الجمهورية الجزائرية الديمقراطية الشعبية
The People’s Democratic Republic of Algeria
وزارة التعليم العالي والبحث العلمي
Ministry of Higher Education and Scientific Research
جامعة محمد بوضياف بالمسيلة
University Mohamed Boudiaf of M’sila

كلية الرياضيات والإعلام الآلي
Faculty of Mathematics and Informatics

قسم الإعلام الآلي
Department of Computer Science

Domain: Mathematics and Computer Science

Thesis Presented to Fulfill the Partial Requirement
for Master's Degree in Computer Science

Specialty: INFORMATION SYSTEM AND SOFTWARE ENGINEERING

Prepared By: ABOUBAKER BENAMRA

Supervised By:
Loucif Hemza

ENTITLED

The conception of a monitoring system based on biometric recognition using a Hybrid approach

---

Jury Members

Said Hamani	Prof	University of M’sila	**President**
Loucif Hemza	Prof	University of M’sila	**Supervisor**
Abdelbaki Bouguerra	Prof	University of M’sila	**Examiner**

Academic Year 2024/2025

Dedication

بسم الله الرحمان الرحيم

(ما يفتح الله للناس من رحمة فلا ممسك لها وما يمسك فلا مرسل له من
بعده وهو العزيز الحكيم)
إلى من غرسا في قلبي حب العلم...

إلى أمي الحبيبة وأبي الغالي، رمز التضحية والدعاء والصبر

إلى أستاذي المشرف لوصيف حمزة، الذي لم يبخل عليّ بنصائح
وتوجيهاته، فله مني كل التقدير والامتنان

إلى إخوتي الأعزاء، الذين كانوا سندًا لي في كل المراحل

إلى شيوخي ومعلمي القرآن الكرام:
الشيخ خريف عبد القادر والشيخ البشير سعدوني وبن حامد سفيان

إلى الذين كانوا نورًا في طريقي بدعائهم وكلماتهم الطيبة ومساندتهم لي

الحمد لله على فضله و عطائه
فخير العطاء عطاء الله

Acknowledgment

Praise be to God alone, and prayers and peace be upon the one after whom there is no prophet, and upon his family and companions and those who came after him. Praise be to Him who opened up to us with His grace and mercy, and guided us to this and provided us with ease. So praise be to Him in the first and the last.

I would like to express my sincere gratitude and deepest appreciation to my supervisor, Mr. Loucif Hamza, for his invaluable guidance, continuous support, and encouragement throughout the preparation of this thesis. His insightful feedback, generosity with his time, and commitment to academic excellence have been instrumental in shaping this research.

This work would not have been possible without his supervision and dedication. I am truly grateful for the opportunity to learn under his direction.

My thanks also ago to the jury members for the honor they have done me by accepting to judge this modest work.

Table of Contents

List of Figures

List of Tables

General Introduction

In today's world, security and identity protection have become fundamental concerns across many domains such as government institutions, banking systems, and corporate infrastructures. Traditional authentication techniques—such as passwords, ID cards, and physical keys—are no longer considered fully secure. These methods are vulnerable to loss, theft, and human error, making them unreliable for high-security systems.

This has led to the emergence of biometric recognition systems, which offer more secure and efficient identification. Biometrics rely on unique, unchangeable characteristics of individuals such as fingerprints, iris patterns, voice, and facial features. Among these, facial recognition has gained particular attention due to its non-intrusive nature, user-friendliness, and suitability for real-time applications.

Facial recognition systems aim to identify or verify a person's identity by analyzing and comparing facial features. However, to ensure accuracy and reliability, the process involves several key steps: facial detection, feature extraction, classification, and identity verification.

Proposed Solution and Objectives:

This work proposes the design and implementation of a biometric monitoring system based on facial recognition. The system integrates two powerful algorithms—Principal Component Analysis (PCA) and Discrete Cosine Transform (DCT)—to extract and classify facial features effectively.
The objectives of this project are:

- To develop a robust facial recognition system that can accurately identify individuals.
- To apply PCA and DCT jointly for improved feature extraction efficiency.
- To implement a classification process that can reliably distinguish between individuals in a database.
- To deploy a working prototype that can be integrated into access control environments.

CHAPTER 1

Facial Detection

1.1 Introduction

Facial detection has become a fundamental component in various biometric systems and computer vision applications. It serves as a critical first step for face recognition, expression analysis, identity verification, and human-computer interaction. Over the years, numerous techniques have been developed to enhance the accuracy and robustness of face detection, making it a continuously evolving research area.

1.2 Why Facial Detection

Face detection plays a pivotal role in enabling machines to interact more intuitively with humans. It provides a non-intrusive, contactless, and widely acceptable means for identification and surveillance. Unlike other biometric modalities, facial images can often be captured remotely in real-time, making them ideal for security systems, mobile devices, and multimedia applications.

1.3 Evolution of Facial Detection

The evolution of face detection spans several decades:

- **1990s:** Basic image processing and rule-based methods.
- **2000s:** Statistical learning approaches (e.g., SVM, PCA).
- **2010s - present:** Deep learning techniques (e.g., CNNs, YOLO) offer high accuracy and real-time performance.
- Each era has introduced new capabilities that improved speed, accuracy, and adaptability under various conditions such as lighting, pose variation, and occlusion.

1.4 Facial Detection Approaches

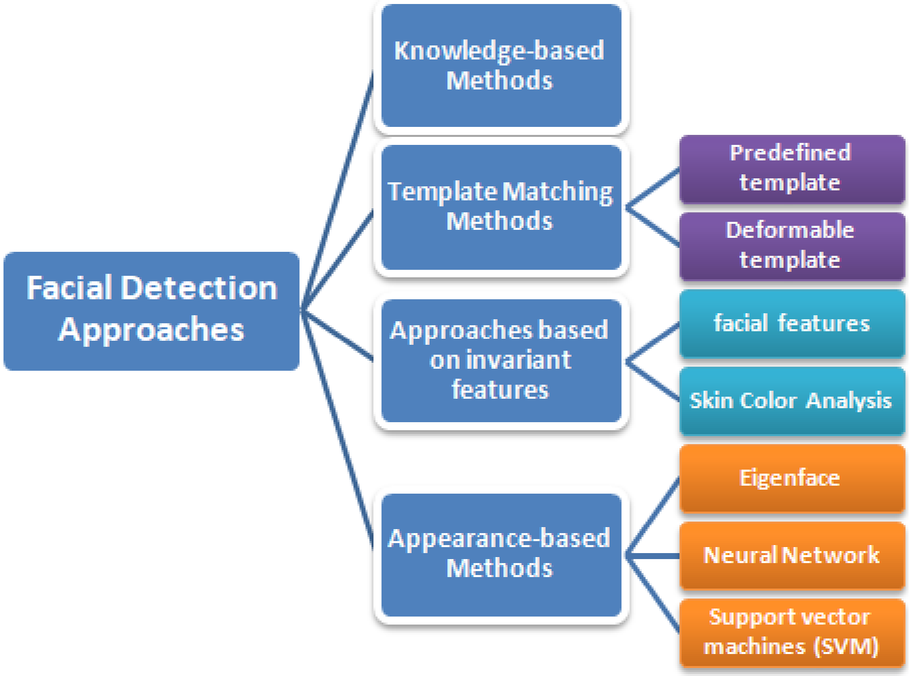


Figure 1.1: Facial Detection Approaches [4]

1.4.1 Knowledge-based Methods

These methods rely on human-coded rules based on facial features such as the position of eyes, nose, and mouth. For example, the eyes are typically located above the nose and mouth. Although intuitive, these methods are sensitive to variations in facial appearance and orientation.

1.4.2 Template Matching Methods

The definition of template matching can be either "manual" or based on predefined functions. The core idea of this approach is to compute the correspondence between filtered facial images and a reference template. Despite its simplicity, this method remains sensitive to variations in lighting conditions, scale, and other transformations. To address these challenges, Sinha [8] introduced an approach relying on a set of invariants that represent the structural model of the face. In order to capture invariance to brightness changes and better distinguish facial components, the algorithm computes the luminance ratio between different facial regions and preserves the directional information of these ratios.In this method, predefined templates (e.g., average face shape) are compared to subregions of the input image. These approaches are relatively simple but not robust against pose and scale changes.

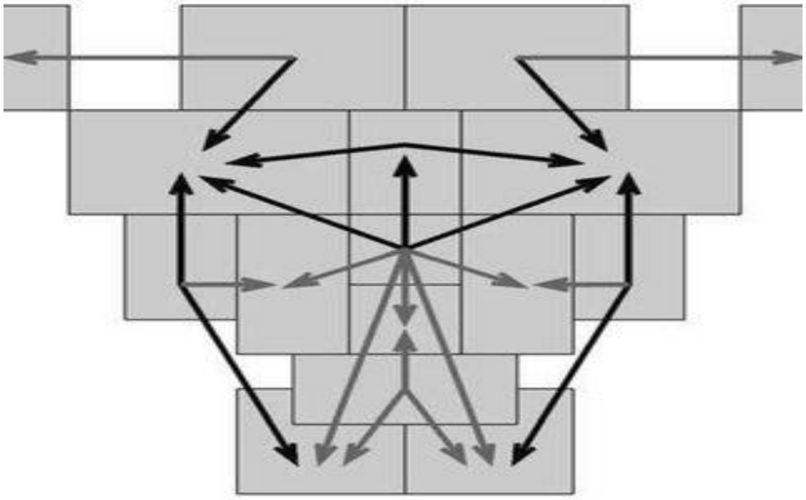


Figure 1.2: Face model consisting of 16 regions (rectangles) associated with 23 relationships (arrows) [5].

The face model is composed of 16 distinct regions (represented as rectangles), each associated through a network of 23 relational links (represented as arrows). These relationships capture spatial and structural dependencies between regions, serving as the foundation for feature extraction and comparison within template matching approaches.

1.4.3 Approaches based on invariant features

These methods are mainly employed for facial localization tasks. Recent algorithms are developed to extract stable structural characteristics of the face, even under variations such as facial expressions, pose changes, or lighting conditions. Once these invariant features are obtained, they are utilized in the process of face identification. The algorithms following this approach are generally categorized into two main groups:

- Algorithms based on facial feature extraction
- Algorithms relying on skin color analysis

1.4.3.1 facial features

These rely on extracting key landmarks or contours of facial components such as the eyes, nose bridge, and mouth corners. Algorithms like Active Shape Models (ASM) and Active Appearance Models (AAM) are commonly used.

1.4.3.2 Skin Color Analysis

These methods utilize color information to detect skin regions in images. Common color spaces include HSV and YCbCr. While efficient, these techniques may suffer from variations in illumination and ethnic diversity.

1.4.4 Appearance-based methods

These approaches typically leverage machine learning techniques, whereby models are trained using datasets composed of facial images that capture a wide range of appearance variations [5]. The fundamental concept behind this methodology is to treat face detection as a binary classification problem — distinguishing between “face” and “non-face” regions. A variety of techniques have been applied within this framework, including Eigenfaces, neural networks, and Support Vector Machines (SVM).

1.4.4.1 Eigenface Method

Based on Principal Component Analysis (PCA), Eigenface reduces facial images to a set of key features. It is efficient for face representation and recognition but sensitive to lighting and expression variations.

1.4.4.2 Neural Networks

Neural networks, particularly Convolutional Neural Networks (CNNs), have revolutionized face detection by automatically learning hierarchical features from data. They offer high accuracy and adaptability.

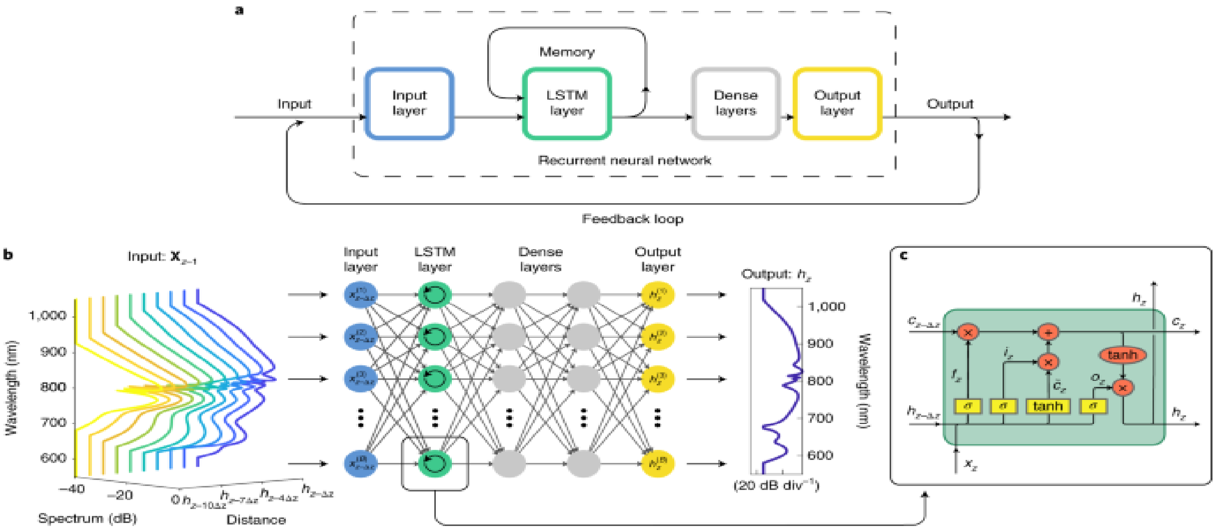


Figure 1.3: Rowley et al neuron network modal [12]

1.4.4.3 Support Vector Machines (SVM) for Face Detection

One of the first statistical methods based on information theory for face detec- tion, SVM is considered as a new model to classify training polynomial function, neural network or radial basis function (RBF).

Most of the aforementioned training classifications are based on the minimiza-tion of training error "empirical error", SVM operates with another principle called "structural risk minimization" which is intended to minimize higher jumps on likely generalized errors.

During learning for each pixel pair in the training set a histogram is used to create probability functions for face classes and non-face classes because pixel values depend on the values of their neighbors, For training Colmenarez and Huang [13] they used a large image set of size 11*11 pixels of face and not face, the learning outcomes form a Look up Table (LUT) set with probability ratios, for the purpose of improving performance.

1.5 Comparison between the different Face Detection

Table 1.1: Represents the advantages and disadvantages of each Approach.

Method	Robustness	Speed	Complexity	Accuracy
Knowledge-based	Low	High	Low	Low
Template Matching	Medium	Medium	Low	Medium
Invariant Features	Medium	High	Medium	Medium
Appearance-based (CNN)	High	High	High	High

1.6 Pre-treatment

The pre-processing phase precedes the face detection stage, and serves to prepare facial images for subsequent enrollment. Often referred to as the normalization phase, it involves generating standardized images from raw data. This typically includes aligning the face at the center of the frame and removing non-informative regions from the background.

To ensure optimal performance of the face recognition system, it is essential that all facial images share consistent dimensions, scale, and color format. Such uniformity significantly enhances the accuracy and efficiency of the signature extraction process. Normalization generally encompasses two main processes: **geometric normalization** (adjusting shape, position, and scale) and **photometric normalization** (adjusting lighting and contrast conditions).

1.6.1 Geometric Normalization

Geometric normalization involves adjusting the spatial properties of the face image to correct differences in scale, rotation, and position. Common techniques include:

- Aligning the face using key landmarks (e.g., eyes, nose).
- Scaling the face to a standard size.
- Cropping the image to remove irrelevant areas.

These operations ensure that each face image occupies a similar geometric space, making it easier for the detection algorithm to operate consistently across different inputs.

1.6.2 Photometric Normalization

Photometric normalization focuses on adjusting the lighting and color conditions of the image to reduce variability due to environmental factors. It may include:

- Histogram equalization to enhance contrast.
- Illumination normalization to correct uneven lighting.
- Conversion to grayscale or a consistent color space (e.g., YCbCr or HSV).

By minimizing the effects of lighting variations, this process helps in extracting more stable and distinctive facial features.

1.7 Facial Detection Applications

Face detection technology plays a crucial role across a wide spectrum of applications, ranging from biometric identification and video conferencing to image/video database indexing and the development of intelligent human–computer interaction systems. In the following section, we present a concise overview of some key application domains where face detection is particularly relevant and impactful.

1.7.1 Face Recognition Systems

As previously discussed, face detection is most commonly employed as a preprocessing step in face recognition systems. Face recognition itself represents one of several approaches to biometric identification. Accordingly, numerous biometric systems integrate face recognition with additional biometric modalities such as voice or fingerprint recognition. For instance, the BioID system [14] utilizes a model-based face detection technique that relies on edge information [15], serving as a preprocessing step in a multimodal biometric framework that incorporates facial features, voice, and lip movement recognition. Other systems include the CSIRO PC-Check system [16], which employs template-based methods, and FaceID by Visage Technologies, which adopts eigenface-based approaches [17][18].

1.7.2 Images and Videos

With the rapid growth of digital image content on the Internet and the widespread integration of digital video in databases, face detection has become a key component in many Content-Based Image Retrieval (CBIR) systems. The face detection approach developed by Rowley et al. [12], based on neural networks, has been employed in WebSeer [19], an image search engine for the World Wide Web.

The core idea behind integrating face detection into CBIR systems is that faces serve as significant semantic indicators of image content. As a result, large-scale digital video libraries—storing terabytes of audiovisual material—have recognized the strategic value of face detection technology. Notable examples include the **Informedia** project [20], which enables search and retrieval of TV news and documentary footage, and **Name-It** [21], which specializes in associating names with detected faces in news video content. Both systems utilize the face detection algorithm proposed by Rowley et al. [12].

1.7.3 Video Conferencing Systems

In video conferencing systems, there is a growing need for automatic camera control that ensures the active speaker remains in focus. A basic strategy involves guiding the camera using simple cues such as motion, audio direction, or skin color. However, a more sophisticated solution is proposed by **Wang et al.** [22], who developed an intelligent video conferencing system utilizing multiple cameras. In this system, the selection of the appropriate camera is dynamically determined based on the estimated gaze direction of the speaker's head.

Facial detection in their method is achieved by extracting features related to motion, contour geometry, skin tone, and facial structure. The estimation of the gazing angle is performed by analyzing the **hairline**, i.e., the boundary between the subject's hair and skin.

1.8 Conclusion

In this chapter, we have outlined the fundamental principles of face detection, presenting the key approaches and techniques commonly employed in this process. A comparative overview of these detection methods was provided, followed by a brief discussion of the intermediate step bridging face detection and recognition. Additionally, we explored a variety of practical applications that rely on face detection technology.

This study has confirmed that face detection constitutes a crucial phase within facial recognition systems. By examining the various automated detection strategies, we were able to highlight the essential facial features typically identified—such as the mouth, nose, and eyes. In the following section, we shift our focus to the main techniques and methodologies associated with face recognition itself.

CHAPTER 2

Facial Recognition

2.1 Introduction

Facial recognition has emerged as a critical necessity in today's world, as it offers a robust means of ensuring the security of individuals and organizations alike. Unlike traditional password-based authentication methods—which are often vulnerable to breaches—facial recognition systems provide a higher degree of reliability by relying on the unique and stable features of the human face.

This process follows the face detection phase, forming the second essential stage in facial analysis. In this section, we address the key challenges associated with facial recognition and examine the main strategies for enhancing its performance. These strategies are generally categorized into three overarching approaches: **global**, **local**, and **hybrid**. Finally, we highlight a number of real-world applications that incorporate these facial recognition systems.

Although the practical implementation of this work remains partial and does not yet meet the desired level of completeness, the theoretical and analytical foundations laid throughout the study contribute meaningfully to understanding and improving facial recognition systems.

2.2 Definition Facial Recognition

Face recognition is a biometric technique used to identify individuals by analyzing their facial features. Since its emergence in the 1960s, this technology has significantly evolved and found widespread application, particularly in the identification of individuals and suspects within major security agencies and government institutions [23].

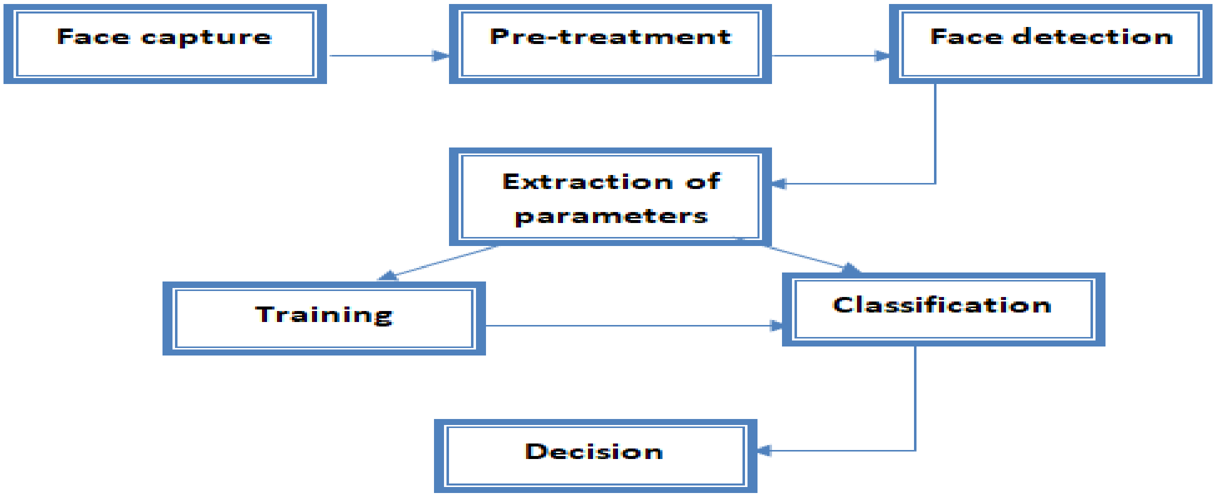


Figure 2.1.1: Representation of a facial recognition system

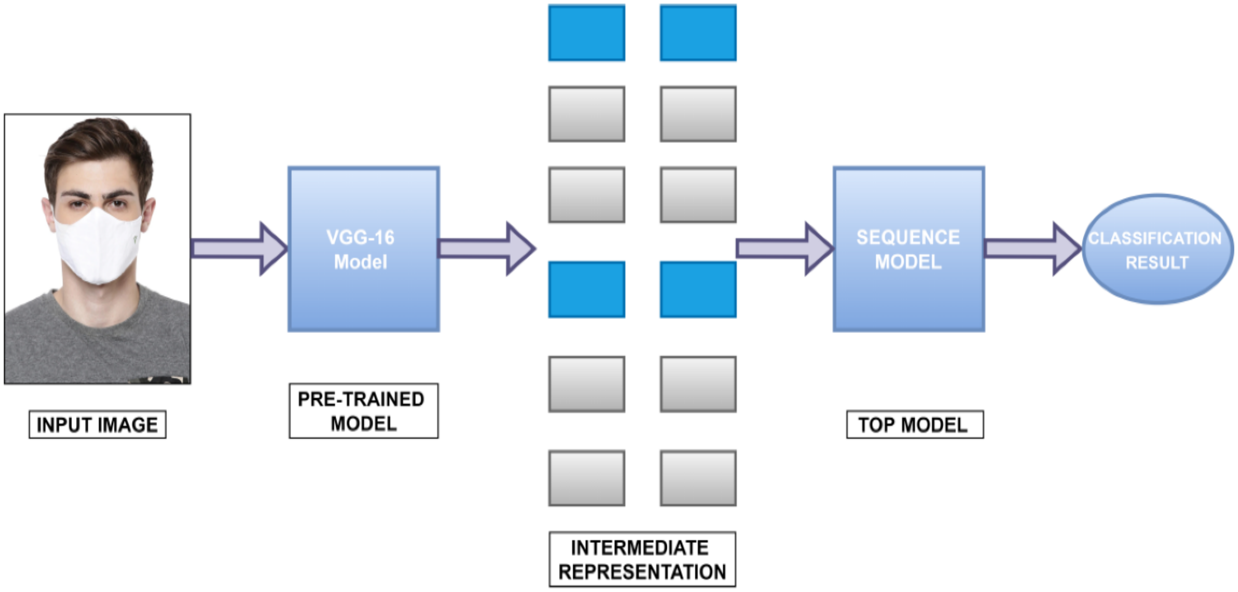


Figure 2.1.2: Automatic Face Recognition System Using Deep Convolutional Mixer Architecture and AdaBoost Classifier

2.3 Main diffculties of face recognition

Facial recognition is considered a high-level visual task for the human brain. While humans are naturally adept at detecting and identifying faces within complex visual environments, replicating this capability in an automated system remains a significant challenge—particularly under varying image acquisition conditions.

Facial images exhibit two primary types of variation: **inter-subject differences** (between individuals) and **intra-subject differences** (within the same individual). The inter-subject differences are relatively limited due to inherent physical similarities among people. However, intra-subject variations tend to be much broader and are influenced by a range of factors, which we analyze in the following section.

2.3.1 Change in illumination

The visual appearance of a face in an image can vary significantly depending on the lighting conditions at the time of capture (see Figure 2.2). These illumination variations pose a serious challenge to the accuracy of facial recognition systems. In many cases, the changes caused by lighting can be more pronounced than the actual physical differences between individuals, leading to misclassification or degraded performance.

This issue was experimentally demonstrated in the work of Adini et al. [24], where a database containing images of 25 individuals was used. Their findings confirmed that lighting variation remains one of the most critical obstacles in face recognition, especially in uncontrolled environments. As a result, managing illumination differences continues to be an active and essential area of research in this field.

Figure 2.2: Example of lighting variation

2.3.2 Variation in Pose

Facial recognition performance drops significantly when pose variations are present in the images. This challenge has been clearly demonstrated through evaluation tests conducted on standard datasets such as **FERET** and **FRVT** [25][26]. Pose variation is thus considered one of the most critical issues affecting the reliability of facial recognition systems.

When the face is rotated at a moderate angle (around 30°), it is still possible to apply geometric normalization by detecting at least two key facial landmarks—typically the eyes. However, when the head rotation exceeds 30°, normalization becomes increasingly difficult, and in many cases impossible (see Figure 2.3), which significantly degrades the system's ability to accurately recognize the face.

Figure 2.3: Example of Variation in Pose

2.3.3 Facial expressions

Facial expression is another key factor that affects the appearance of the face in an image (see Figure 2.4). The deformations caused by expressions are typically concentrated in the lower part of the face—particularly around the mouth and jaw—while the upper facial region tends to remain relatively stable. In many cases, this upper-region information is sufficient for identification.

However, since facial expressions alter the visual structure of the face, they inevitably lead to a decline in recognition accuracy. Identifying faces under varying expressions remains a complex and ongoing challenge in the field. Recent research suggests that temporal information—i.e., changes over time—can provide valuable clues to help address this issue [27].

Figure 2.4: Example of facial expressions

2.3.4 Presence or absence of structural components

The presence of structural accessories such as beards, mustaches, or eyeglasses can significantly affect the appearance of the face. These elements may alter key facial attributes such as shape, color, and even the perceived size of the face. Moreover, they can obscure essential facial landmarks, thereby disrupting the recognition process. For instance, opaque glasses can mask the shape and color of the eyes, making it difficult for the system to detect them accurately. Similarly, facial hair such as mustaches or beards can distort the contour of the lower face, leading to errors in identification or even failure in the recognition process.

2.3.5 Partial Occlusions

Faces may be partially occluded either by elements within the environment or by worn accessories such as glasses, scarves, or veils. In biometric systems, it is essential that recognition methods remain **non-intrusive**, meaning they should function without requiring active cooperation from the individual being identified. Consequently, the ability to detect and recognize **partially occluded faces** is of great importance.
In this regard, **Gross et al. [27]** investigated the impact of occlusion caused by sunglasses or the masking of the lower facial region using the **AR database [28]**. The experimental results showed that facial recognition performance **significantly decreases** under such conditions, highlighting the **vulnerability** of current algorithms to occlusion-related challenges.

2.4 Facial Recognition Approaches

Various methods have been proposed for facial recognition, each addressing different challenges related to variability in facial appearance. According to **Tan et al. [29]**, these approaches can be broadly **classified into three main categories**, each representing a distinct philosophy in handling facial data:

1. **Global Approaches**
2. **Local Approaches**
3. **Hybrid Approaches**

This classification provides a structured framework to analyze and compare different facial recognition techniques based on how they represent and process facial features.

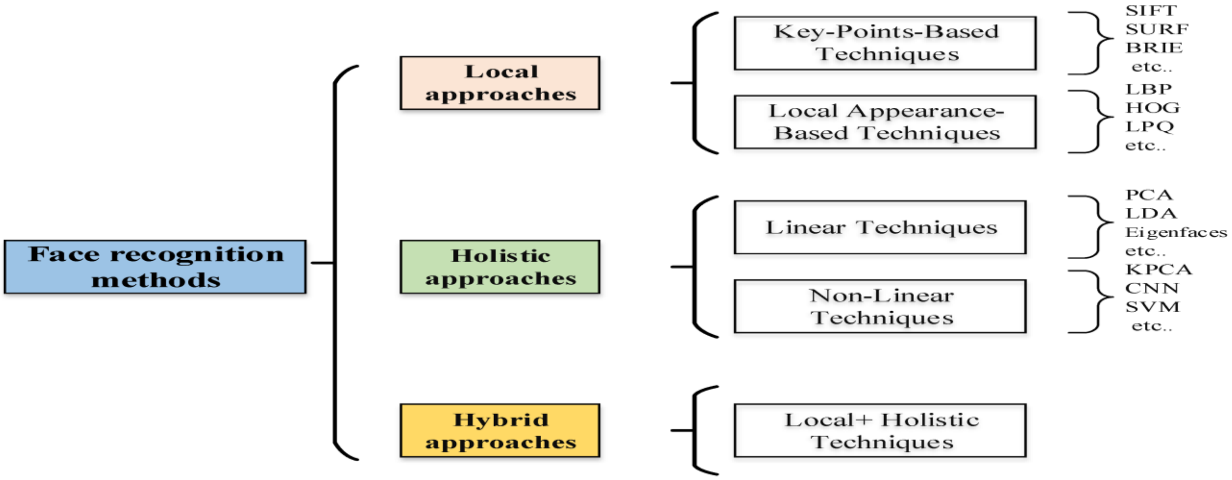


Figure 2.5: Facial Recognition Approaches

2.4.1 Global Approaches (Holistic Approache)

Also referred to as the **holistic approach**, this method aims to represent the entire facial image as a **single high-dimensional vector**. As described by **O'Toole et al. [30]**, the face is represented by concatenating the gray-level values of all pixels into an n×mn \times mn×m vector. This representation has the advantage of **implicitly preserving both texture and shape information**, which are essential for accurate face recognition. Furthermore, it captures the **overall structure of the face** more effectively than local representations [30].

However, a significant **drawback** of this approach lies in the **large dimensionality of the image space**, which complicates the classification process and increases computational cost.

Within global methods, **Xiao Guang Lu [31]** identified **two subcategories**:

- **Linear techniques**
- **Non-linear techniques**

These subtypes reflect different ways of managing and reducing the high-dimensional data to improve classification efficiency and recognition accuracy.

2.4.1.1 Principal Component Analysis (PCA)

One of the most widely used techniques in facial recognition is the **Eigenfaces method**, proposed by **Turk and Pentland [10]**. This method is based on **Principal Component Analysis (PCA)**, a mathematical approach used to reduce the dimensionality of a dataset while preserving the most significant variance. In the context of facial recognition, PCA enables the representation of facial images through a **set of principal components**, allowing any face to be reconstructed from a **mean face** and a weighted combination of **eigenfaces**.

The **strength** of PCA lies in its **simplicity**, **speed**, and **efficiency**, making it a popular choice in identity recognition systems. It allows for optimal projection into a reduced-dimensional space, which simplifies both computation and storage.

However, this method is **not without limitations**. PCA-based recognition is notably **sensitive to variations in illumination**, **facial expressions**, and **pose**, which can significantly impact recognition accuracy.

A more detailed explanation of the algorithm and its implementation will be provided in the following chapter.

2.4.1.2 Latent Dirichlet Allocation (LDA)

The technique known as **Fisherfaces** was first introduced by **Belhumeur et al. in 1997**. This method is based on **Linear Discriminant Analysis (LDA)**, which aims to **maximize the separation between different classes**. To implement this approach, it is essential to organize a **training dataset** into multiple classes — where each class corresponds to a single individual, and contains **multiple images per person**.

Fisherfaces is widely used for **classification** and **dimensionality reduction** tasks. Unlike PCA which preserves overall variance, LDA emphasizes the **discriminative features** that help distinguish between individuals.

However, one limitation of this approach is its **inability to handle high-dimensional data directly**. When dealing with large image datasets, the algorithm requires a **preprocessing step** to reduce dimensionality. In such cases, **PCA is applied first** to the raw data, and the resulting lower-dimensional representation (face space) is then used as input for the LDA step [32].

2.4.2 Local Approaches

Local-based facial recognition methods focus on **specific regions or features** of the face rather than analyzing it as a whole. Compared to holistic approaches, **local methods are considered more mature** and robust, particularly in handling variations such as expression or partial occlusion.

In these methods, the face is represented using a **set of low-dimensional feature vectors**, each corresponding to a **distinct region or characteristic point** of the face, instead of a single high-dimensional global vector [33].

The local approach is typically classified into **two main categories**:

- **Feature-based methods**: These techniques rely on the **detection and extraction of key facial landmarks**, such as the corners of the eyes, mouth, or the tip of the nose.
- **Appearance-based methods**: These approaches divide the face into **multiple regions**, and extract **local descriptors or scores** based on the **appearance (texture, intensity)** within those specific regions.

2.4.2.1 Feature-based methods

Feature point extraction methods can be categorized into two main types: **geometric-based approaches** and **graph-based approaches**.

Geometric-based approach:

This method relies on identifying the relative positions of key facial components such as the eyes, nose, and mouth. Many engineering techniques use interest points corresponding to these facial elements. However, this approach faces certain limitations, especially in its purely geometric form:

- Geometric features are often difficult to extract in challenging scenarios involving variable lighting or occlusions.
- Geometric features alone may not provide sufficient information to represent a face comprehensively.

Graph-based approaches:

These methods use a graph structure to represent the local facial features. In this representation, the face recognition task is treated as a graph-matching problem. In 1992, **Man** [34] demonstrated the effectiveness of this technique using a dataset of 86 facial images with variations in expressions and poses, achieving an average recognition rate of around 90% [35].

However, once the topological graph is constructed, it remains fixed, while facial input images can vary significantly due to changes in expression, head orientation, etc. To address this limitation, several advanced methods have been proposed, including **Elastic Graph Matching (EGM)** and **Elastic Bunch Graph Matching (EBGM)** [35].

2.4.2.2 Appearance-based methods

These techniques primarily rely on analyzing distinct regions of the face. The overall facial model is constructed through the integration of several local models, which remain largely unaffected by variations such as smiling or wearing glasses.

Two main parameters are used to define the local facial regions: their **location** and **size**. The characteristics of these local regions are identified through the analysis of **grayscale intensity values**, which serve to capture and preserve important **texture information** [36].

2.4.3 Hybrid Approaches

Hybrid methods combine both holistic and local approaches to enhance the performance of facial recognition systems. Since local and global features possess distinct properties, their integration aims to leverage the strengths of each, thereby improving classification accuracy.

Table 2.1: Comparison of methods based on local or global characteristics.

Factors for change	local feature	Global feature
illumination	very sensitive	sensitive
expression	not sensitive	sensitive
Pose	sensitive	very sensitive
noise	very sensitive	very sensitive

2.5 Facial Recognition Applications

Facial recognition technology has become an indispensable tool in various fields. Its applications are not limited to the computer science sector but extend to many industries, including education, law enforcement, and others.

2.5.1 Security

Face recognition technology serves as an additional authentication method for accessing personal accounts, whether on personal computers, banking platforms, or email services. Adding this extra layer of security is invaluable, especially when an individual's financial or personal information is at risk. For instance, Automated Teller Machines (ATMs) are already equipped with cameras to deter tampering; these cameras can also be utilized for identification purposes, granting access only if the user's face matches the system records. Protecting such data with biometric security systems like facial recognition is crucial. Facial recognition is currently employed as a form of access control. Jeffrey S. Coffin proposed a security system that uses facial recognition to verify individuals and determine their clearance levels (Coffin, 1999). While biometric security in popular media often focuses on retinal or fingerprint scans, facial recognition remains a powerful biometric tool capable of enhancing any access control system [37].

2.5.2 Attendance Systems

Educational systems have several processes that can be enhanced by implementing facial recognition technology. One key task is taking attendance, which is essential to confirm student presence. However, as class sizes increase, especially in large lecture halls or auditoriums, this process becomes more time-consuming and challenging. Although not widely adopted yet, such systems are already in place.

Abhishek Jha developed an automated attendance system that holds great potential for the education sector [38].

This system significantly reduces the time spent on attendance by enabling instructors to begin lessons immediately instead of calling out names one by one. Many universities have even abandoned manual attendance due to the impracticality of managing large student populations. By automating attendance, institutions can efficiently monitor student participation in lectures.

2.5.3 Law Enforcement

Law enforcement is another sector that stands to gain significantly from facial recognition technology. One of the key responsibilities of police officers is to locate and apprehend criminals. Facial recognition software can streamline this task by automatically identifying suspects without requiring extensive manpower beyond the actual arrest. Cameras are installed nationwide—ranging from traffic and street cameras to private security systems. Authorities can integrate their criminal databases with facial recognition algorithms, enabling continuous tracking of offenders across different locations worldwide.

Additionally, issuing speeding tickets is another task that consumes police officers' time. Sensors can detect when a vehicle exceeds speed limits, and cameras equipped with facial recognition can identify the driver, automatically issuing a speeding ticket. Although installing such cameras and sensors may currently involve high costs, advancements in technology are steadily reducing these expenses [37].

2.6 Face Image Databases

Table 2.2: Face Image Database.

Data Set	Location	Description
MIT Database [10]	ftp://whitechapelmediamitedu/ pub/images/	Faces of 16 people, 27 of each person under various illumination conditions, scale and head orientation.
FEBET Database [39]	http://www.nist.gov/humanid /feret	A large collection of male and female faces Each image contains a single person with certain expression.
UMIST Database [40]	http://images.ee.umist.ac.uk/ danny/database.html	564 images of 20 subjects. Each subject covers a range of poses from profile to frontal views.
University of Bern Database	ftp://iamftp.unibesch/ pub/Images/FaceImages/	300 frontal face images of 30 people (10 images per person) and 150 profile face images (5 images per person).
Yale Database [41]	http://cvc.yale.edu	Rice images with expressions, glasses under different illumination conditions.

AT&T (Olivetti) Database [35]	http://www.uk.research.att.com	90 subjects, 10 images per subject.
Harvard Database [42]	ftp://ftp.hrl.harvard.edu/pub/faces/	Cropped, masked face images under a wide range of lighting conditions.
M2VTS Database [43]	http://poseidon.csd.auth.gr/M2VTS/index.html	A multimodal dat4vacP containing various image sequences.
Purdue AR Database [28]	http://rvILectpurdue.eduraleix/aleixface DB.html	3,276 face images with different facial expressions and occlusions under different illuminations.

2.7 Conclusion

In this chapter, we provided an overview of facial recognition, highlighting the key challenges encountered in the process. We then explored various approaches used in facial recognition systems. Additionally, we introduced several practical applications that leverage facial recognition technology, along with a review of prominent facial image databases that support research and development in this field.

In the following chapter, we will delve into detailed explanations of important algorithms such as Principal Component Analysis (PCA) and Discrete Cosine Transform (DCT). We will also cover the computational steps involved in these methods, including how to calculate the Euclidean distance, which is fundamental for measuring similarity in facial recognition tasks.

CHAPTER 3

Classification and Parameter Extraction

3.1 Introduction

In facial recognition, it is essential to extract distinctive facial features and compare them with those stored in predefined databases using specialized algorithms. This chapter introduces the two algorithms chosen for feature extraction and classification: Principal Component Analysis (PCA) and Discrete Cosine Transform (DCT). We will explore how these algorithms function from a mathematical perspective, and we will detail the process of calculating Euclidean distances to assess similarity between faces. Through this, we aim to highlight how these techniques contribute to building an efficient and reliable facial recognition system.

3.2 Principal Component Analysis

3.2.1 Definition

The role of facial recognition systems is to differentiate image data belonging to various categories (i.e., different individuals). Although this data can be noisy—due to varying lighting conditions or backgrounds—the input facial images are not entirely random. There are consistent patterns that tend to appear across all facial data. These recurring patterns, such as the presence of key facial elements (eyes, nose, mouth) and their relative distances, form the foundation of facial recognition and are referred to as *eigenfaces*.

These features can be extracted from raw image data using a mathematical technique known as Principal Component Analysis (PCA). The concept of representing human faces through principal components was first introduced by Sirovich and Kirby in 1987. Later, in 1991, Turk and Pentland applied this idea to facial detection and recognition. The *eigenface* approach is widely regarded as the first practical technology in the field of facial recognition and has laid the groundwork for numerous commercial systems. Since its inception, the method has undergone various enhancements and has inspired the development of more advanced recognition techniques.

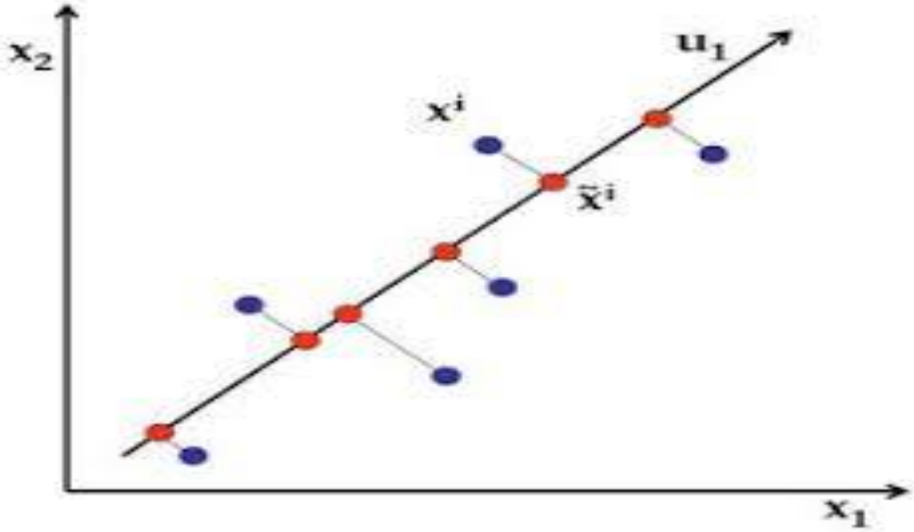


Figure 3.1: Example of projection following PCA .

3.2.2 PCA Algorithm

The process of computing *eigenfaces* using the PCA algorithm involves a series of structured mathematical steps aimed at reducing the dimensionality of facial image data while preserving the most important features. These steps allow the system to represent faces in a compact and discriminative form, which improves recognition performance and efficiency.

Below are the main steps involved in the calculation of eigenfaces:

3.2.2.1 Prepare the data

A two-dimensional facial image can be transformed into a one-dimensional vector by concatenating all its rows (or columns) into a single, long vector. Suppose we have a total of **M** such vectors, each of size **N** (where *N* = *number of rows* × *number of columns* in the image). In this case, the training dataset can be represented as a set of image vectors:
$\Gamma_1, \Gamma_2, \Gamma_3, ..., \Gamma\_M$.

3.2.2.2 Subtract the mean

The average face matrix Ψ\PsiΨ must first be computed by averaging all training images. This average is then subtracted from each original face image Γi\Gamma_iΓi, and the result is stored in a new variable Φi\Phi_iΦi, which represents the mean-centered version of each face:

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \tag{3.1}$$

$$\Phi_i = \Gamma_i - \Psi \tag{3.2}$$

This step ensures that all facial images are centered around the mean face, which is essential for applying Principal Component Analysis.

3.2.2.3 Calculate the co-variance matrix

In the next step, the covariance matrix A is calculated to capture the distribution of the face data in the feature space. This matrix is essential for identifying the directions (principal components) that represent the maximum variance in the data. It is computed as follows:

$$A= \Phi T\Phi \tag{3.3}$$

3.2.2.4 Calculate the eigenvectors and eigenvalues

At this stage, it is necessary to determine the eigenvectors _Xi and their associated eigenvalues _λi.

3.2.2.5 Calculate eigenfaces

$$[\Phi]X_i = f_i \tag{3.4}$$

where X_i are eigenvectors and f_i are eigenfaces

3.2.2.6 Classifying the faces

The new image is transformed into its eigenface components. The resulting weights form the weight vector Ω^{T}_{new} :

$$\omega_k = \Omega_k^{T} (\Gamma_{new} - \Psi) \quad \text{and} \quad k = 1.2.3....M \tag{3.5}$$

$$\Omega^{T}_{new} = [\omega_1 \omega_2 \omega_3 .... \omega_M] \tag{3.6}$$

The Euclidean distance [13-19] between two weight vectors $d(\Omega i,\Omega j)$ provides a measure of similarity between the corresponding images i & j. If the Euclidean distance between Γ_{new} and other faces exceeds some threshold value θ, one can assume that Γ_{new} is not a face at all, $d(\Omega i,\Omega j)$ also allows one to construct "clusters" of faces such that similar faces are assigned to one cluster [45]

3.2.3 Distance Measures

When comparing two feature vectors generated by the Biometric Feature Extraction Module, the system can perform either a similarity assessment or a distance-based evaluation. One common method involves using Euclidean distance, which belongs to the broader class of Minkowski distances of order p, defined within an N-dimensional Euclidean space $\mathbb{R}^N$, where N represents the dimensionality of the space [46].

Consider two vectors $X = (x_1, x_2, ..., x_n)$ et $Y = (y_1, y_2, ..., y_n)$, the distance of Minkowski of order p noted L_p is defined by:

$$L_p = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p} \tag{3.7}$$

3.2.3.1 Euclidean distances:

Distance City Block (L1) Pour p = 1, on obtient la distance City-Block (ou distance de Manhattan) :

$$L_1(x, y) = \sum_{i=1}^{n} |x_i - y_i| \tag{3.8}$$

Euclidean distances (L2) For p = 2, the Euclidean distance is obtained:

$$L_2(x, y) = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \tag{3.9}$$

The objects can then appear in very different ways depending on the distance measurement chosen.

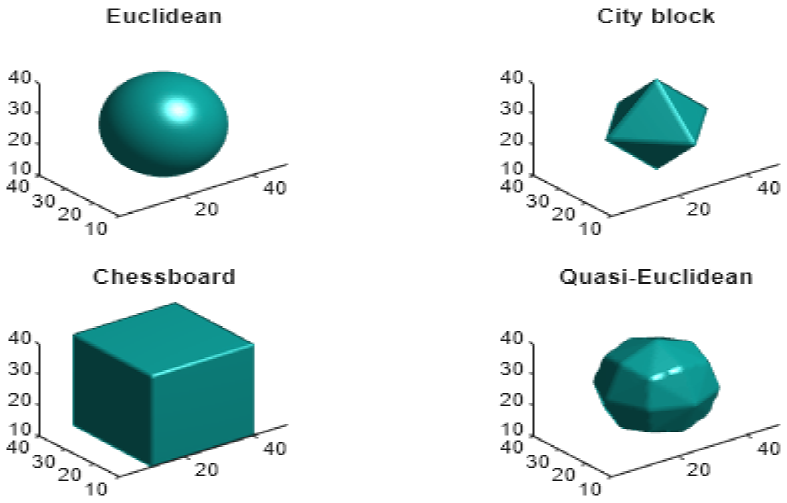


Figure 3.2: Representation of a sphere with the Euclidean distance and the City-Block distance [46]

3.3 Discrete Cosine Transform

3.3.1 Definition

The Discrete Cosine Transform (DCT) is a widely adopted technique, particularly renowned in the domains of image and video compression. Originally introduced by Ahmed et al. in 1974, DCT enables the conversion of image signals from spatial to frequency domains. Its effectiveness led to its integration into the first international image compression standard, JPEG, established in 1992, where it was embedded in both the encoder and decoder processes. More recently, DCT has been employed in facial recognition systems. In this context, it serves to reduce redundancy within an image by transforming it into the frequency domain, allowing for the extraction of the most relevant components (i.e., coefficients) that can be used for accurate identification [47].

3.3.2 Discrete Cosine Transform Encoding

3.3.2.1 The One-Dimensional DCT

The general equation for a 1D (N data items) DCT is defined as follows:

$$F(u) = \alpha(u) \sum_{i=0}^{N-1} A(x) * \cos \frac{u(2x+1)\Pi}{2N} \quad (3.10)$$

for u = 0,1,2,.…,N-1 . Similarly, the inverse transformation is defined as

$$A(x) = \sum_{u=0}^{N-1} \alpha(u) F(u) \cos \frac{u(2x+1)\Pi}{2N} \quad (3.11)$$

for x = 0,1,2,....,N-1 . In both equations Equation 3.10 and Equation 3.11 $\alpha(u)$ is defined as

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & \text{for } u = 0 \\ \sqrt{\frac{2}{N}} & \text{for } u \neq 0 \end{cases} \quad (3.12)$$

It is clear from Equation 3.10 that for u = 0

$$F(u=0) = \sqrt{\frac{1}{N}} \sum_{x=0}^{N-1} A(x) \tag{3.13}$$

the first transform coefficient is the average value of the sample sequence. In literature, this value is referred to as the DC Coefficient. All other transform coeffi- cients are called the AC *Coefficients*[4].

The plot of $\sum_{x=0}^{N-1} \cos \frac{u(2x+1)\Pi}{2N}$ for N = 8 and varying values of u is shown in Figure Figure 3.3. In accordance with our previous observation, the first the top- left waveform (u = 0) renders a constant (DC) value, whereas, all other waveforms (u = 1,2,...,7) give waveforms at progressively increasing frequencies [48].

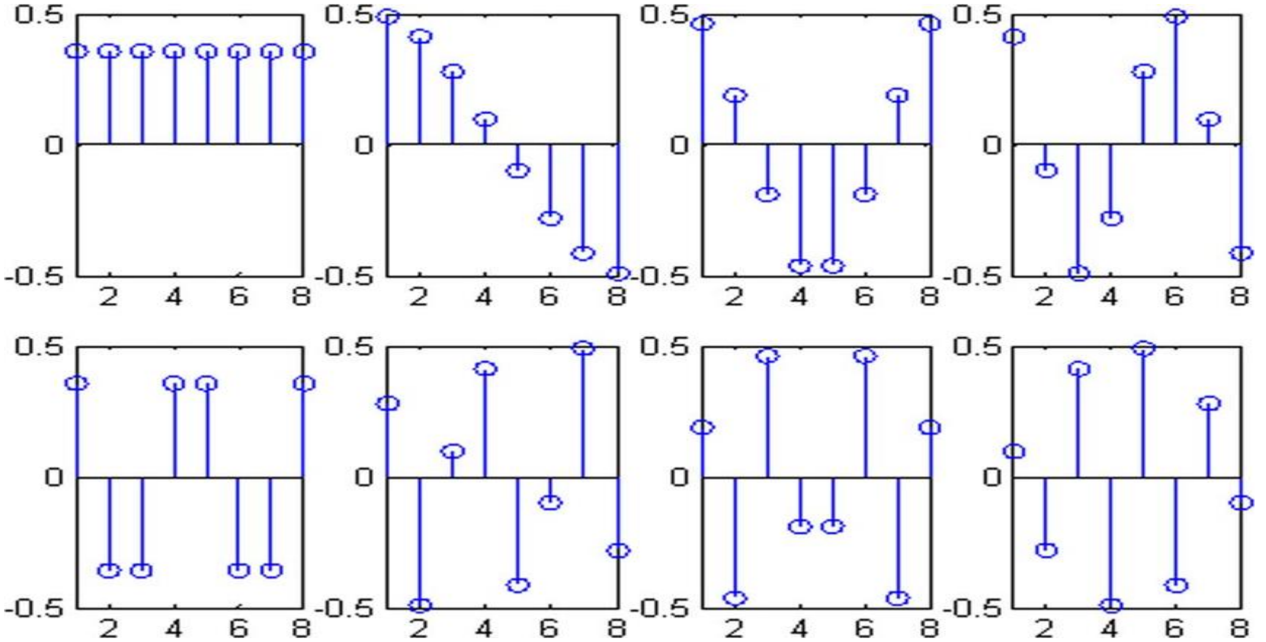


Figure 3.3: One dimensional cosine basis function (N=8).

3.3.2.2 The Two-Dimensional DCT

The objective is study the efficacy of DCT on images. This necessitates the extension of ideas presented in the last section to a two-dimensional space. The 2-D DCT is a direct extension of the 1-D case and is give by

$$F(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} A(x,y) \cos\frac{u(2x+1)\Pi}{2N} \cos\frac{v(2y+1)\Pi}{2N} \qquad (3.14)$$

for u ,v = 0,1,2,...,N-1 and $\alpha(u)$, $\alpha(v)$ are defined in Equation 3.12. The inverse transform is defined as

$$A(x,y) = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} \alpha(u)\alpha(v)F(u,v) \cos\frac{u(2x+1)\Pi}{2N} \cos\frac{v(2y+1)\Pi}{2N} \qquad (3.15)$$

for x,y = 0,1,2,...,N-1

The two-dimensional (2-D) basis functions used in DCT can be constructed by taking the product of one-dimensional (1-D) basis functions oriented horizontally with another set of the same 1-D functions oriented vertically [48]. When the dimension N=8N = 8N=8, the resulting set of 2-D basis functions illustrates a gradual increase in frequency across both the vertical and horizontal axes. Notably, the top-left basis function is produced by multiplying the DC (zero-frequency) component of the 1-D basis with its own transpose. This specific function remains constant across the entire image and is known as the **DC coefficient**, representing the average intensity of the block.

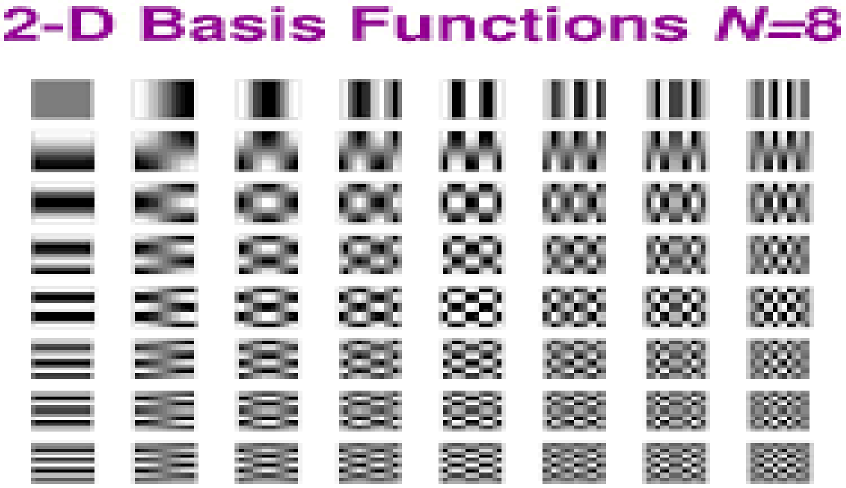


Figure 3.4: Two dimensional DCT basis functions (N = 8). Neutral gray represents zero,white represents positive amplitudes, and black represents negative amplitude [48]

3.3.3 Properties of DCT

In the previous section, the mathematical foundation of the Discrete Cosine Transform (DCT) was introduced. However, a more intuitive perspective—particularly as it applies to image processing—was not discussed. In this section, we aim to illustrate some of the practical and intuitive characteristics of DCT that make it especially useful in image processing tasks. Through examples, we will highlight how DCT captures essential image features, compresses data efficiently by concentrating energy into fewer coefficients, and reduces redundancy—all of which are crucial for applications like image compression, enhancement, and recognition.

3.3.3.1 Decorrelation

The primary advantage of applying image transformation techniques like the Discrete Cosine Transform (DCT) lies in their ability to eliminate redundancy between adjacent pixels. By doing so, the transform produces a set of uncorrelated coefficients that can be encoded independently and more efficiently. As demonstrated in Figure 3.5, the normalized autocorrelation of the image drops significantly after the DCT is applied, with minimal amplitude across all lags. This clearly indicates that DCT provides strong decorrelation capabilities, making it highly effective for tasks like compression and feature extraction in image processing.

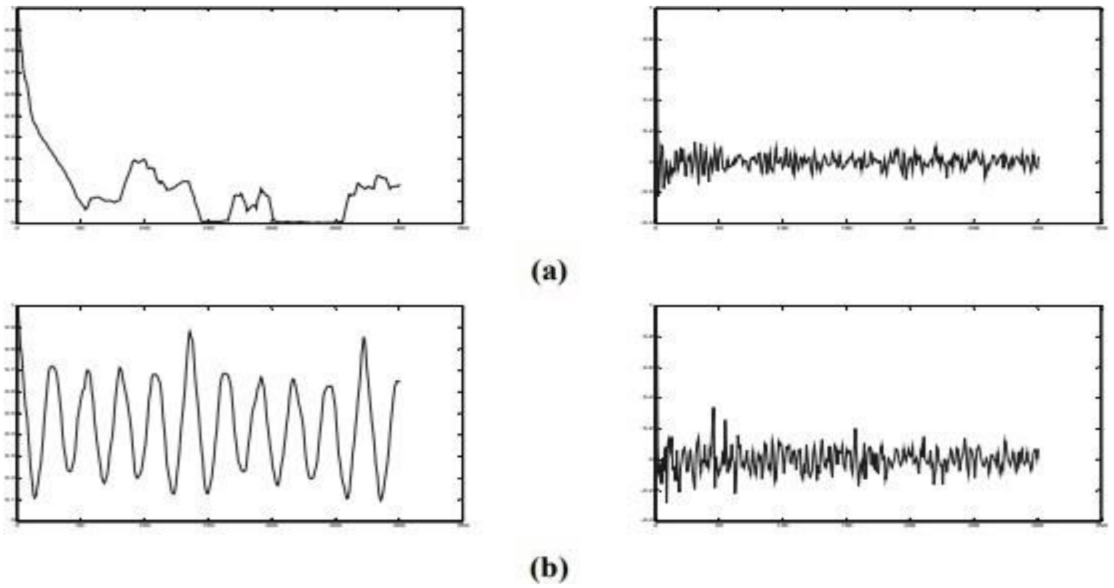


Figure 3.5: (a) Normalized autocorrelation of uncorrelated image before and after DCT- (b) Normalized autocorrelation of correlated image before and after DCT.

3.3.3.2 Energy Compaction

The effectiveness of a transformation technique can be directly assessed by how well it concentrates the input data into a minimal number of significant coefficients. This capability is crucial because it enables the quantizer to eliminate coefficients with smaller amplitudes—those contributing little information—without causing noticeable visual degradation in the reconstructed image. The Discrete Cosine Transform (DCT) is particularly known for its strong energy compaction properties, especially when applied to images with high correlation between neighboring pixels, making it ideal for compression and efficient feature representation.

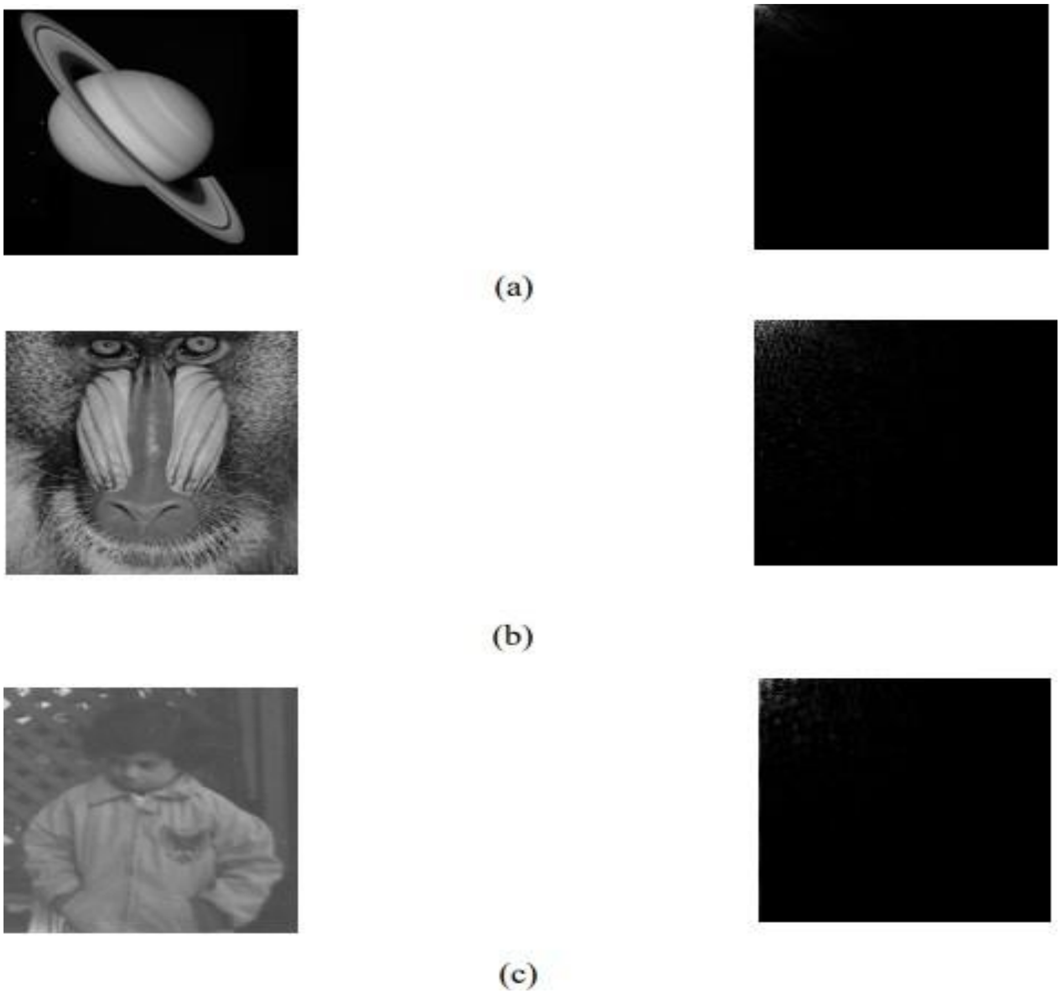


Figure 3.6: (a) Saturn and its DCT-(b)Baboon and its DCT-(c)Child and its DCT

The application of the DCT to these images provides very good energy com- paction in the low-frequency region of the transformed image. Therefore, from the previous images, it can be noted that the DCT makes an excellent energy com- paction for correlated images.

3.3.3.3 Separability

The DCT transform equation Equation 3.14 can be expressed as

$$F(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \cos\frac{u(2x+1)\Pi}{2N} \sum_{y=0}^{N-1} A(x,y) \cos\frac{v(2y+1)\Pi}{2N} \qquad (3.16)$$

for u ,v =0,1,2,...,N-1.

This property, known as separability, has the principle advantage that C(u, v) can be computed in two steps by successive 1-D operations on rows and columns of an image. This idea is graphically illustrated in Figure Figure 3.7. The arguments presented can be identically applied for the inverse DCT computation [49].

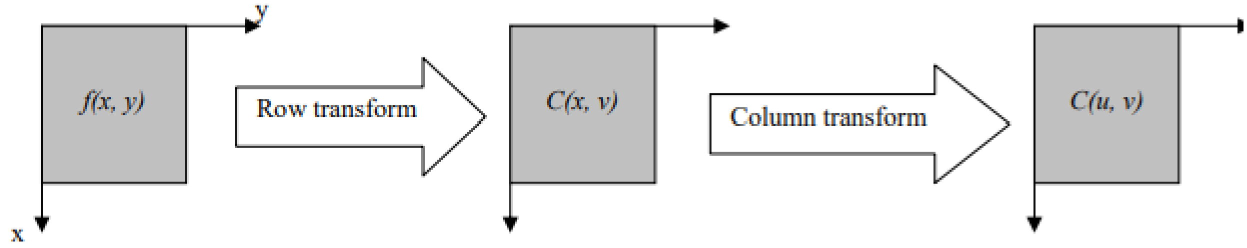


Figure 3.7: Computation of 2-D DCT using separability property

3.3.3.4 Symmetry

Another look at the row and column operations in Equation page 50 reveals that these operations are functionally identical. Such a transformation is called a symmetric transformation. A separable and symmetric transform can be expressed in the form [50].

$$T = kfk \qquad (3.17)$$

3.3.3.5 Orthogonality

In order to extend ideas presented in the preceding section, let us denote the inverse transformation of Equation 3.17 as :

$$T = k^{-1} f k^{-1} \tag{3.19}$$

As discussed previously, DCT basis functions are orthogonal. Thus, the inverse transformation matrix of k is equal to its transpose i.e. $k^{-1} = k^{T}$.Therefore, and in addition to its decorrelation characteristics, this property renders some reduction in the pre-computation complexity.

3.3.4 DCT versus DFT and KLT

DCT = Discrete Cosine Transform
DFT = Discrete Fourier Transform
KLT = Kamunen-Loeve Transform

At this stage, it is crucial to highlight the advantages of the Discrete Cosine Transform (DCT) in comparison to other widely-used image transformation techniques, specifically the Karhunen–Loève Transform (KLT) and the Discrete Fourier Transform (DFT).

The **Karhunen–Loève Transform (KLT)** is a statistical linear transform whose basis vectors are derived from the image data itself, making it adaptive. KLT is theoretically optimal for energy compaction, concentrating most of the signal energy into a few coefficients. However, this optimality comes at the cost of practicality—KLT is data-dependent and generally non-separable, meaning that a full matrix multiplication is needed for each image block. This leads to very high computational complexity, especially when no fast transform (like FFT) is available. Despite the development of some faster KLT algorithms, their implementation remains more complex and computationally demanding than DCT or DFT.

On the other hand, the **Discrete Fourier Transform (DFT)** is linear, separable, and symmetric, much like the DCT. It benefits from fixed basis functions and supports efficient computation through the Fast Fourier Transform (FFT). While DFT performs reasonably well in terms of decorrelation and energy compaction, it is inherently complex-valued, meaning both magnitude and phase must be processed—adding further processing overhead. Additionally, DFT assumes periodicity in the signal, which can lead to boundary discontinuities and artificial high-frequency components. After quantization, this often results in *Gibbs Phenomenon*, where edge artifacts appear due to the misrepresentation of signal boundaries.

In contrast, **DCT offers a balanced trade-off**: it is computationally efficient, thanks to fast algorithms; real-valued and therefore simpler to implement; and it provides excellent energy compaction—especially for natural images—without suffering from the boundary artifacts common in DFT. These properties make DCT a superior choice for image analysis, particularly in facial recognition and compression tasks.

3.4 Conclusion

In the penultimate chapter, we examined two of the most widely used algorithms in facial recognition, highlighting their key characteristics. We first defined the PCA algorithm, detailing its computational steps and the process for calculating Euclidean distances. We then introduced the DCT algorithm, explaining its mathematical formulation in both one-dimensional and two-dimensional forms. Additionally, we emphasized the main features of the DCT and compared its performance with other transformations such as the DFT and KLT.

CHAPTER 4

System Design and Practical Implementation

4.1 Introduction

In this final chapter, we focus on the practical implementation of the concepts discussed in the previous chapters. We present the development environment, the technologies employed, and the interactive user interfaces of the web-based application. Additionally, we detail the overall design architecture and the core functionalities implemented in the application's backend.

4.2 Work Environment

we will present the hardware and software environments of our work.

4.2.1 Hardware Environment

We used a computer which has the following characteristics:

Type: Dell Inc Latitude E5470

Processor: Intel(R) Core(TM) i7-6820HQ CPU @ 2.70GHz, 2701 MHz

RAM: 16.00 Go

System Type: Microsoft Windows 10 Professionnel

And Pc

Processor: Intel(R) Core(TM) i5-6500 CPU @ 3.20GHz, 3.19 GHz

RAM: 8.00 Go

System Type: Microsoft Windows 10 Professionnel

4.2.2 Software Environment

We implemented the application in Python language under the Visual studio code environment

4.2.2.1 Python(Django)

Python : is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Devel- opment, as well as for use as a scripting or glue language to connect existing components together. Python's simple, easy to learn syntax emphasizes read- ability and therefore reduces the cost of program maintenance. Python supports modules and packages, which encourages program modularity and code reuse. **Django :** is a Python-based free and open-source web framework that follows the model template views (MTV) architectural pattern.

4.2.2.2 Visual Studio Code

Visual Studio Code is a freeware source-code editor made by Microsoft for Win- dows, Linux and mac-OS. Features include support for debugging, syntax high- lighting, intelligent code completion, snippets, code refactoring, and embedded Git. Users can change the theme, keyboard shortcuts, preferences, and install extensions that add additional functionality.

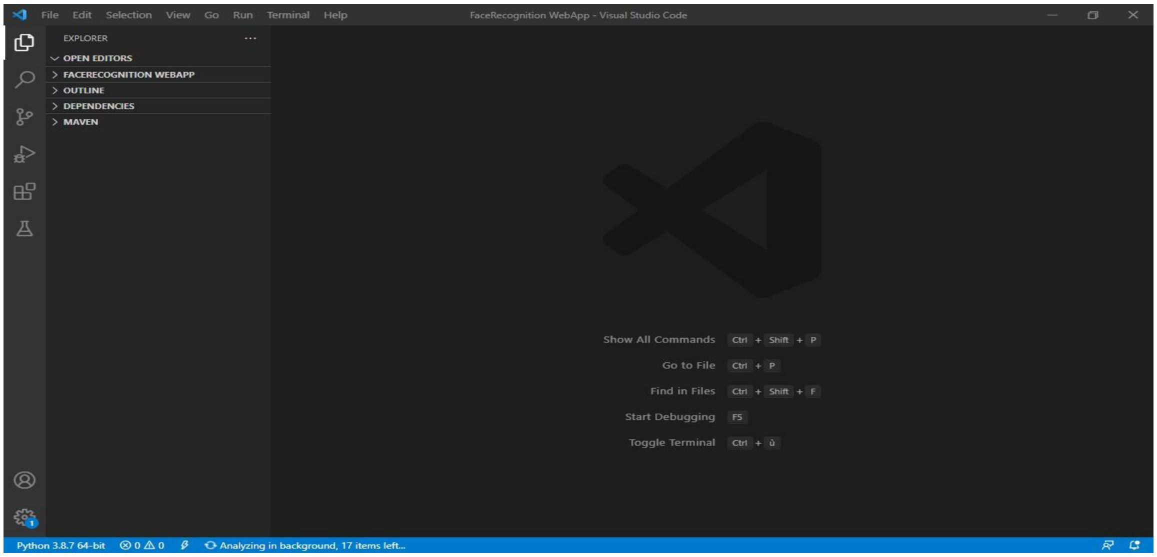


Figure 4.1: Visual Studio Code Environment

4.2.2.3 OpenCV

OpenCV (Open Source Computer Vision Library) is a library of programming func- tions mainly aimed at real-time computer vision. Originally developed by Intel, it was later supported by Willow Garage then Itseez (which was later acquired by In- tel). The library is cross-platform and free for use under the open-source Apache 2 License. Starting with 2011, OpenCV features GPU acceleration for real-time operations.

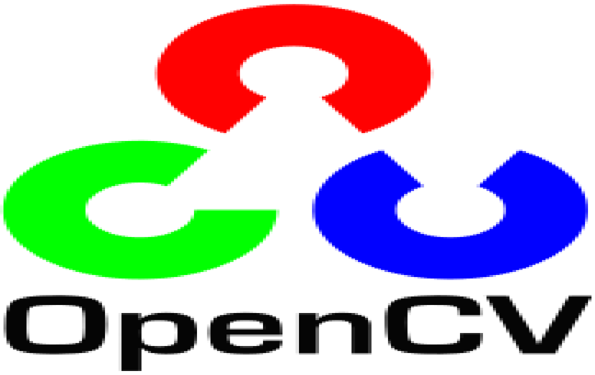


Figure 4.2: OpenCV Environment

4.2.2.4 MySQL

MySQL is an open-source relational database management system (RDBMS). Its name is a combination of "My", the name of co-founder Michael Widenius's daughter, and "SQL", the abbreviation for Structured Query Language. A relational database organizes data into one or more data tables in which data types may be related to each other; these relations help structure the data. SQL is a language programmers use to create, modify and extract data from the relational database, as well as control user access to the database. In addition to relational databases and SQL, an RDBMS like MySQL works with an operating system to implement a relational database in a computer's storage system, manages users, allows for network access and facilitates testing database integrity and creation of backups.

Figure 4.3: MySQL Database

4.3 Conception of the application

4.3.1 System Use Cases

4.3.1.1 Recording

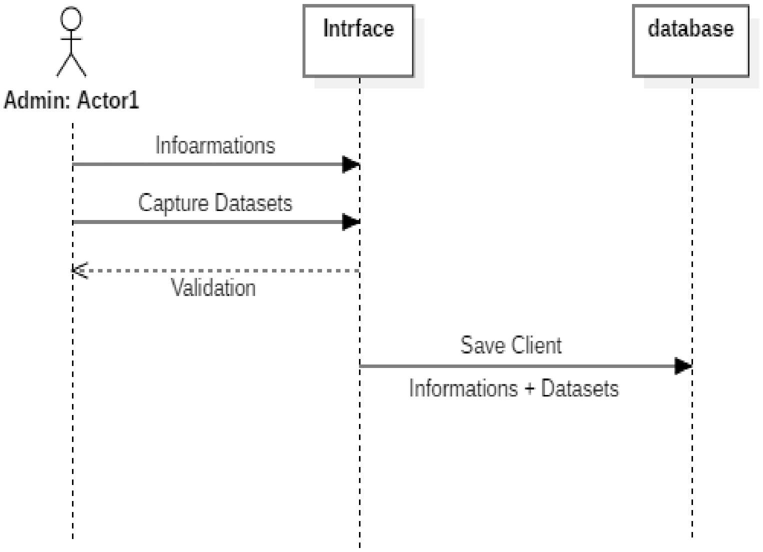


Figure 4.4: sequence diagram for registration of a client in the database

4.3.1.2 Training

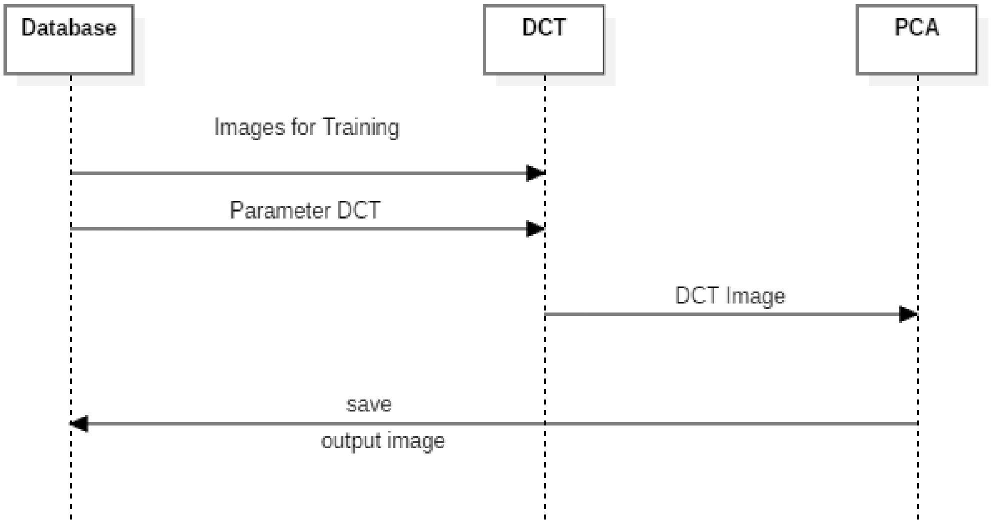


Figure 4.5: Sequence Diagram For Training

4.3.1.3 Recognition

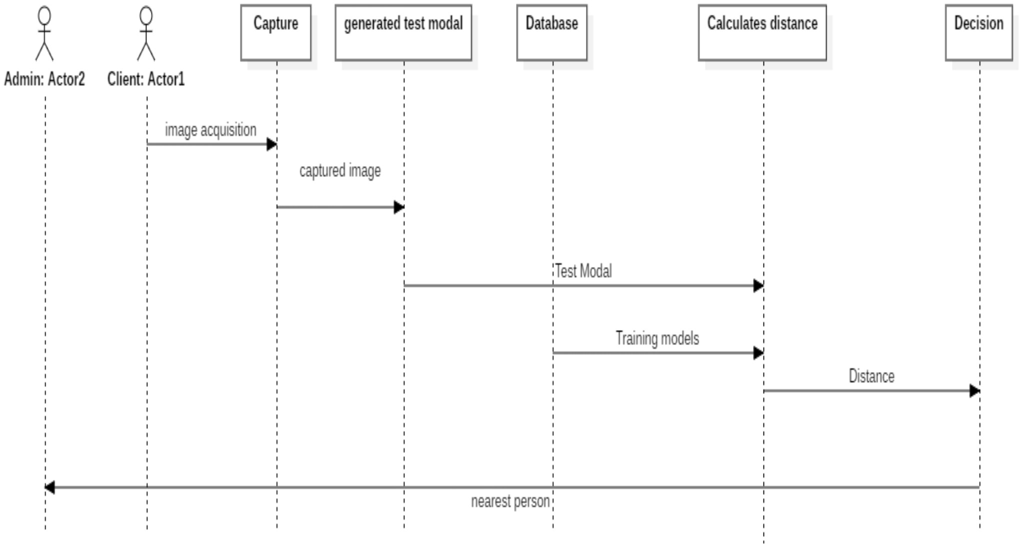


Figure 4.6: Sequence Diagram For Recognition

4.4 data structure and Implementation

4.4.1.1 Detection and Recognition

Methods

Recognition_Video: For facial recognition in a video

Recognition_image: For facial recognition in pictures

Detect_face: For facial detection in the video

unFlatten:

dist: For the calculation of distance

4.4.1.2 Clients and Training

Methods

addClient: To add a new client

Clients_list: For the presentation of all clients

Client_profile: To display all client information and datasets

Client_delete: For client deletion

Client_edit: To modify client information

create_dataset: To take pictures of the client's face by camera.

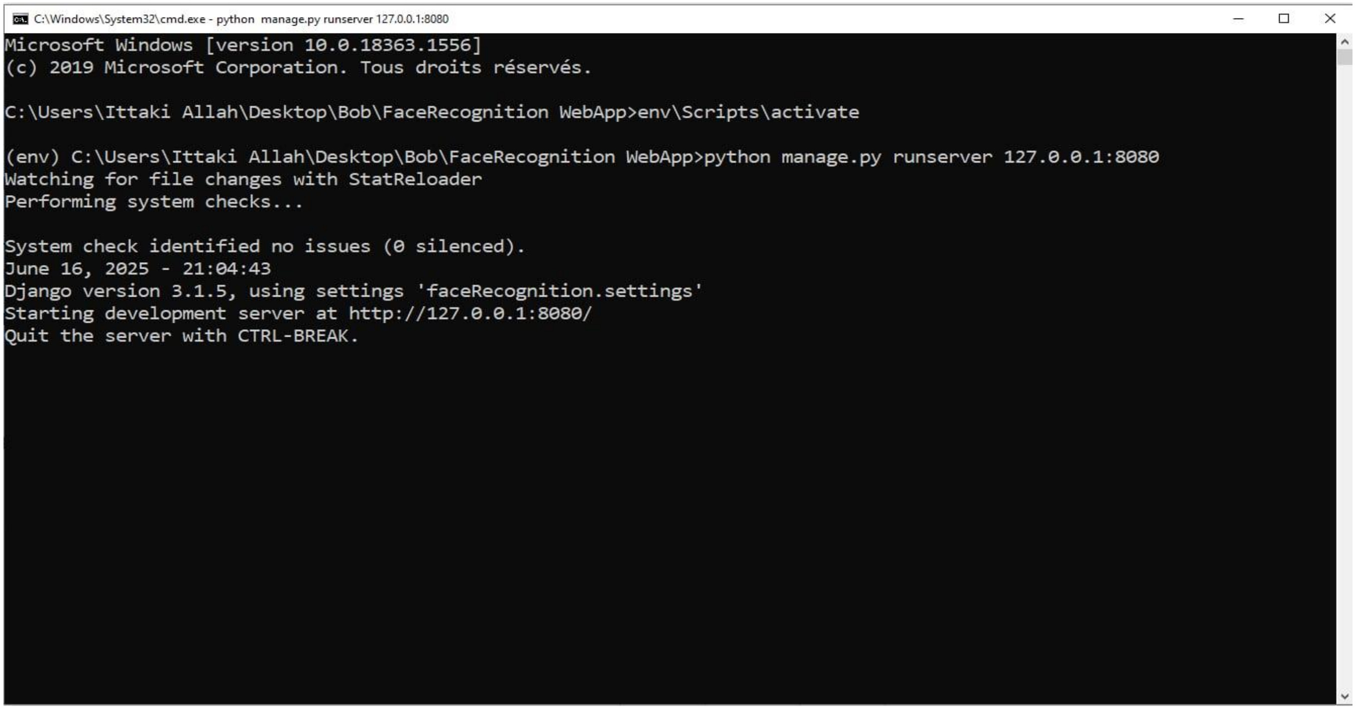
upload_dataset: To upload client face images from the device

Train: To train the client's face images in one image

4.5 Presentation of the application

In this part, we're going to explain our application, most of its pages, and how the facial recognition technology that we explained in the past works.

4.5.0.1 Server launch

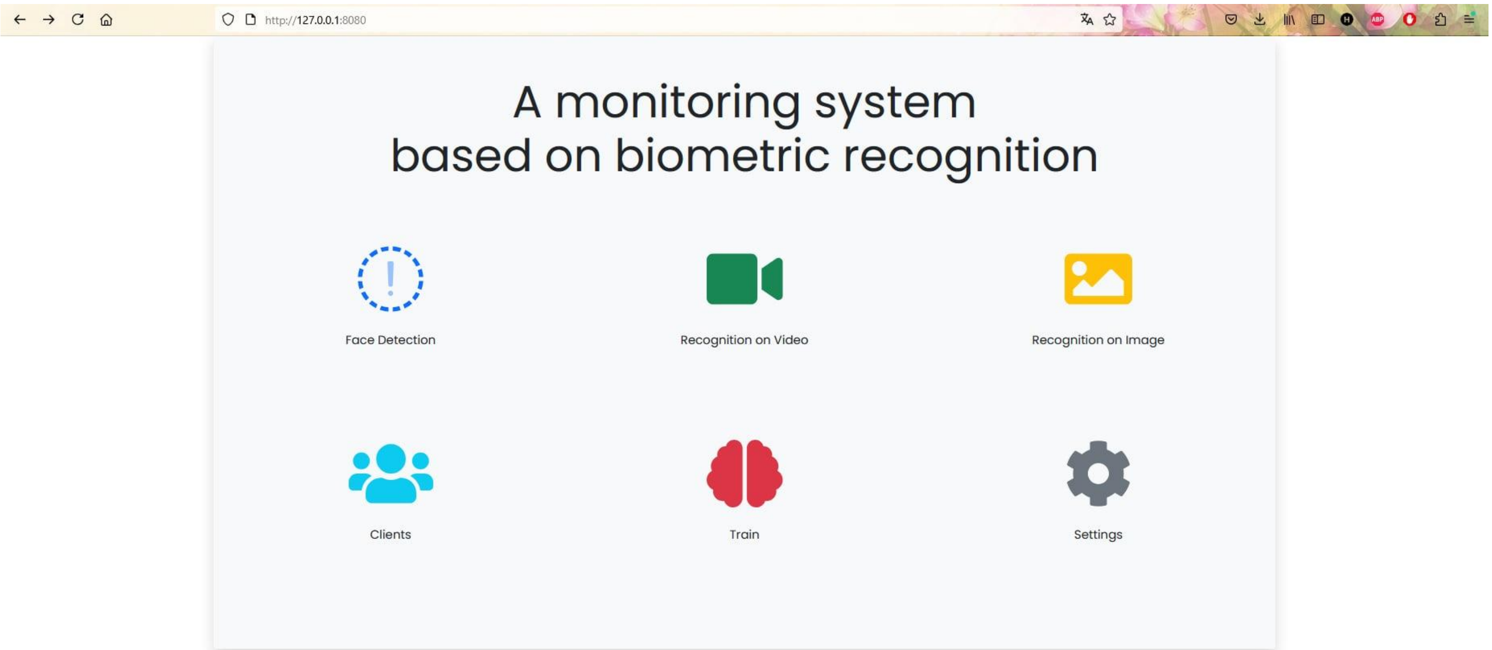


```
Microsoft Windows [version 10.0.18363.1556]
(c) 2019 Microsoft Corporation. Tous droits réservés.

C:\Users\Ittaki Allah\Desktop\Bob\FaceRecognition WebApp>env\Scripts\activate

(env) C:\Users\Ittaki Allah\Desktop\Bob\FaceRecognition WebApp>python manage.py runserver 127.0.0.1:8080
Watching for file changes with StatReloader
Performing system checks...

System check identified no issues (0 silenced).
June 16, 2025 - 21:04:43
Django version 3.1.5, using settings 'faceRecognition.settings'
Starting development server at http://127.0.0.1:8080/
Quit the server with CTRL-BREAK.
```

Figure 4.7: Server launch

.

4.5.0.2 Home page



A monitoring system based on biometric recognition

Figure 4.8: Application Homepage

On this page we find the main tasks of the application:

Face Detection : Page containing facial detection in an image or video.

Recognition on video : A page containing facial recognition from a video source.

Recognition on Image : Page containing facial recognition in an image.

Clients : Page containing client list.

Train : Page containing the process of training client facial images.

Settings : Page containing application settings

Note: Some of the tasks mentioned are in progress and due to time constraints they will be activated later.

4.5.0.3 Recognition in Video Page

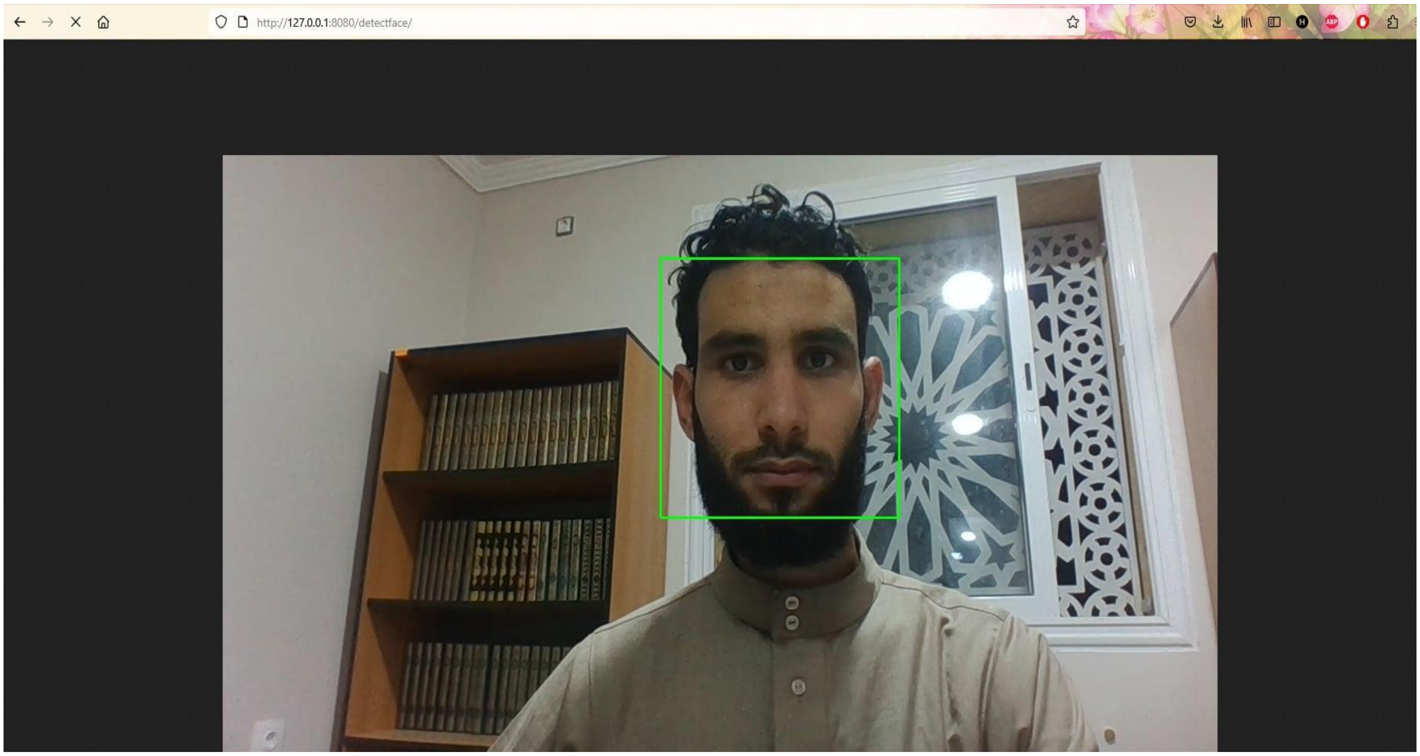


Figure 4.9: Example Recognition in Video

4.5.0.4 Recognition in Image Page

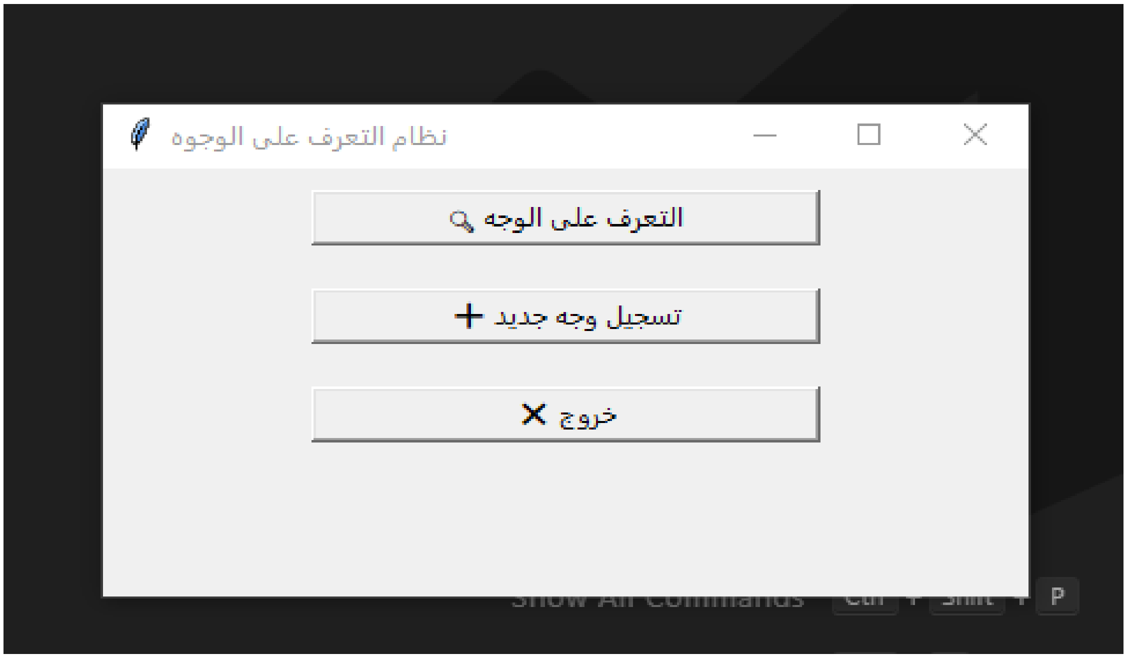


Figure 4.10: Home page Recognition in an image

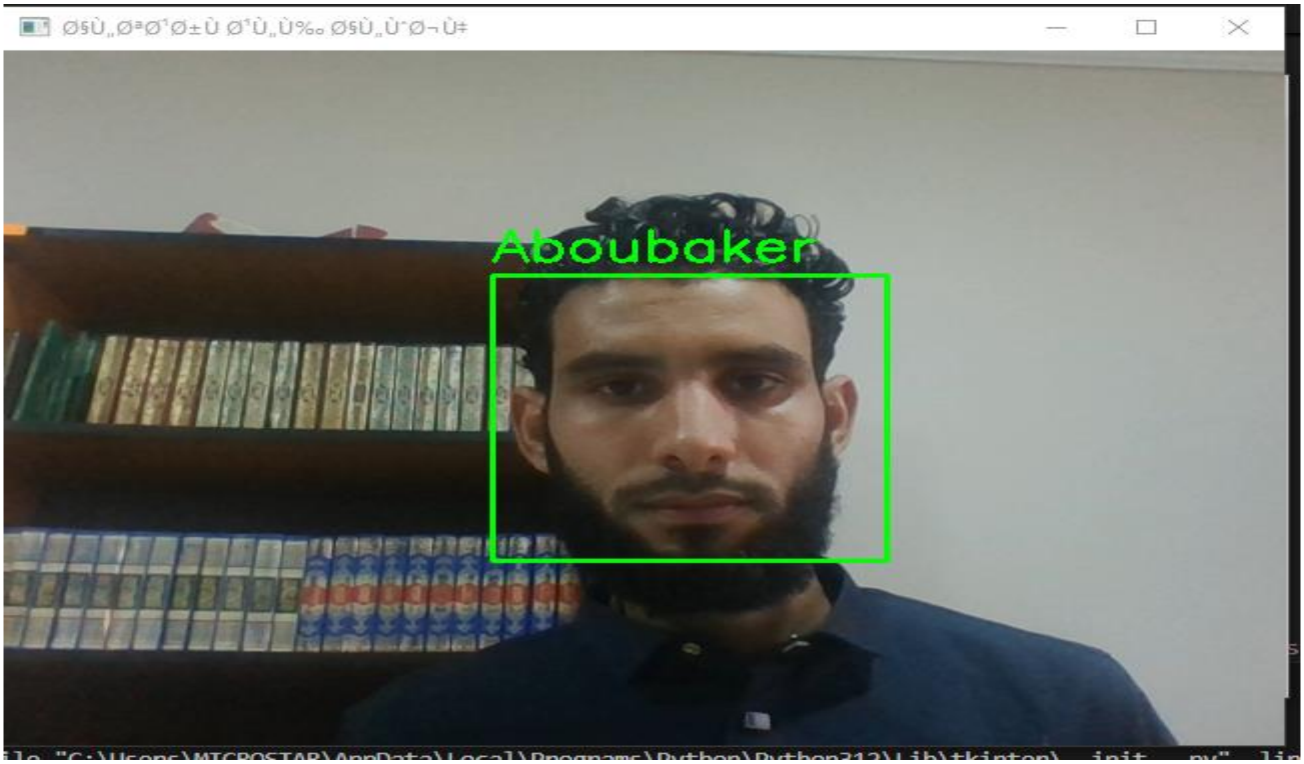


Figure 4.11: Example Recognition in an image

4.6 Conclusion

In this final chapter, we have presented the outcomes of our research on facial recognition based on the two previously discussed algorithms, supported by illustrative images and a detailed description of the development environment and the associated applications utilized throughout the implementation. Furthermore, we aim to enhance the graphical user interface by completing the activation of the remaining functional buttons and integrating additional windows to offer a more comprehensive user experience. Looking ahead, we also aspire to broaden the scope of biometric recognition by incorporating additional modalities such as fingerprint and voice recognition, thereby creating a more robust and inclusive identification system.

Bibliography

[1] T. Sakai, M. Nagao, and T. Kanade, *Computer analysis and classification of photographs of human faces*. Kyoto University, 1972.

[2] R. Chellappa, C. L. Wilson, and S. Sirohey, “Human and machine recognition of faces: A survey,” *Proceedings of the IEEE*, vol. 83, no. 5, pp. 705–741, 1995.

[3] R. Brunelli and T. Poggio, “Face recognition: Features versus templates,” *IEEE transactions on pattern analysis and machine intelligence*, vol. 15, no. 10, pp. 1042–1052, 1993.

[4] M.-H. Yang, D. J. Kriegman, and N. Ahuja, “Detecting faces in images: A sur- vey,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 24, no. 1, pp. 34–58, 2002.

[5] B. Sofiane, “Détection et identification de personne par méthode biométrique,” *Mémoire de Magister en Electronique. Université Mouloud Mammeri de Tizi- Ouzou (UMMTO)*, 2006.

[6] C. Kotropoulos and I. Pitas, “Rule-based face detection in frontal views,” in *1997 IEEE International Conference on Acoustics, Speech, and Signal Pro- cessing*, vol. 4. IEEE, 1997, pp. 2537–2540.

[7] T. Kanade, “Picture processing by computer complex and recognition of hu- man faces,” *Ph. D. Thesis, Kyoto University*, 1973.

[8] P. Sinha, “ªprocessing and recognizing 3d forms, º phd thesis,” *Massachusetts Inst. of Technology*, 1995.

[9] A. L. Yuille, P. W. Hallinan, and D. S. Cohen, “Feature extraction from faces using deformable templates,” *International journal of computer vision*, vol. 8, no. 2, pp. 99–111, 1992.

[10] M. Turk and A. Pentland, “Eigenfaces for recognition,” *Journal of cognitive neuroscience*, vol. 3, no. 1, pp. 71–86, 1991.

[11] S. G. Ababsa, “Authentification d’individus par reconnaissance de caractéris- tiques biométriques liées aux visages 2d/3d,” *Evry-Val d’Essonne*, 2008.

[12] H. A. Rowley, S. Baluja, and T. Kanade, “Neural network-based face detec- tion,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 20, no. 1, pp. 23–38, 1998.

[13] A. J. Colmenarez and T. S. Huang, “Pattern detection with information-based maximum discrimination and error bootstrapping,” in *Proceedings. Fourteenth International Conference on Pattern Recognition (Cat. No. 98EX170)*, vol. 1. IEEE, 1998, pp. 222–224.

[14] R. W. Frischholz and U. Dieckmann, “Biold: a multimodal biometric identifica- tion system,” *Computer*, vol. 33, no. 2, pp. 64–68, 2000.

[15] D. P. Huttenlocher, G. A. Klanderman, and W. J. Rucklidge, “Comparing im- ages using the hausdorff distance,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 15, no. 9, pp. 850–863, 1993.

[16] G. Poulton, N. Oakes, D. Geers, R. Qiao, M. Seneviratne, N. Frampton, and Y. Choi, “The csiro pc-check system,” 1999.

[17] A. Pentland, B. Moghaddam, T. Starner *et al.*, “View-based and modular eigenspaces for face recognition,” 1994.

[18] M. S. Bartlett and T. J. Sejnowski, “Viewpoint invariant face recognition us- ing independent component analysis and attractor networks,” in *Advances in neural information processing systems*, 1997, pp. 817–823.

[19] C. Frankel, M. J. Swain, and V. Athitsos, “Webseer: An image search engine for the world wide web,” Citeseer, Tech. Rep., 1996.

[20] H. D. Wactlar, T. Kanade, M. A. Smith, and S. M. Stevens, “Intelligent access to digital video: Informedia project,” *Computer*, vol. 29, no. 5, pp. 46–52, 1996.

[21] S. Satoh, Y. Nakamura, and T. Kanade, “Name-it: Naming and detecting faces in news videos,” *Ieee Multimedia*, vol. 6, no. 1, pp. 22–35, 1999.

[22] C. Wang, S. Griebel, and M. Brandstein, “Robust automatic video- conferencing with multiple cameras and microphones,” in *2000 IEEE Interna- tional Conference on Multimedia and Expo. ICME2000. Proceedings. Latest Advances in the Fast Changing World of Multimedia (Cat. No. 00TH8532)*, vol. 3. IEEE, 2000, pp. 1585–1588.

[23] S. Yessaadi, “Un modèle basé template matching/réseaude neurones pour la reconnaissance des visages,” Ph.D. dissertation, Annaba, 2006.

[24] Y. Adini, Y. Moses, and S. Ullman, “Face recognition: The problem of compensating for changes in illumination direction,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 19, no. 7, pp. 721–732, 1997.

[25] D. Blackburn, M. Bone, and P. J. Phillips, “Face recognition vendor test 2000,” Tech. rep. http://www. frvt. org, Tech. Rep., 2001.

[26] P. J. Phillips, P. J. Grother, R. J. Micheals, D. M. Blackburn, E. Tabassi, and M. Bone, “Face recognition vendor test 2002: Evaluation report,” 2003.

[27] R. Gross, J. Shi, and J. F. Cohn, *Quo vadis face recognition?* Citeseer, 2001.

[28] A. M. Martinez, “The ar face database,” *CVC Technical Report24*, 1998.

[29] X. Tan, S. Chen, Z.-H. Zhou, and F. Zhang, "Face recognition from a single image per person: A survey," *Pattern recognition*, vol. 39, no. 9, pp. 1725– 1745, 2006.

[30] A. J. O'Toole, H. Abdi, K. A. Deffenbacher, and D. Valentin, "Low-dimensional representation of faces in higher dimensions of the face space," *JOSA A*, vol. 10, no. 3.

[31] X. Lu, "Image analysis for face recognition," *Personal notes*, p. 36, 2003.

[32] C. Fiche, "Repousser les limites de l'identification faciale en contexte de vidéo-surveillance," Ph.D. dissertation, Grenoble, 2012.

[33] S. Guerfi, "Authentification d'individus par reconnaissance de caractéristiques biométriques liées aux visages 2d/3d," Ph.D. dissertation, Université d'Evry- Val d'Essonne, 2008.

[34] R. Chellappa, B. Manjunath, and C. Malsburg, "A feature based approach to face recognition," in *IEEE Conference on Computer Vision and Pattern Recog- nition*, 1992, pp. 373–378.

[35] F. S. Samaria, "Face recognition using hidden markov models," Ph.D. disser- tation, University of Cambridge Cambridge, UK, 1994.

[36] S. Chen, J. Liu, and Z.-H. Zhou, "Making flda applicable to face recognition with one sample per person," *Pattern recognition*, vol. 37, no. 7, pp. 1553– 1555, 2004.

[37] A. Chaudhry and H. Elgazzar, "Design and implementation of a hybrid face recognition technique," in *2019 IEEE 9th Annual Computing and Communi- cation Workshop and Conference (CCWC)*. IEEE, 2019, pp. 0384–0391.

[38] A. Jha, "Class room attendance system using facial recognition system," *The International Journal of Mathematics, Science, Technology and Management*, vol. 2, no. 3, pp. 4–7, 2007.

[39] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, “The feret evaluation methodology for face-recognition algorithms,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 22, no. 10, pp. 1090–1104, 2000.

[40] D. B. Graham and N. M. Allinson, “Characterising virtual eigensignatures for general purpose face recognition,” in *Face Recognition*. Springer, 1998, pp. 446–456.

[41] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, “Eigenfaces vs. fisher- faces: Recognition using class specific linear projection,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 19, no. 7, pp. 711–720, 1997.

[42] P. Hallinan, “A deformable model for face recognition under arbitrary lighting conditions,” Ph.D. dissertation, PhD thesis, Harvard University, 1995.

[43] S. Pigeon and L. Vandendorpe, “The m2vts multimodal face database (re- lease 1.00),” in *International Conference on Audio-and Video-Based Biomet- ric Person Authentication*. Springer, 1997, pp. 403–409.

[44] L. Sirovich and M. Kirby, “Low-dimensional procedure for the characterization of human faces,” *Josa a*, vol. 4, no. 3, pp. 519–524, 1987.

[45] H. Kekre, S. D. Thepade, and A. Maloo, “Performance comparison for face recognition using pca, dct &walshtransform of row mean and column mean,” *ICGST International Journal on Graphics, Vision and Image Process- ing (GVIP)*, vol. 10, no. 2, pp. 9–18, 2010.

[46] A. Nouioua, “La reconnaissance faciale,” Ph.D. dissertation, Faculté des Mathématiques et de l’Informatique-UNIVERSITE MOHAMED BOUDIAF DE . . ., 2013.

[47] S. Akrouf, M. A. Sehili, A. Chakhchoukh, M. Mostefai, and C. Youssef, “Face recognition using pca and dct,” in *2009 Fifth International Conference on MEMS NANO, and Smart Systems*. IEEE, 2009, pp. 15–19.

[48] W. B. Pennebaker and J. L. Mitchell, *JPEG: Still image data compression standard*. Springer Science & Business Media, 1992.

[49] J. Modestino, D. Daut, and A. Vickers, "Combined source-channel coding of images using the block cosine transform," *IEEE Transactions on Communi- cations*, vol. 29, no. 9, pp. 1261–1274, 1981.

[50] H. Radha, "Lecture notes: Ece 802-information theory and coding," 2003.