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THEME

Face Based Automatic Kinship Verification

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Dedication

I dedicate this graduation to the pure soul of my father, may God have mercy on him.

To my dear mother, the light of my life, I ask God to extend her life.

To my brothers and sisters.

To my big family

To my friends and everyone who stood with me to encourage me

Dehimi Mokhtar

To my dear parents, for all their sacrifices, love, tenderness and support throughout my studies

my brothers and my sister

My cousins

To all my friends who have always encouraged me, and to whom I wish more success.

Tidjani Menal Bouchra

dedicate this humble work :

to the light of my life , my Parents , for their love, support ,

to my lovely sister and To my brothers .

To my partners in the work .

To all people I love...

Chaouche Amani Aicha .

I dedicate this my graduation to the one who taught me giving and to the one whose name I carry with pride. I ask God to extend your life “dear father ” .

to the pure soul of my mother, may God have mercy on her.

to the person who was the reason for my success and illuminated my path “my dear grandmother” may God prolong her life.

to my support and my inspiration for " my dear husband".

Hamaiti Nour El Houda

Abstract :

In this master thesis, we focus on the use of computer vision techniques to automatically detect Relationships between two people of their faces; The main points of this study are highlighted in the following context:

The most important challenge is how to describe the face, how to recognize it from the different facial features of the children, and then how to relate them to the corresponding parents without being affected by the different challenges.

We propose effective tagging of contextually conscious local binary traits KinFaceW-II (LBP and CNN) to check kinship.

Keywords: biometric. kinship. verification. CNN.

Résumé :

Dans ce mémoire de maîtrise, nous nous concentrons sur l'utilisation des techniques de vision par ordinateur pour détecter automatiquement les relations entre deux personnes de leurs visages ; Les principaux points de cette étude sont mis en évidence dans le contexte suivant :

Le défi le plus important est de savoir comment décrire le visage, comment le reconnaître à partir des différentes caractéristiques faciales des enfants, puis comment les relier aux parents correspondants sans être affectés par les différents défis.

Nous proposons un marquage efficace des traits binaires locaux conscients du contexte KinFaceW-II (LBP et CNN) pour vérifier la parenté.

Mots clés : biométrie. parenté. vérification. CNN.

ملخص

في رسالة الماجستير هذه، نركز على استخدام تقنيات الرؤية الحاسوبية للكشف تلقائيًا للعلاقات بين شخصين من وجوههم؛ يتم إبراز النقاط الرئيسية لهذه الدراسة في السياق التالي:

التحدي الأهم هو كيفية وصف الوجه، وكيفية التعرف عليه من ملامح الوجه المختلفة للأطفال، ثم كيفية ربطهم بالأباء المقابلين دون أن يتأثروا بالتحديات المختلفة.

نقترح وضع علامات فعالة للسمات الثنائية المحلية الواعية للسياق (KinFaceW-II وLBP وCNN) للتحقق من القرابة.

الكلمات الرئيسية: البيومترية. القرابة. تَحَقُّق. الشبكة العصبية الالتفافية.

Contents

	page
Acknowledgements	I
Dedication	ii
Abstract	iv
List of Figures	X
List of Tables	xi
Abbreviations	xii
General Introduction	1
Chapter I: The biometric	
I.1 Introduction	3
I.2 Definition of Biometrics	3
I.3 History of Biometrics	4
I.4- Biometric modalities and comparison	5
I.4.1 Modalités Biologiques	6
I.4.2 Modalités Comportementales	6
I.4.3 Modalités Morphologiques	6
I.5 Comparison between biometric techniques	9
I.6 Applications of the biometric system	10

I.6.1 Commercial applications	10
I.6.2 Government applications	10
I.6.3 Legal applications	10
I.7 Biometric systems and their modes of operation	10
I.7.1 Enrollment method	10
I.7.2 Authentication mode (verification)	11
I.7.3 Identification mode	12
I.8 Types of biometric systems	14
I.8.1- Mono-modality	14
I.8.2- Multi-modalit	14
I.9 Evaluation of a biometric system	15
I.9.1- False rejection rate FRR (False Rejection Rate)	15
I.9.2- False acceptance rate FAR (False Acceptance Rate)	15
I.9.3- Equal error rate EER (Equal Error Rate)	15
I.10 Advantages and disadvantages of biometrics	16
I.11 Conclusion	17
Chapter II: Facial Kinship Verification	
II.1- Introduction	18
II.2-Kinship terminology	18
II.3-kinship in computer vision	18

II.4-Face Verification and kinship verification	19
II.5-System design	21
II.6-Applications	21
II.6.1-Security	22
II.6.2-Social media analysis	22
II.7-challenges	22
II.8-Databases and State of the art in Kinship verification	23
II.8.1-Approaches based on hand-crafted features	24
II.8.2-Approaches based on deep learning features	29
II.9-Conclusion	31
Chapter III: Experimental-Evaluation	
III.1-Introduction	32
III.2-Kinship system	32
III.3-Experimental Evaluation	36
III.4- Results and Analysis	36
III.5-Conclusion	40
General Conclusion	41
Annexe	42

List of Figures

Figure 1.1 Classification of a number of biometric modalities.

Figure 1.2 Different Biometrics characteristics.

Figure 1.3 Enrollment of a person in a biometric system.

Figure 1.4 Authentication of an individual in a biometric system.

Figure 1.5 Identification of an individual in a biometric system.

Figure 1.6 Architecture générique d'un système biométrique.

Figure 1.7 Illustration of the FRR and the FAR.

Figure 2.1 example of kinship verification via face images.

Figure 2.2 Sample of kinship dataset (a) father son (FS), (b) father daughter (FD), (c) mother daughter (MD), (d) mother son (MS).

Figure 2.3 An illustration of some kinds of kinship from two databases. Face images from the first to second row are from the KFW-I database. Face images from the third to fourth row are from the KFW-II database.

Figure 3.1 General scheme for checking kinship based on facial images.

Figure 3.2 KinFaceW-II datasets, respectively. From top to bottom are the F-S, F-D, M-S, and M-D kinship relations

Figure 3.3 Example of 5-cross validation.

Figure 3.4 example of a deep CNN

Figure 3.5 Face description using LBP.

List of Tables

Table 1.1 Comparison of some biometric modalities. For performance, the number of stars is related to the value of the recognition rate

Table 1.2 summarizes a comparison of biometric traits

Table 1.3 Advantages and disadvantages of biometrics

Table 2.1: Difference between kinship and face verification system

Table 2.2 A summary of some handcrafted feature-based methods

Table 2.3 Descriptive Summary of other deep learning approaches

Table 3.1 Affinity Verification Accuracy in Percentage of Proposed Method on KinFaceW-II Databases with Feature Selection

Table 3.2 Affinity Verification Accuracy in Percentage of Proposed Method on KinFaceW-II Databases with and without feature selection

Table 3.3 Kinship verification accuracy in % of proposed method on KinFace W-II databases.

Abbreviations

BSIF: Binarized Statistical Image Features

CLBP : complete LBP

CNN : Convolutional Neural Network

CNNs: Convolutional Neural Networks

DPM: deformable parts-based model

EER : Equal Error Rate

FAR : False Acceptance Rate

FRR : False Rejection Rate

GGOP: Gabor-based gradient orientation pyramid

HOG: histograms of oriented Gradients

IFVF: inheritable Fisher vector feature

KNN : K-Nearest-Neighbor

LBP : Local Binary Patterns

LDP: local directional pattern

LFDA: local feature-based discriminate analysis

LPQ: Local Phase Quantization

MB: multi-block

ML: multi-level

SIFT : scale invariant feature transform

SPLE: Spatial Pyramid LEarning

SVM : Support vector machines

VGG-F : Visual Geometry Group

VGG-Face : Visual Geometry Group Face

ROC : Receiver Operating Characteristic

General Introduction

Researchers of many fields have pursued the creation of systems capable of human abilities. One of the most admired humans' qualities is the vision sense, something that looks so easy to us, but it has not been fully understood yet. In the scientific literature, face recognition has been extensively studied and; in some cases, successfully simulated.

Researchers have devoted a substantial amount of effort in studying face identification methods in the context of computer vision, image processing, and pattern recognition due to the wide acceptability of face as biometric. Biometrics is a way of automatic identification or verification of the person on their physical, chemical or behavioral properties. It is a scientific way to analyze the biological unique patterns of the individual person through the face, fingerprint or voice, etc

According to the Biometric International Group, nowadays Biometrics represent not only a main security application, but an expanding business.

However, face recognition is not an easy task. Systems can be trained to recognize subjects in a given case. But along the time, characteristics of the scenario (light, face perspective, quality) can change and mislead the system. In fact, the own subject's face varies along the time (glasses, hats, stubble). These are major problems with which face recognition systems have to deal using different techniques.

Kinship is the web of social relationships that form an important part of the lives of all humans in all societies, although its exact meanings even within this discipline are often debated. Anthropologist Robin Fox says that the study of kinship is the study of what humans do with these basic facts of life – mating, gestation, parenthood, socialization, siblingship etc. Human society is unique, he argues, in that we are "working with the same raw material as exists in the animal world, but [we] can conceptualize and categorize it to serve social ends." These social ends include the socialization of children and the formation of basic economic, political and religious groups.

The rest of thesis is divided as following:

Chapter 1, details the Biometric task. We give an overview of Biometric by introducing some concepts, definitions , history and modalities required for understanding this topic. After that, talk about comparison between biometric techniques and applications of the biometric system. We also explained their modes of operation and architecture of biometric system. finally, we mentioned types, evaluation , advantages and disadvantages.

Chapter 2, details the facial kinship verification task. We give an overview of automatic kinship verification from faces by presented some notions, definitions and terminology required for understanding this topic. Next, we describe the system design of facial kinship verification. Also some applications and the challenges related to facial kinship verification. We summarize some existing database.

Chapter 3, The experimental results of facial kinship verification analysis are View and discuss. We investigated kinship verification, four main types of kinship relationships were used in this study: father-daughter relationship (F-D), father-son relationship (F-S) and mother-daughter relationship (M-D) and mother-son(M-S) . we have used two different types: LBP, CNN (VGG face, VGG F). CNN" the network learns the filters that in traditional algorithms were hand-engineered Several models have been extracted from CNN " and LBP assigns a label to every pixel of an image by thresholding its value with neighbourhood pixels and considering the result as a binary number.

Chapter I :
The biometric

Chapter I The biometric

I.1- Introduction:

The biometric traits possessed by each individual are unique and has the potential to recognize an individual. Biometric traits can be physical and behavioral. Therefore, biometrics are used for verification or identification of individuals for many critical applications like border control, access control, immigration, forensic and different law enforcement. There are two phases in every conventional biometric system : Enrolment phase and authentication or identification. In the enrolment stage, the original biometric trait is captured and saved in the database. During the authentication stage, the system matches that stored template every time the user access the system by providing the live biometric [1].

I.2- Definition of Biometrics :

The word "biometrics" comes from two Greek words meaning "measure of life" (the word "bio" means life and "measurement" means measurement). Biometrics is a branch of biology that uses measurement and statistical analysis to understand humans or animals [2].

They are human physical or behavioral characteristics that can be used to digitally identify a person to give them access to systems, devices, or data. Examples of these vital identifiers are fingerprints, facial patterns, voice or writing rhythm. Each of these identifiers is unique to the individual and can be used together to ensure greater accuracy in identification .

Biometrics is also the most appropriate way to identify and validate individuals in a reliable and rapid manner .

I.3- History of Biometrics :

Since his existence, man has always tried to find the differences between himself and his entourage and exploit them in his daily needs.

The Chinese were the first to use fingerprints 1,000 years ago for document signing purposes. Afterwards, it was the turn of the anatomist MARCELLO MALPIGHI (1628-1694) who studied them with a new instrument called a microscope. Then the Czech physiologist JAN EVANGELISTA PURKINGE (1787-1869) tried to categorize them according to certain characteristics [3]

Towards the end of the 19th century, Dr. HENRY FAULDS (1843-1930), a surgeon in Tokyo, took the first step towards developing a system for identifying individuals based on statistical methods for the classification of impressions.

At the moment, one of his contemporaries, the French ALPHONSE BERTILLON (1853-1914), was testing a method of identifying prisoners called judicial anthropometry. BERTILLON took photographs of human subjects, measured certain parts of their bodies (heads, limbs, etc.) and the dimensions were noted on photos and on cards for later identification purposes. This was the birth of the first database containing information from individuals [3]. And since then, these recognition systems have continued to develop and become more efficient.

I.4- Biometric modalities and comparison

Biometric modalities are the biometric characteristics with which it is possible to verify the identity of an individual. **Figure 1.1** illustrates an example of some biometric modalities. These modalities are based on the analysis of data related to the individual and are generally classified into three categories [4,5]: biological, behavioral and morphological.

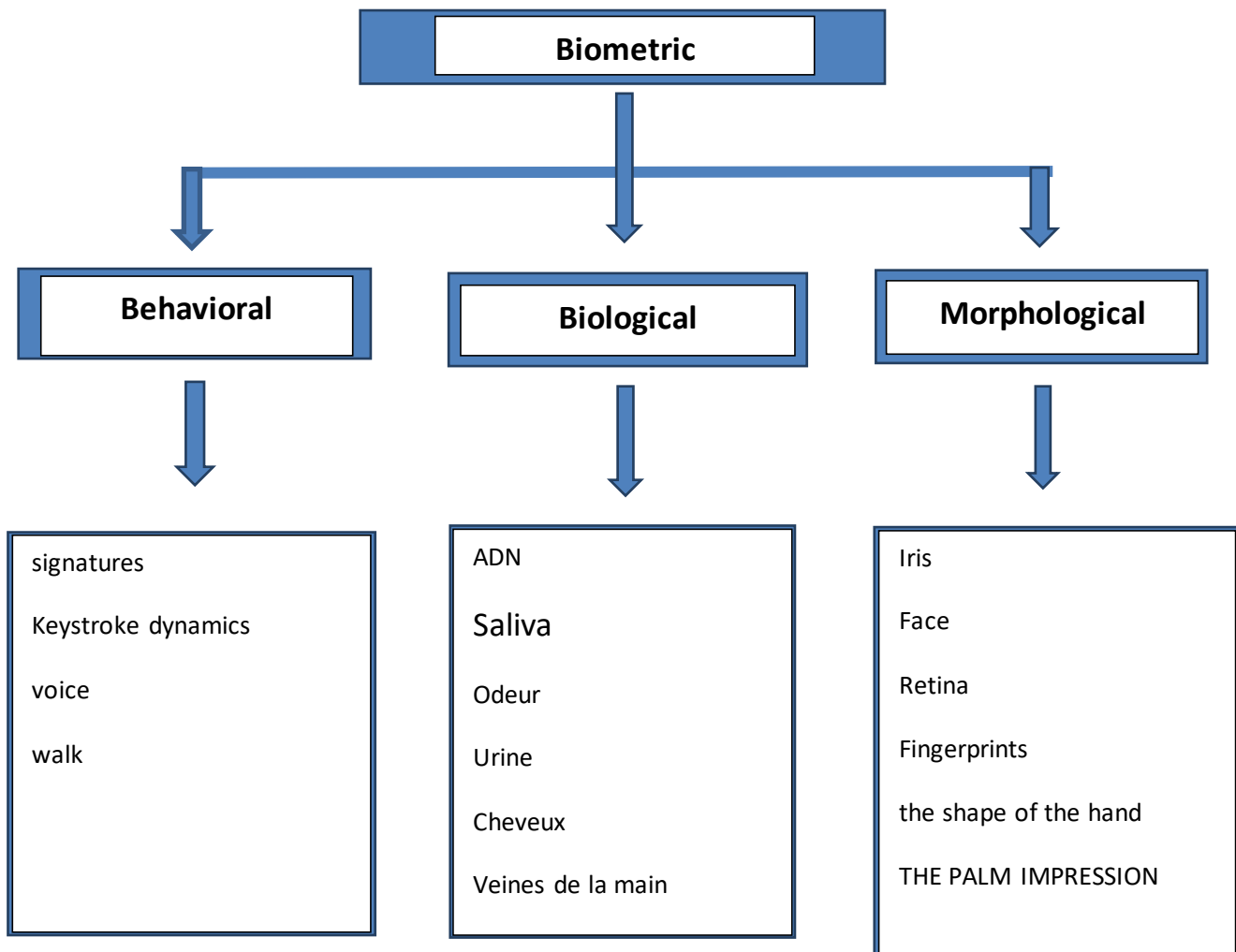


Figure 1.1 Classification of a number of biometric modalities.

I.4.1- Biological Modalities

This category is based on the analysis of biological characteristics related to the individual (example: saliva, DNA, etc.). Indeed, the biological data of each individual constitutes a personal signature.

I.4.2- Behavioral Modalities

This category is based on the analysis of an individual's behavior (example: way of walking, typing dynamics, voice, etc.).

I.4.3- Morphological modalities

Morphological biometrics are based on particular physical traits that are, for all people, permanent and unique. Several modalities have been used to extract this information such as the face (2D and 3D), the fingerprint, the geometry of the hand, the iris, etc.

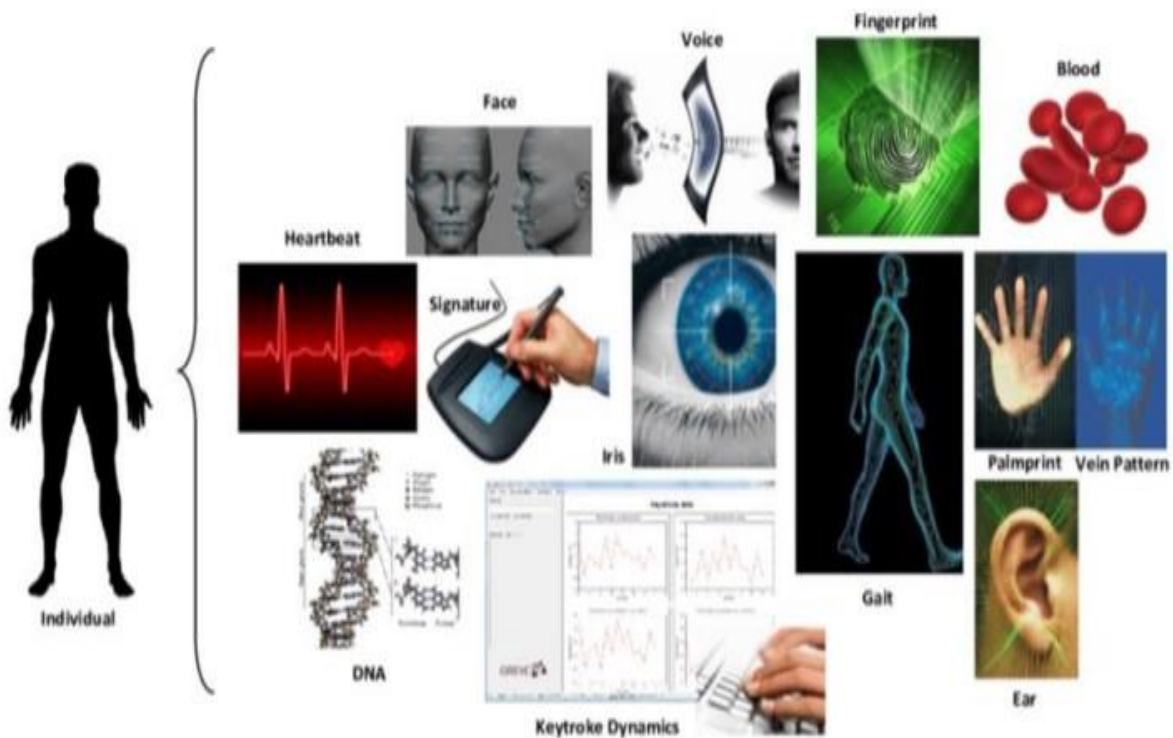


Figure 1.2: Different Biometrics characteristics

Chapter I The biometric

Practically any morphological or behavioural characteristic can be considered a biometric characteristic, provided that it satisfies the following properties [7]:

- **Universality**: means that each individual to be identified must possess this characteristic.
- **Uniqueness**: means that the information should be dissimilar as possible between the different individuals.
- **Permanence**: the modality remains stable throughout the life of the person.
- **Collectability**: the information must be collectable and measurable using an appropriate sensor for use in comparisons.
- **Performance**: it aims at efficiency in speed of execution and accuracy of recognition.
- **Acceptability**: means that:
 - Individuals agree to present their biometric traits to the system.
 - the system must meet certain criteria (ease of acquisition, speed, etc.).

Indeed, each modality has these biometric characteristics but with different properties and degrees. **Table 1.1** compares the main biometric modalities according to these properties (universality, uniqueness, permanence, collectability, acceptability and performance).

Chapter I The biometric

Table 1.1: Comparison of some biometric modalities. For performance, the number of stars is related to the value of the recognition rate [6].

Information	Universality	Uniqueness	Permanence	Collectabilité	Acceptability	Performance
AND	Yes	Yes	Yes	Weak	Weak	*****
Blood	Yes	No	Yes	Weak	Non	*
Typing dynamics	Yes	Yes	Weak	Yes	Yes	***
Voice	Yes	Yes	Weak	Yes	Yes	*****
Iris	Yes	Yes	Yes	Yes	Weak	*****
Face	Yes	No	Weak	Yes	Yes	****
Fingerprint	Yes	Yes	Yes	Yes	Moyenne	*****

Table 1.1 shows that no feature is therefore ideal.

Each feature can be more or less adapted to particular applications. For example, DNA-based analysis is one of the most effective techniques for verifying an individual's identity or identifying them. Nevertheless, it cannot be used for logical or physical access control for reasons of computational time, as well as people do not agree to donate some of their blood to do a check.

The choice of a particular biometric modality also depends on the local culture of the users. In Asia, methods requiring physical contact such as fingerprints are rejected for hygienic reasons while contactless methods are more widespread and accepted.

I.5- Comparison between biometric techniques:

Each technology has advantages and disadvantages, acceptable or unacceptable depending on the application. These solutions are not competitors, they do not offer the same levels of security or the same ease of use. **Table 1.2** summarizes a comparison of biometric traits

Technique	Advantages	Disadvantages
Fingerprints	- Cost - Average ergonomics	- Average acceptability - Possibility of attack
hand shape	-Very ergonomic - Good acceptability	- Bulky and expensive system - Possible disruption by injury
Face	- Cost - Good acceptability	- Twins, disguise vulnerability to attacks (easy to fake)
Retina	- Reliability - Sustainability	- Very low acceptability - Lighting constraint
Iris	- Reliability	- Very low acceptability - Lighting constraint
Voice	- Reliability	-Vulnerable to attack (easy to tamper with)
Signature	- Ergonomics	- Dependent on the emotional state of the unreliable person

Table 1.2: comparison of biometric traits.

I.6- Applications of the biometric system

Nowadays biometric systems are increasingly used in civil applications. The applications of biometrics can be divided into three main groups. [6]

I.6.1- Commercial applications:

Such as computer network opening, electronic data security, e-commerce, Internet access, credit card, physical access control, cell phone, medical records management, distance study etc.

I.6.2- Government applications:

Such as National ID Card, Driving License, Social Security, Border Control, Passport Control, etc.

I.6.3- Legal applications:

Such as body identification, criminal investigation, terrorist identification, etc. [6]

I.7- Biometric systems and their modes of operation:

A biometric system is basically a pattern recognition system that uses an individual's biometric data. Depending on the context of the application, the biometric system operates in three modes: enrollment, verification or identification and classification. [8]

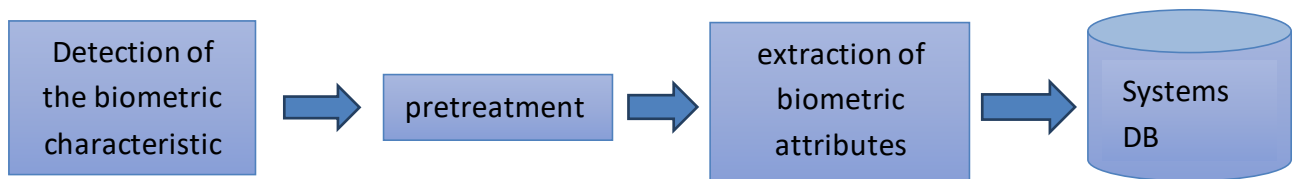
I.7.1- Enrollment method:

This is the first phase of any biometric system, during which the biometric characteristics of an individual are recorded in the database for the first time.

This registration may be accompanied by the addition of biographical information in the database. Which will be used later in the authentication phase.

Chapter I The biometric

During enrollment, biometric characteristics are extracted using appropriate algorithms, these characteristics will be reduced later to minimize the amount of data stored, thus facilitating verification and identification.



Biometric sensor

Enrollment

Figure 1.3: Enrollment of a person in a biometric system.

I.7.2- Authentication mode (verification):

When a biometric system operates in authentication mode (**Figure 1.4**), the user asserts his identity and the system checks whether this assertion is valid or not.

The biometric system asks the user for their identity and tries to answer the question, "is this person X?" ". In a verification application the user announces his identity via a password, an identification number, a user name, or any combination of the three. The system also solicits biometric information from the user, and compares the characteristic data obtained from the entered information, with the registered data corresponding to the claimed identity, this is a one-to-one (1:1) comparison). The system will or will not find a match between the two. Verification is commonly used in access control and payment authentication applications. [9]

Authentication by biometrics is stronger than that using conventional means of identification such as cards, keys or passwords because it constitutes a strong and permanent link between a physical person and his identity.

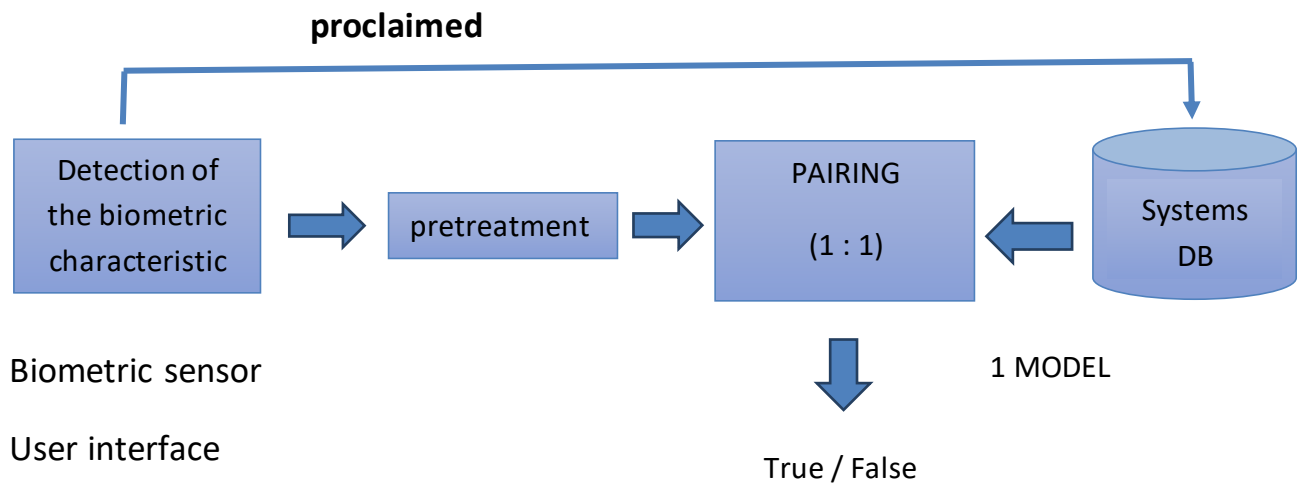


Figure 1.4: Authentication of an individual in a biometric system. [9]

I.7.3- Identification mode:

It makes it possible to establish the identity of a person from a database, the biometric system asks and tries to answer the question, “who is person X? is a one-to-many (1: N) comparison.[11]

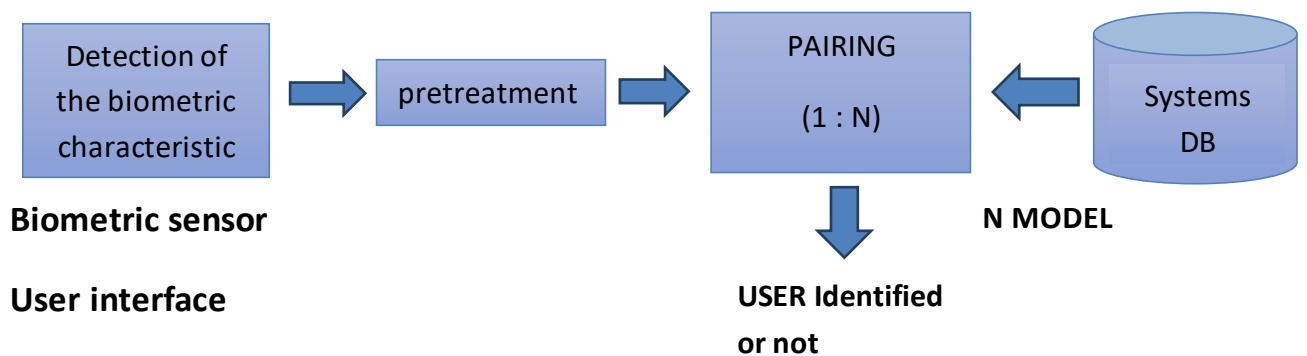


Figure 1.5: Identification of an individual in a biometric system. [11]

Chapter I The biometric

The architecture of a biometric system contains five modules as shown in **Figure 1.6** [7]:

- **Capturing features :**

Collection of certain physiological, behavioral or biological characteristics presented by means of a biometric capture terminal (biometric sensor), which restores this characteristic in the form of a captured biometric sample. The quality of the sensor can greatly influence the performance of the system.

- **Feature extraction :**

This phase generally includes; a segmentation process aimed at locating the feature information in the captured biometric sample, a feature extraction process. Only relevant parameters are extracted from the captured biometric sample and a quality control process assesses the validity of the samples.

- **Comparison :**

Compares the set of extracted features with one or more previously stored references and the comparison results (degrees of correspondence) are transmitted to the decision subsystem. The identity of the user may or may not match the identity sought.

- **Decision :**

Determines whether or not the user's identity matches the claimed (authentication) or sought (identification) identity. Identifying a person is based on the degree of similarity between the extracted characteristics and the stored patterns.

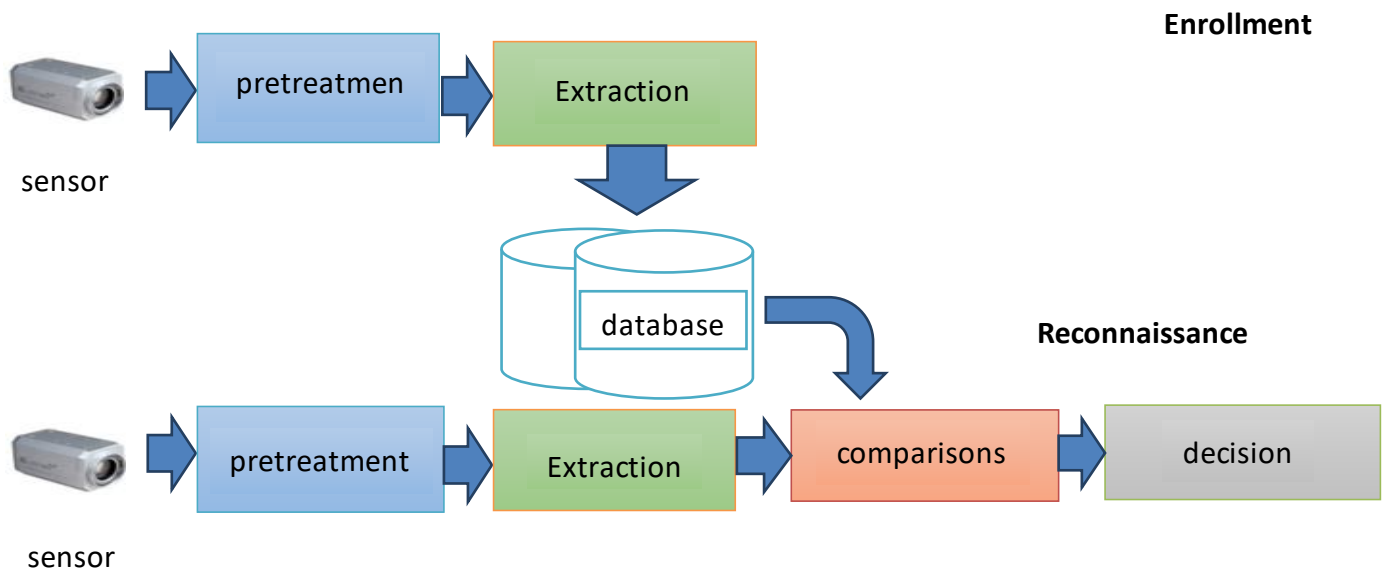


Figure 1.6 : Generic architecture of a biometric system [7]

I.8- Types of biometric systems :

I.8.1- Mono-modality:

Monomodal biometrics is a person authentication technology based on a single biometric modality. Before proceeding to propose a biometric system, it is necessary to choose the most appropriate modality for the application. [12]

I.8.2- Multi-modality :

Multimodal biometrics consists of combining several biometric systems, which increases the amount of information discriminating the people to be identified. Indeed, it makes it possible to reduce certain limitations of unimodal biometric systems.

Multi-modality is an alternative that makes it possible to systemically improve the performance of a biometric system. [10]

I.9- Evaluation of a biometric system:

When biometric systems are used it is difficult to obtain 100% error free results. The reason may be to be found in differences in environment during data acquisition and in differences in hardware.

used. The most often used performance evaluation parameters are the false acceptance rate and the false rejection rate, which can be adapted according to the system used **Figure 1.7** :

I.9.1- False rejection rate (FRR) :

Proportion of legitimate user transactions rejected in error. These transactions are rejected, by the matching algorithm, due to false mismatch as well as those rejected due to an acquisition failure. for example, in the case of a fingerprint-based system, incorrect positioning of the finger on the sensor or dirt can produce false rejections.

I.9.2- False acceptance rate (FAR) :

This rate determines the probability that a system will recognize a person who normally should not have been recognized. It is a ratio between the number of people who were accepted when they should not have been and the total number of unauthorized people who tried to be accepted.

I.9.3- Equal error rate (EER) :

This rate is calculated from the first two criteria and is a common performance measurement point. This point corresponds to where $FRR = FAR$, i.e. the best compromise between false rejects and false accepts.

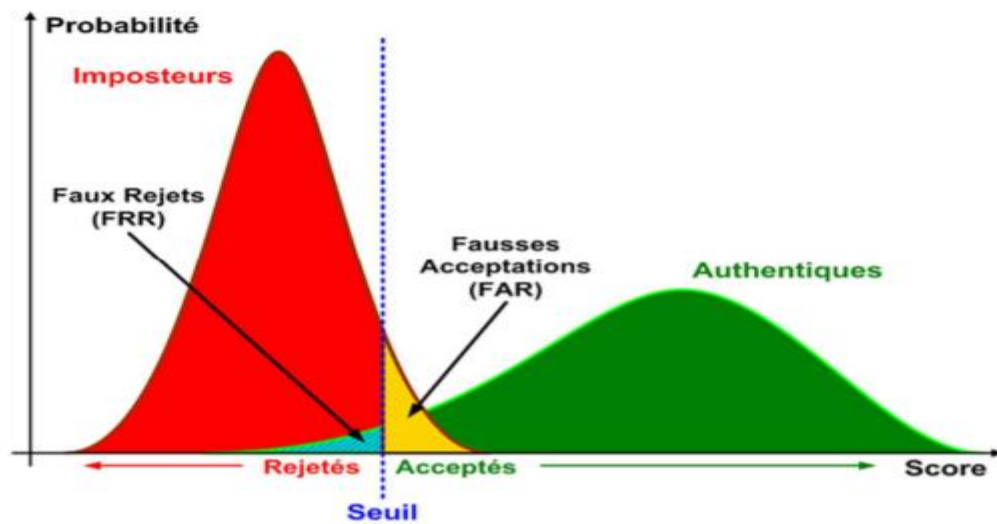


Figure 1.7: Illustration of the FRR and the FAR.

I.10- Advantages and disadvantages of biometrics:

Advantages	Disadvantages
<ul style="list-style-type: none"> • Quicker Authentication • improves The System Security • Complete Control Over Access • Scalability • Flexible • Complete Data Accuracy • Less Processing Time • Increased Security • Ease Of work 	<ul style="list-style-type: none"> • Intra-class variability and inter-class similarity • Segmentation • Noisy input & population coverage • System performance (error rate, speed, cost) • The individuality of biometric characteristics • Fusion of multiple biometric attributes • Scalability • Attacks on the biometric system

Table 1.3: Advantages and disadvantages of biometrics

I.11- Conclusion:

Through this chapter, we introduce the concept of biometrics, its history, various applications, advantages and disadvantages. In the next chapter we will discuss face verification and kinship verification, using images of faces based on the feature selection method.

Chapter II :

Facial Kinship Verification

Chapter II.....Facial Kinship Verification

II.1- Introduction:

Kinship verification, one of the basic topics in computer vision and pattern recognition, has received substantial attention in recent years. Many approaches have been proposed to kinship verification in unconstrained environments, while each of these approaches consists in checking if two persons are from the same family or not through facial images. Verifying kinship through facial images is difficult due to the high degree of variability of the visible effects such as genetic difference, gender difference and age gap.

II.2-Kinship terminology:

Before embarking on the nature of the problem and the solutions, we need to be familiar with different kinship terms, which will determine the course and ambit of this study. In general, kinship may indicate similarity, familiarity, or closeness between entities on the basis of some or all of the basic traits or features. Kinship is a broad term that has different molds of meaning based on the framework or context in which it operates. Kinship can be formulated or labeled as kin relationship. In the anthropological context, kinship refers to the network of social relationships between people that form an important part of the lives of most humans in most societies. Nevertheless, in other contexts, kinship may have different meanings. In biology, kinship typically refers to the degree of genetic relatedness or coefficient of relationship between individual members of the same species. Moreover, different societies classify kin relationships differently and therefore use different systems of kinship terminology. [13]

II.3-kinship in computer vision:

Automatic facial kinship verification is a challenging topic in computer vision due to its complexity and its important role in many applications. Automatic kinship verification system tries to recognize the relationships between people based only on

Chapter II.....Facial Kinship Verification

photographs of their faces. Kin recognition is the task of training the machine to recognize the genetic kin and non-kin based on features extracted from digital images and try to determine whether or not kinship exists between a pair of faces, but they do not aim to recognize the exact type of kinship. [14]

Kinship verification is a difficult problem in computer vision since it faces many obstacles similar to face recognition issues, such as low-resolution images, lighting shifts, pose variations, aging effects, mixed ethnicities, and different age groups. Furthermore, the kinship system is a classification system for people who are related by kinship based on patterns such as their faces. [15]

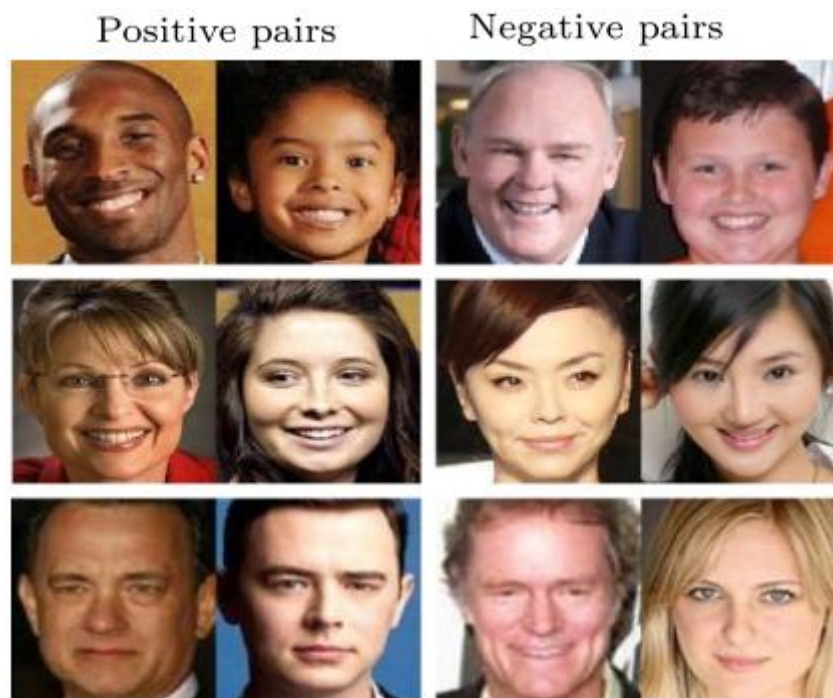


Figure2.1: example of kinship verification via face images.

II.4-Face Verification and kinship verification:

Kinship can operate in either or both of two modes, namely, kinship verification (or authentication): this mode verifies the existence of kin relationship between a pair of images [13], Face verification is the process of matching a group of faces or two sides

Chapter II.....Facial Kinship Verification

together, the goal of which is to verify the correct person, in other words the task of comparing a candidate's face with another face and verifying whether they are identical or no[16], That is verification of kinship and verification of the face are two different matters among themselves, but they have basic evidence that is the common factor between them.

- Face verification: Is this same person? (1:1) -

- Kinship verification: verifies the existence of kin relationship between a pair of images or more (1: N).

Facial Verification	Kinship Verification
Extract features from same person	Extract features from different person
Verify or identity	Verify the relationships
Same trait of query image1 and query image 2	Different trait of query image1 and query image 2
Height level system	Highest level system
The most common application is the security, monitoring and extensively by government a agencies	Studying the biological relationship and utilizes by people and less by government a agencies
In decision stage Matched or not matched	In decision stage Kin or not kin

Table 2.1: Difference between kinship and face verification system.[13]

II.5-System design:

The automatic detection of kinship from facial images is a difficult problem that recently received attention from the computer vision and pattern recognition research community. Kinship is a genetic relationship between two family members. Specifically, there are four different types of kinship relations: Mother-Daughter (M-D), Father-Daughter (F-D), Mother-Son (M-S) and Father-Son (F-S) kinship relations see **Figure 2.2.**[17]

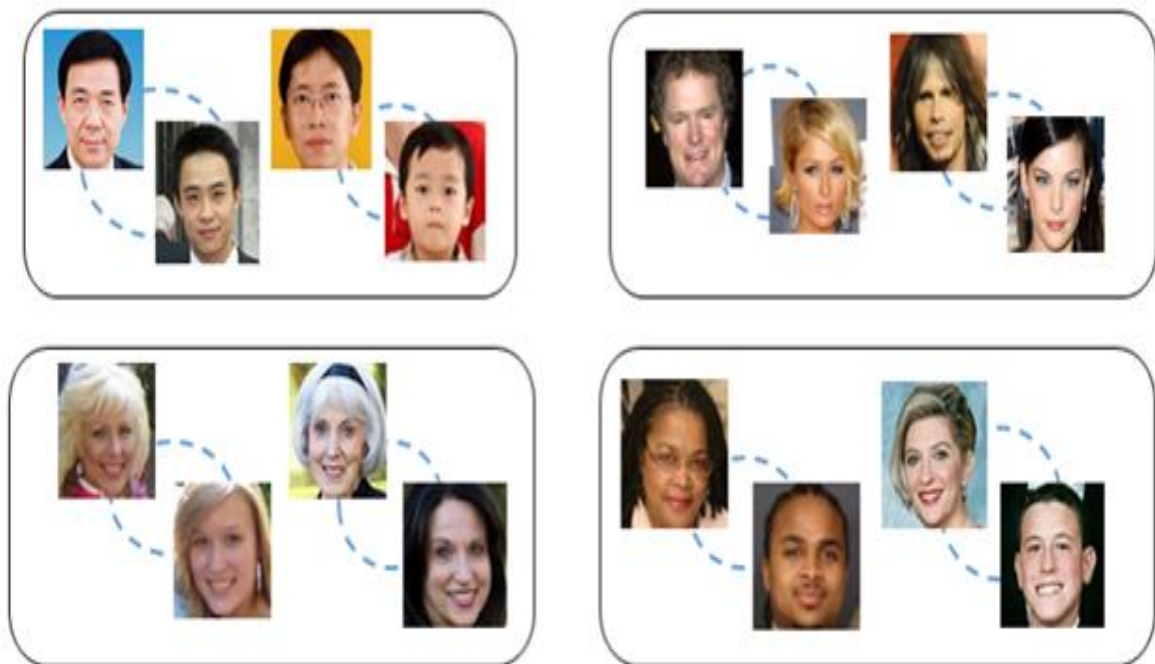


Figure2.2: Sample of kinship dataset (a) father son (FS), (b) father daughter (FD), (c) mother daughter (MD), (d) mother son (MS).

II.6-Applications:

Nowadays, we can find that there are familiar applications for face recognition in various fields. The most common applications are surveillance, security, entertainment, access control, suspect tracking, and forensic. Kinship recognition is

Chapter II.....Facial Kinship Verification

the most interesting aspect related to the relationship of people in the images, and has a significant influence on real applications and many areas. [18]

II.6.1-Security:

Security is a crucial concern of today's world with cross-countries terrorism threat. Face plays an important role in establishing security. One of the most important and worldwide spread applications is biometrics which aims at identifying or authenticating persons based on their physiological or behavioral traits. Along with fingerprint, face is the most widely used biometric modality. Face biometrics are used in identity documents, such as passports, national identity cards, driving licenses, etc. Other applications for face as a biometric include secure access to buildings, electronic devices, e-commerce services, etc. Surveillance is another important security issue where face analysis and recognition plays an important role. [19]

II.6.2-Social media analysis:

Today, Photos and videos of individuals, family, friends, group of people, etc. are among the most shared types of data in social networks. Therefore, developing effective automatic face analysis tools for analyzing, understanding and exploiting these data gained a remarkable attention these last years. [19]

II.7-challenges:

In reality, we may argue that these issues are things shared by identity recognition and parenthood. These structures can be influenced by effects such as lighting, lack and presence of structural elements, occlusions, emotions, facial expression, makeup, cosmetic surgery, ageing, rotations, pose changes, noise, size, cluttering and resolution, twins, and so on [20] [21] [22] [23]. These are the most critical and popular problems in these two areas.

II.8-Databases and State of the art in Kinship verification:

kinship verification through facial image analysis has the current best-performing kinship verification algorithms typically represent faces with over-complete low-level features and strongly depend on the choice of metric learning algorithms. However, such low-level features cannot well represent the underlying information of kinship implied in facial images, and thus the performance of current kinship verification is still unsatisfying. Meanwhile, we find that deep models play a key role in effectively extracting high-level features for face identification [24, 25]. Based on the existing studies Some kinds of kinship from the KinFaceW database are shown in Figure 1.10

Kinship is a genetic relationship between two family members, including parent-child, siblingsibling, and grandparent-grandchild relations. Since a genetic test may not always be available for checking kinship, an unobtrusive and rapid computer vision solution is potentially very useful. Kinship may be verified between people that have different sex and different ages (e.g. father-daughter), which makes this problem especially challenging. Humans use an aggregate of different features to judge kinship from facial images. Furthermore, depending on the age of the person assessed for kinship, humans use different sets of features consistent with the expected aging-related form changes in faces. For example, upper face cues are more prominently used for kids, as the lower face does not fully form until adulthood.[26]

several scientists have investigated the kinship verification via facial images, different approaches have been proposed. These methods can be roughly divided into two approaches. The first one based on Hand- Crafted Feature-based methods. The second one based on the Deep Learning Feature-based methods.



Figure 2.3: An illustration of some kinds of kinship from two databases. Face images from the first to second row are from the KFW-I database. Face images from the third to fourth row are from the KFW-II database.

II.8.1-Approaches based on hand-crafted features:

hand-crafted features that are designed beforehand by human experts to extract a given set of chosen characteristics.

Handcrafted techniques are dependent on the various methods of manual extraction of low-level features. These techniques are considered old kinship verification methods that always extract facial images handcrafted descriptors and use them for training classifiers. A summary of handcrafted feature-based techniques is in **Table 2.2.**[27]

Chapter II.....Facial Kinship Verification

Study	Features	Method	Datasets
Fang et al. (2010)	Color, Facial parts, Facial-distances, HOG	Facial feature extraction & forward selection methodology	150 public figures pairs
Zhou et al. (2011)	SPLE	SPLE descriptor +SVM	400+ public figures pairs
Zhou et al. (2012)	Gabor magnitude	GGOP	1,000 images
Liu, Puthenpathussery & Liu, 2015	Color SIFT	IFVF	KinFaceW-I KinFaceW-II
Chergui et al. (2018)	LPQ, LDP	Multi-Level LDP and LPQ	CornellKinFace UB KinFace KinFaceW-I KinFaceW-II

Chapter II.....Facial Kinship Verification

Mukherjee & Meenpal (2019)	CLBP	CLBP and LFDA	KinFaceW-I KinFaceW-II
Chergui et al. (2019a)	LBP, BSIF, LPQ	Mixing different descriptors	CornellKinface UB KinFace Family 101 KinFaceW-I KinFaceW-II
<i>Goyal & Meenpal (2019)</i>	HOG, LBP	Feature descriptors+ SVM classifier	KinFaceW-I
<i>Almuashi et al. (2021)</i>	HOG	Feature learning & handcrafted features fusion	KinFaceW-I KinFaceW-II

Table 2.2: A summary of some handcrafted feature-based methods [27]

Chapter II.....Facial Kinship Verification

Fang et al. (2010) proposed using methods for feature extraction, selection, and labeling face image pairs as “related” or “unrelated” in an intuitive way. They used a discriminative features list, such as hair color, eye color, skin color, and distance from nose to mouth, and merged them into a feature vector. They operated on a parent-child database of about 150 pairs of celebrities and public figures. They implemented KNN and SVM techniques to train a classifier on those various vectors and pairs of two unrelated people’s images.

Zhou et al. (2011) introduced an automated system for verifying kin relationships based on uncontrolled facial image analysis. Their research’s primary aim was to push verification of kinship from facial image research towards real scenarios., they concentrated on fully-automated verification of kinship from facial images under uncontrolled circumstances that place no constraints of posture, illumination, background, and expression. They used the spatial pyramid learning (SPLE) feature descriptor.

Zhou et al. (2012) introduced a Gabor-based gradient orientation pyramid (GGOP) technique for representing features for verifying kinship from facial images under uncontrolled circumstances. To enhance multiple feature information, they proposed a new feature weighting technique to extract complementary information for verifying kinship. Experimental results had shown the effectiveness of their technique for kinship verification.

Liu, Puthenputhussery & Liu (2015) presented an inheritable Fisher vector feature (IFVF) technique for verifying kin relationship. The Fisher vector was first extracted for every image by merging densely sampled SIFT features in opposing space of color. An inherited transformation that increased the similarity between kinship images while decreasing simultaneous learning for each image pair based on the Fisher vectors between non-kinship images was used. Consequently, the IFVF was exploited by seeking the inherited transformation on the Fisher vector for every

Chapter II.....Facial Kinship Verification

image. In the end, they proposed a fractional power cosine similarity measurement that showed its theoretical roots in the Bayes decision rule for minimum error for verifying kin relationship. They worked on two datasets (KFW-I and KFW-II). Experimental findings indicated that their technique was capable of achieving good results compared to the existing techniques for verifying kinship.

[Chergui et al. \(2018\)](#) proposed that in order to verify kin relationship from face images, they used LPQ, local directional pattern (LDP), and multi-level (ML) descriptors. Their experimental findings showed that their technique produced a better performance than previous techniques. They operated on CornellKinFace, UB KinFace, KFW-I, and KFW-II datasets.

[Mukherjee & Meenpal \(2019\)](#) proposed a technique depending on CLBP and local feature-based discriminate analysis (LFDA) to enhance the accuracy of verifying kinship. These two techniques resulted in long feature vectors. Only the entire feature vector-based LFDA feature selection technique increased the compiler's speed and chose the most suitable features. They used a KNN classifier. They worked on datasets of KFW-I and KFW-II.

[Chergui et al. \(2019a\)](#) introduced a technique depending on various mixed descriptors, such as LBP, LPQ, binary statistical image features (BSIF), and the multi-block (MB) representations. They also investigated the influence of various features for verifying kin relationships. Their technique was tested on five datasets, which are CornellKinFace, UB KinFace, Family 101, KFW-I, and KFW-II.

[Goyal & Meenpal \(2019\)](#) proposed variable descriptors of features (LBP and HOG) to detect salient features. They also used an SVM classifier to gain knowledge of facial features extracted. They operated on the KFW-I dataset. Their findings

Chapter II.....Facial Kinship Verification

indicated that the LBP-SVM approach outperformed HOG-SVM.

Almuashi et al. (2021) they presented a method, a fusion strategy made up of handcrafted (low-level feature) and feature learning techniques (high-level feature) along with features that subtract the absolute value for the face pair. They applied HOG descriptor to extract hand-crafted features while CNN was used to represent the feature learning.

II.8.2-Approaches based on deep learning features:

Deep learning methods are proposed to automatically learn and understand features from large amounts of data, such as images, instead of manually designing features.

Because the features extracted by the lower levels of a CNN strongly depend on the training set, special care must be taken in the selection of the dataset. The choice of a representative training dataset is usually performed by generating or selecting huge training sets, in the order of millions of images . This solution, however, is far from ideal, as it requires considerable human effort in the selection of images suitable for building the training set and substantial computational power during the training phase. Both these drawbacks can partially be overcome by exploiting semi-supervised and unsupervised techniques and parallel computing to reduce the human labor and the computational costs involved in the training.[28]

In **Table 2.3**, we provide a brief descriptive summary of several recent deep learning methods, including the approach proposed here for comparison purposes .

Chapter II.....Facial Kinship Verification

Paper	Features extracted using CNN
Here	Using deep layers, shallow layers, and the scores obtained by CNN
[14]	Representation of images as strings of the top layers of pretrained CNNs
[15]	The convolutional layers of a CNN are used as a filter bank
[16]	Representation of images using the seventh fully connected layer of a CNN on ImageNet
[17]	Representation of images using the last convolutional layer of a CNN
[18]	Representation of images using five convolutional layers and two fully connected layers
[19]	Lower-layer features are used
[20]	Features are extracted from the first few layers of a pre-trained CNN model
[21]	Top-layer activations are used as features

Table 2.3: Descriptive Summary of other deep learning approaches

Chapter II.....Facial Kinship Verification

II.9-Conclusion:

In this chapter, an overview of automatic face-based relationship screening is presented. Use some terms and definitions. Description of a face kinship system design review.

We discussed some exciting applications for the continuous research in this topic. We have also enumerated a number of practical challenges that restrain the facial kinship verification problems and we summarized the existing databases. Also, we have presented the main state of the art and an overview of automatic kinship verification approaches.

Chapter III : **Experimental-Evaluation**

III.1-Introduction:

Automatic kinship verification, as a classical Boolean problem, is used to predict whether given face images have kin relations. The most basic kinship verification is 1-vs-1 verification, where two face images are given as inputs and the output is a decision whether the two persons are members of the same family, As a natural extension of 1-vs-1 verification, tri-subject verification is a special kinship verification problem of deciding whether a child is related to a pair of parents, which is essentially a 2-vs-1 verification, . For example, when comparing two faces, one is a father and the other is a son, the prospective mother could be known if an image of the wife of the father is available. Thus tri-subject verification aims to check the kinship between a pair of parents and a child. recognized that a childs face more closely resembles their parents at younger ages. They adopted transfer learning to narrow the appearance gap between the older faces and the younger faces. deep learning has achieved significant progress in several kinship recognition tasks.

III.2-Kinship system :

General scheme for checking kinship based on facial images. This kinship system consists of the following basic components which are shown in **Figure 3.1**:

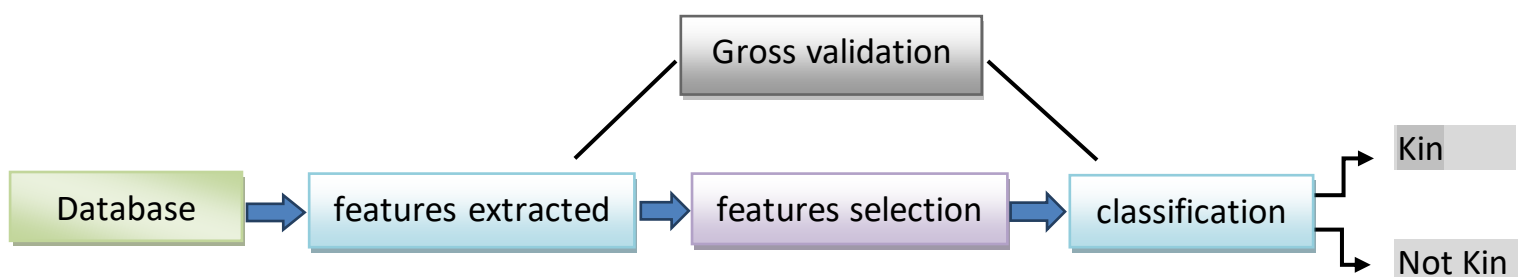


Figure 3.1 General scheme for checking kinship based on facial images.

- **Database:** The KinFaceW-II dataset was used. In which there are four kinship relationships: father-son (F-S), father-daughter (F-D), mother-son (M-S), and mother-daughter (M-D). Each relation contains 250 pairs and has been

resized to 64 x 64 pixels .



Figure 3.2 KinFaceW-II datasets, respectively. From top to bottom are the F-S, F-D, M-S, and M-D kinship relations

- **feature extraction:** we have used two different types: hand-crafted features and deep learning features LBP and CNN (VGG-face, VGG-F) are selected for their popularity in computer vision and showed very promising results in different problems.
- **LBP:**

Mathematically, the LBP operator is defined as The face image is divided into 4×4 non overlapping blocks and the size of each block is 16×16

LBP operator assigns a label to every pixel of an image by thresholding its value with neighbourhood pixels and considering the result as a binary number. [29]

- **CNN:**

CNN is a Deep Learning algorithm that can take in an input image, assign importance to various objects in the image and be able to differentiate one from the other. CNNs use relatively little preprocessing compared to other algorithms and this means that the network learns the filters that in traditional algorithms were hand-engineered. Several models have been extracted from CNN. The network is composed of 13 linear convolution layers (conv), each followed by a non-linear rectification layer (relu). Some of these rectification layers are followed by a nonlinear max pooling layer (mpool). Following are two fully connected layers (fc) both outputting a vector of size 4096 [30] .

- **VGG_Face:**

VGG-face is a complete face recognition system that includes a deep convolution neural network for recognition and a deformable parts model (DPM) for face detection and localization the basic architecture of the algorithm consists of 37 layers, and the layers include convolutions, relu normalization, pooling, full connected layers. [31]

- **VGG_F:**

VGG-F is a pre-trained model provided by MatconvNet [16], a MATLAB toolkit that implements convolutional neural networks (CNNs) for computer vision applications. [32]

- **Feature Selection:**

In machine learning, Feature Selection (FS) is a data preprocessing step that is applied after feature extraction step. Feature selection method aims to select the most

relevant subset of extracted features to provide a useful classification with the smallest error and to discard non-relevant features. In this dissertation, we used Fisher/Correlation feature selection using Wrapper for Spider toolbox [33], [34] and [35].

- **Classification and Decision:**

kinship Verification is bi-classification problem where the pair of input faces is classified as positive (the true pairs of parents and children) or negative (the false pairs of parents and children).

- **Cross validation:**

("cross-validation") is a method for estimating the reliability of a model based on a sampling technique. In our experiment "k-fold cross-validation" was used.

- **K-fold Cross Validation:**

The data is first partitioned into k equally (or approximately equally) sized segments or folds in k-fold cross-validation. Following that, k iterations of training and validation are done, with each iteration holding out a separate fold of the data for validation while the remaining k-1 folds are used for instruction. Prior to splitting data into k folds, it is standard practice to stratify it. Stratification is the method of rearranging data so that each fold is an accurate representation of the whole. To put it another way, the K-fold Cross-validation is a computer-intensive methodology that employs all available examples as both teaching and evaluation examples.

Figure 3.3 depicted a 5-cross validation example.

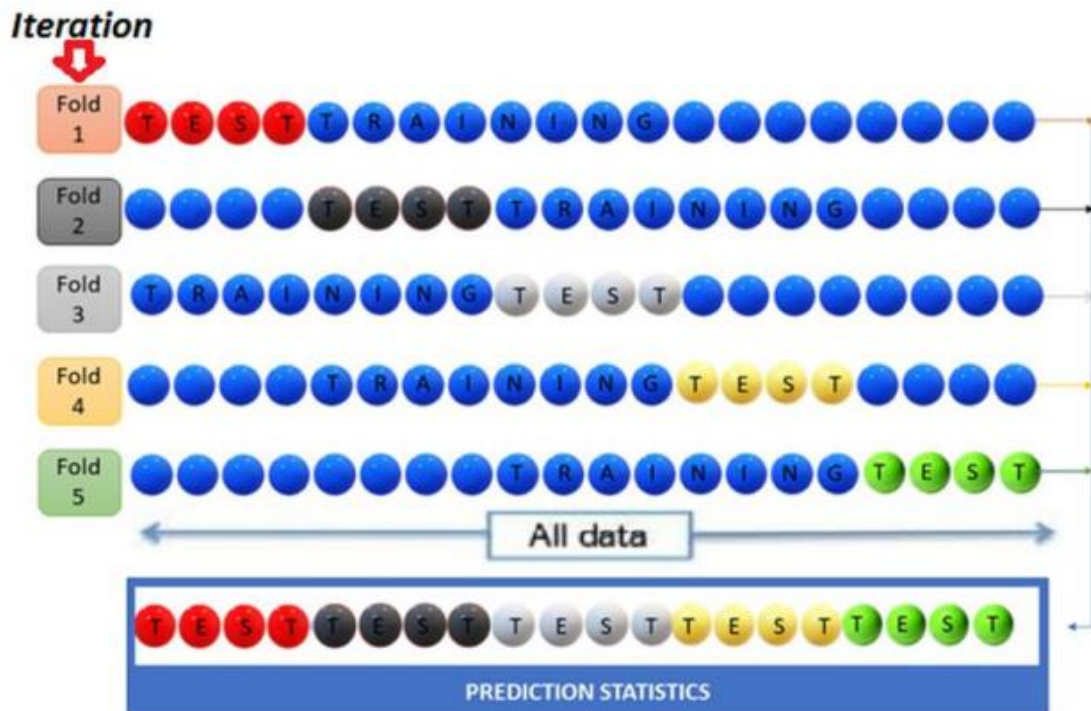


Figure 3.3: Example of 5-cross validation.

III.3-Experimental Evaluation:

For the experiments, same number of negative pairs (no kin relation) as positive pairs (with a kin relation) is created by associating faces from persons which do not have a kinship relation. We apply the features selection technique to select the most relevant features. We perform 5-fold cross validation and compute the mean accuracy of the five folds. Finally, the cosine similarity of each test pair is computed. We report the mean verification accuracy of the four kinship subsets as the measure of system performance. To evaluate the performance of system, the Receiver Operating Characteristic (*ROC*) is used.

III.4-Results and Analysis:

To achieve the best performance, we tested different size of features to be selected on KinFaceW-II (F-S relationship) and then applied for the rest of relationships. The results are shown in Table 3.1 and 3.2

Chapter III.....Experimental-Evaluation

After changing various times the number Select parameter, the best result was 0.33.

	0.1	0.3	0.32	0.33	0.4	0.5	0.6	0.8	1
Accuracy (%)	74.60	70.48	75.20	75.20	74.60	74.20	74.00	74.40	74.60

Table 3.1: Affinity Verification Accuracy in Percentage of Proposed Method on KinFaceW-II Databases with Feature Selection

Featureselection	FS	FD	MS	MD	MEAN
With (%)					
LBP	75.20	75.20	74.60	74.00	74.75
VGG-Face	72.60	78.00	78.80	75.80	76.30
VGG-F	76.20	79.80	82.60	82.40	80.25
Without (%)					
LBP	74.60	76.00	72.60	73.00	79.30
VGG-Face	68.80	72.40	77.80	71.80	72.70
VGG-F	76.00	79.20	81.00	81.00	79.30

Table 3.2: Affinity Verification Accuracy in Percentage of Proposed Method on KinFaceW-II Databases (with and without)Feature selection

Chapter III.....Experimental-Evaluation

Discussion:

With Feature selection Our results show that the average accuracy of human performance on the task of kinship verification is 74.75 - 80.25 % on the Four relationships. The best verification accuracy is obtained for M-S with 82.60 % .

Without Feature selection Our results show that the average accuracy of human performance on the task of kinship verification is 72.70 - 79.30 % on the Four relationships. The best verification accuracy is obtained for M-S and M-D with 81.00 %.

We noticed that with choosing the feature, the results are better. than without selecting the feature .

Table 3.3: The accuracy of checking kinship in % of the method proposed on KinFace W-II Databases (LBP, VGG-Face, VGG-F) .

Techniques	FS	FD	MS	MD	MEAN
LBP	75.20	75.20	74.60	74.00	74.75
VGG-Face	72.60	78.00	78.88	75.80	76.32
VGG-F	76.20	79.80	82.60	82.40	80.25

Table 3.3: Kinship verification accuracy in % of proposed method on KinFace W-II databases.

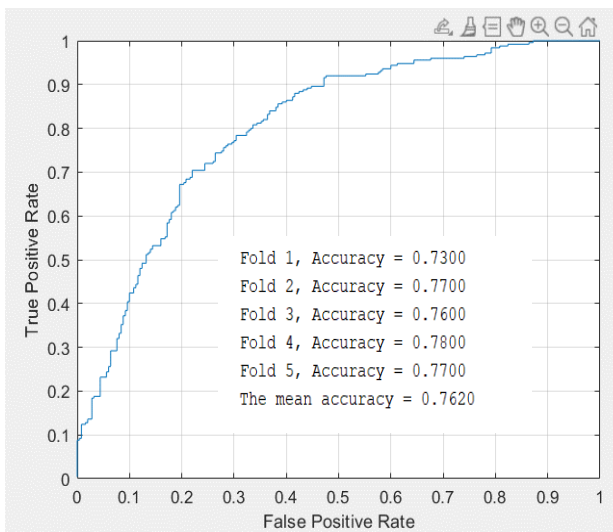
We note that the results obtained for VGG_Face are better than LBP, and VGG_F are better than VGG_Face and LBP

Chapter III.....Experimental-Evaluation

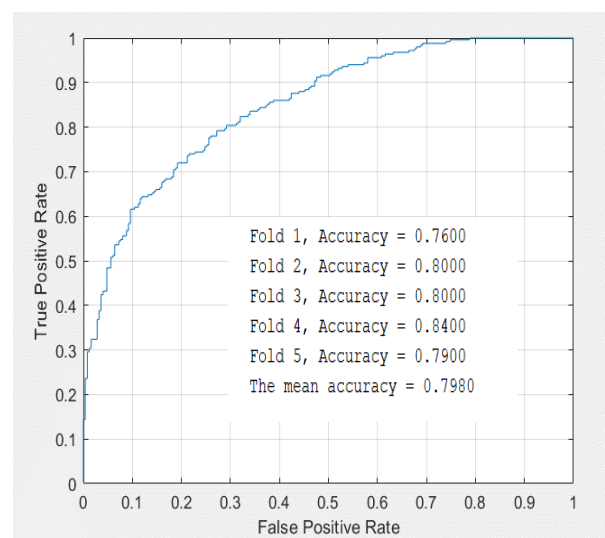
These are the curves obtained from Matlab after changing the values on all KinFace - II database F-D, F-S, M-D, and M-S:

$$\text{Accuracy} = \frac{TP + TN}{P + N}$$

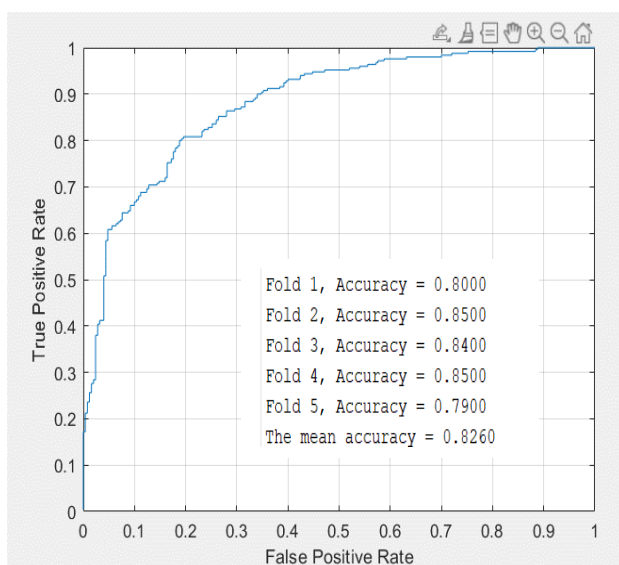
Where TP is the number of image that classified correctly as positive pairs, TN is the number of image that correctly classified as negative pairs, P is the number of all positive pairs, and N is the number of all negative pairs



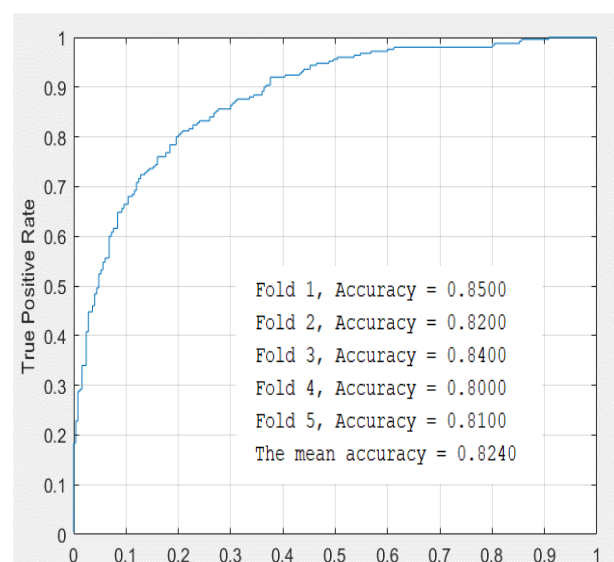
F-D



F-S



M-D



M-S

III.5-Conclusion:

In this study we addressed automatic kinship verification from facial images of four linkages: F-S, F-D, M-S and M-D. Using LBP and CNN (VGG_Face, VGG_F), It selects the strong features and neglects the weak ones to improve the performance of family validation.

General Conclusion

We used a comprehensive discussion of the important concepts needed to understand kinship recognition through facial images. In addition, we showed technologies and features. We also explained the distinctive features that are commonly utilized to serve as yardsticks in measuring efficiency of kinship verification and identification that may have increased or reduced the severity of problems and challenges.

The performance of a recognition system largely relies on representations of feature. For this, we recommend taking advantage of the Deep Learning (DL) technique in order to addressing this problem. Because, deep learning recognition methods automatically learn and understand features from a massive amount of data like text and image, rather than designing features manually. In this, that automatically features derived from learning algorithms can provide highly informative representations for a classification task and thus lead to improved accuracy.

These methods have been validated on the basis of Kin Face in the Wild-II (KinFaceW-II) data, and have been implemented in Matlab.

Research in kinship domain is still new and further exploration will definitely open up to new more interesting direction. In the foreseeable future, the products of this research will bring advantages to various domain area and benefit to mankind.

Annexe A

Deep neural networks have been recently outperforming the state of the art in various classification tasks. Particularly, convolutional neural networks (CNNs) demonstrated impressive performance in object classification in general and face recognition in particular.

- **CNNs** : are hierarchical machine learning models which are able to learn complex representations of images and signals using vast amounts of training data. Inspired by the human visual system, CNNs progressively extract sophisticated representation of the input by learning transformations in multiple layers. **Fig. 3.4** illustrates an example of a deep CNN. A deep CNN is formed by alternating many convolutional and subsampling layers. Usually, the top of the network is composed by one or more fully connected layers and a classification layer.[36]

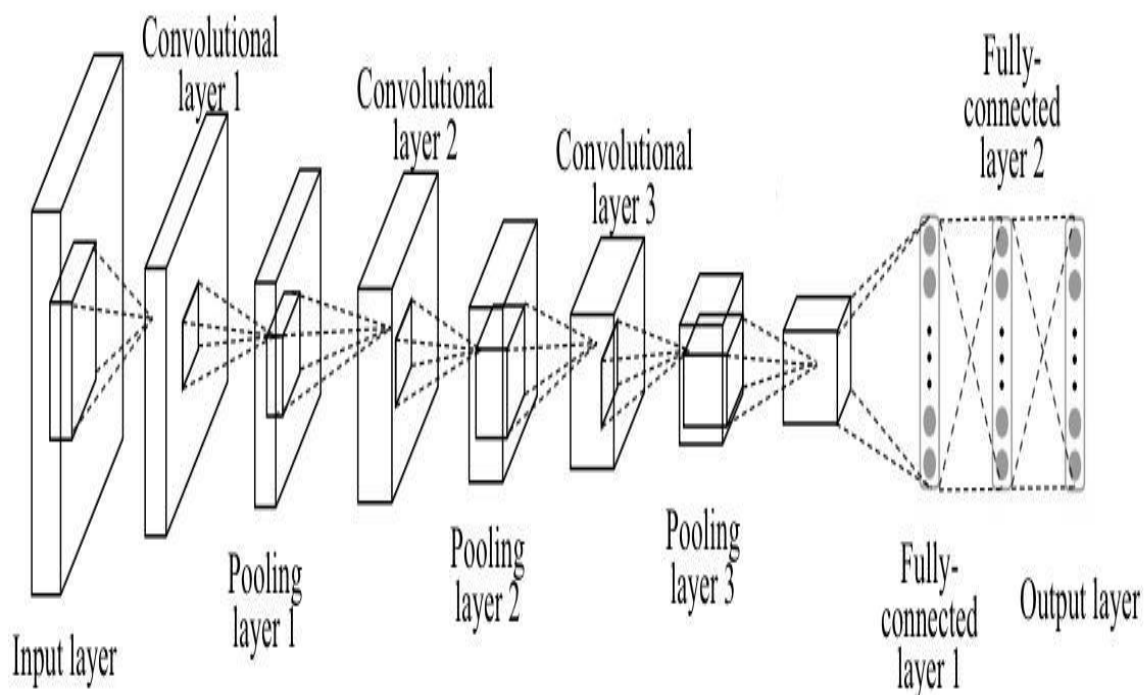


Figure 3.4 example of a deep CNN [36]

Annexe B

➤ Face representation using LBP :

In LBP-based approaches, an image is generally described using the histogram of the LBP codes composing the image. This histogram representation does not encompass the location information. Therefore, this representation is not suitable for face images as the face is a structured object, where the position of its parts (i.e., eyes, nose, mouth, etc.) is very important for matching between two facial images. In order to avoid facial spatial information loss, Ahonen et al. subdivided the face images into several small blocks. Then, LBP feature is extracted from each block separately, building a per block local descriptor. The final face descriptor is obtained by combining all the local descriptors from the different blocks. This scheme is illustrated in Fig. 3.5

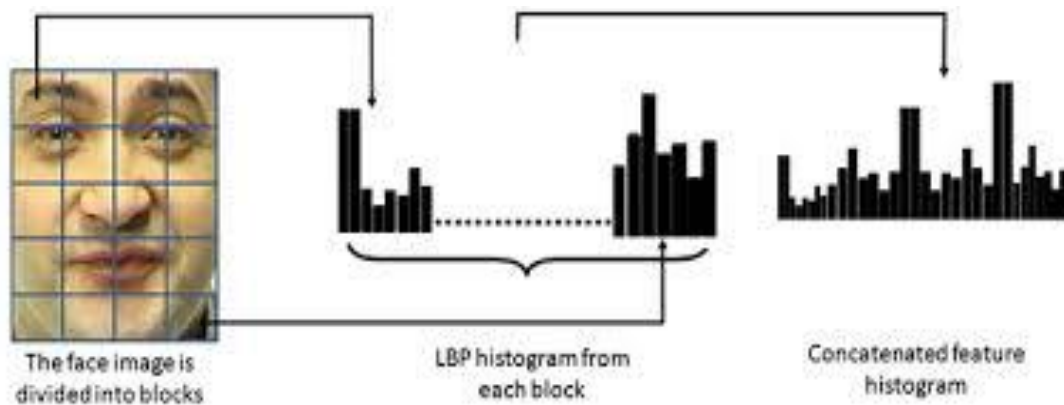


Figure 3.5: Face description using LBP [36]

In this original LBP based face representation and most of its variants, extracted histograms over different blocks are generally sparse. In other words, most of bins in the histogram are zero or near to zero, particularly in the case of small face blocks. Indeed, the number of LBP labels in a block depends on its size. On one hand, large blocks produce dense histograms that badly represent local face changes. On the other hand, small blocks are robust to local changes but create unreliable sparse histograms, as the number of histogram bins exceeds by far the number of LBP patterns in the block. [36]

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