1}^{n} |x_i - y_i|;$$

- Cosine similarity is a metric that determines how two vectors (words, sentences, features) are similar to each other. Basically, it is an angle between two vectors.

$$\cos(\boldsymbol{X}, \boldsymbol{Y}) = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{m} x_i^2 \sum_{i=1}^{m} y_i^2}};$$

$$d(\boldsymbol{X}, \boldsymbol{Y}) = -\cos(\boldsymbol{X}, \boldsymbol{Y}),$$

Range of cosine distance is from 0 to 2, 0 — identical vectors, 1 — no correlation, 2 — absolutely different.

b. Cluster

- SVM (highly recommend): Finds a hyperplane that maximizes the margin between the closest data points of each class
- KNN : The K-NN method classifies new instances based on their resemblance to previous examples, storing all available data and adding additional data points to facilitate categorization into well-suited categories.
- LDA: Aims to find a linear hyperplane that best separates different classes in the data. It maximizes the ratio of between-class scatter to within-class scatter.
- Decision Tree: Creates a tree-like structure that makes sequential decisions based on feature values to classify data points.
- NB : Employs Bayes' theorem to calculate the probability of a data point belonging to a specific class based on its features

III. Solution

1. Task 1

a. Description

Input: Set of images

1. Read Training Set of NxN images
2. Resize image dimensions to N^2x1
3. Select Training Set of N^2xM dimensions
4. Calculate Euclidean distances between the image and eigenfaces
5. Calculate eigenface of image in question
6. Create reduced eigenface space
7. Find average face, subtract from the faces in Training Set, create matrix A
8. Calculate eigenfaces
9. Calculate covariance matrix: AA'
10. Calculate eigenvectors of covariance matrix
11. Find minimum Euclidean distance

Output: image with the minimum Euclidean distance => Label

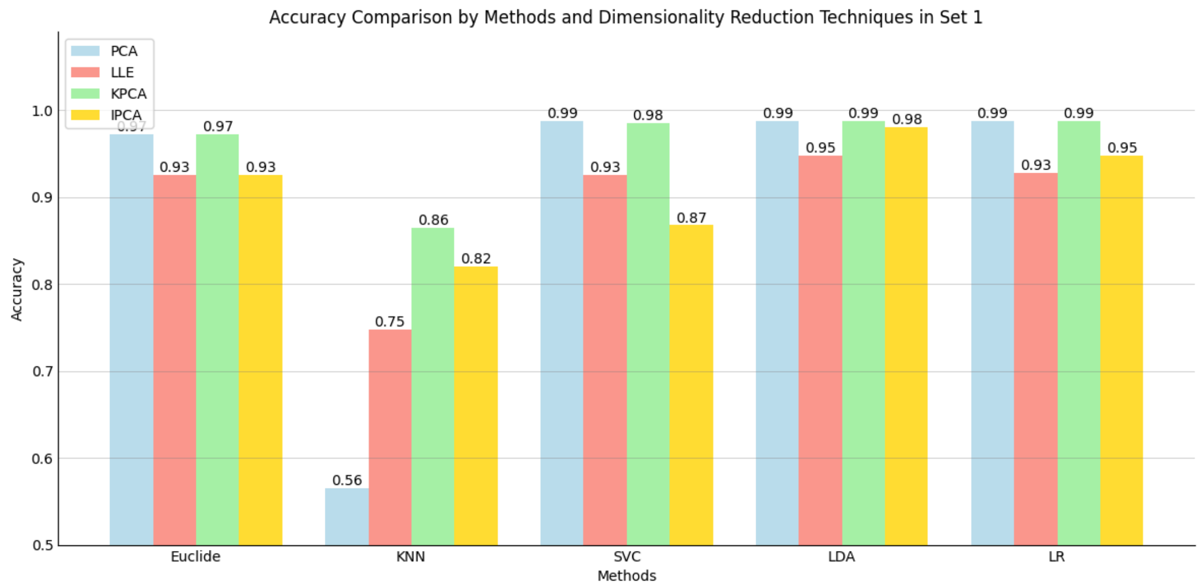
2. Task 2

a. Description

In this task, we might try out other methods in each key process (feature extraction, face recognition. Parameter tuning and cross-validation approaches such as LeaveOneOut, Kfold are used.

b. Result

	PCA	LLE	KPCA	IPCA
Euclidean	0.9725	0.925	0.9725	0.925
Manhattan	0.965	0.95	0.9625	0.9375
Minkowski	0.9725	0.925	0.9725	0.925
KNN	0.87	0.7475	0.865	0.82
NB	0.855	0.925	0.85	0.8675
DT	0.565	0.85	0.58	0.5325
SVC	**0.9875**	0.92	0.985	0.9525
LDA	**0.9875**	0.9475	**0.9875**	0.98
LR	**0.9875**	0.9275	**0.9875**	0.9475

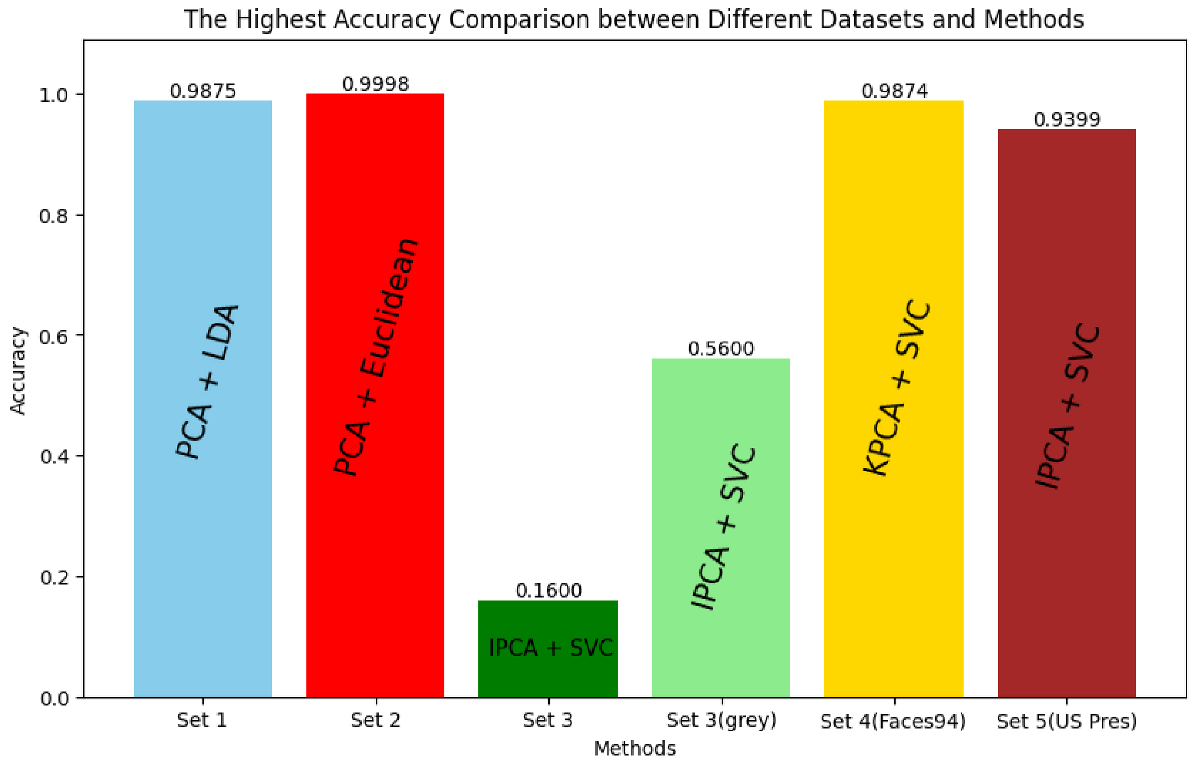


3. Task 3

a. Description

Each dataset has its own characteristics, challenges like facial expression, face angle and light condition. So we wonder if these algorithms above might remain the top model when implementing on other datasets.

b. Result



IV. Summary

After extensive testing and refinement across diverse datasets, several conclusions have been derived.

1. Firstly, the significance of scaling has been underscored. For instance, within our third dataset, a notable disparity in scores between the color and black-and-white versions highlights the importance of scaling.
2. Secondly, Support Vector Machine (SVM) exhibits consistent efficacy across all datasets, consistently achieving high accuracy rates.
3. Thirdly, Incremental PCA and Kernel PCA demonstrate comparable performance, yielding similar scores across the analysis.

V. Future work

At present, our predictive capabilities are confined to the current normal dataset. However, we have outlined a series of steps to be pursued given adequate time and resources:

1. Initially, our focus will be on finalizing our face detection program, akin to the approach adopted by the Mai Anh Group, enabling prediction via camera input.
2. Subsequently, attention will be directed towards refining algorithms for broader identification purposes, facilitating the integration of our recognition system with existing criminal databases.
3. Given the potential implications for law enforcement, prioritizing accuracy becomes paramount. Thus, efforts will be dedicated to ensuring our system can efficiently search and match individuals within large-scale databases, while minimizing false recognition.
4. The subsequent phase involves the implementation of real-time surveillance and monitoring capabilities. While these are operationalized, the development of a robust monitoring system capable of detecting and flagging individuals with known criminal records in dynamic and densely populated environments is imperative.
5. Collaboration among computer scientists, criminologists, psychologists, and other pertinent experts is envisaged to delve deeper into the multifaceted influences on criminal behavior. This interdisciplinary approach aims to forecast criminal activity and devise appropriate responsive measures.

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