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Face Kinship Verification Using Retinex Filter and Elliptical Mask based New Version of Gabor Filter

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Dedication

It is with genuine gratitude and warm regard that I dedicate this thesis to

To Allah who gave me the will, the confidence, and the courage to do this modest work.

My Amazing mother ***Gania Atchi*** *source of love and strength without her encouragement I would never have been able to complete my studies.*

My dear father ***Mustapha*** *the reason of what I become now and his affection which led me to finish my project.*

My beloved sisters and brothers ***Ahmed, Khaoula, Khadidja, Aicha, Hadil, Assmaa, Billel*** *who have always loved me, cheered for me and believed in me****,*** *their support and encouragement can never be replaced.*

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To My collages and virtual friends.

I love you all May ALLAH (SWT) grant you Jannah Firdaus.

Maria.

Dedication

I dedicated this modest work to those who are dearest

To my parents who gave me life the symbol of tenderness, who sacrificed themselves for my happiness and success, who gave meaning to my life, and who was the shadow during all the years of study.

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To my family.

To my friends.

.

Abderrahim.

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ملخص

يعد مظهر الوجه البشري مؤشرًا مهمًا لقياس التشابه الجيني لأن الأطفال وأولياء أمورهم مرتبطون بيولوجيًا ، وعادة ما يشبه الأطفال والديهم أكثر من الاقارب الآخرين. بدافع من هذه النتيجة ، قام باحثو رؤية الكمبيوتر بالبحث في مشكلة التحقق من القرابة من خلال تحليل صورة الوجه و تم الحصول على بعض النتائج المشجعة ، و لكن لا تزال هذه المشكلة دون حل خاصة عندما تم التقاط صور الوجه في بيئة غير مقيدة مما يجعل هذه المشكلة صعبة للغاية. في مذكرتنا ، نقدم نظام التحقق من القرابة الذي يبدأ بزوج من صور الوجه للطفل والوالد ، ثم كنتيجة نهائية ، يتم تحديد ما إذا كان هناك علاقة قرابة بين الشخصين أم لا. الخطوة الأولى في نهجنا هي المعالجة المسبقة للوجه بطريقتين: مرشح Retinex وقناع إهليلجي ، ثم يتم استخدام مرحلة الاستخراج بناءً على موجات Gabor التي تكون قبل طريقة تقليل الأبعاد القوية المسماة TXQDA . أخيرًا ، القرار ما إذا كانت هناك قرابة أم لا. و لقد أجرينا العديد من التجارب لإثبات فعالية نهجنا مع قاعدة بيانات Cornell KinFace المعيارية. تشير نتائجنا إلى أن نظامنا قوي مقارنة بالنُهج الحالية الأخرى.

الكلمات الرئيسية: الذكاء الاصطناعي, التحقق من القرابة بالوجه ، التعلم الآلي ، القياسات الحيوية ، مرشح Retinex ، القناع الإهليلجي ، موجات Hist-Gabor، رؤية الكمبيوتر ، TXQDA.

Abstract

The human facial appearance is an important cue for genetic similarity measure because children and their parents are biologically related and children usually resemble their parents more than other adults. Motivated by this finding, computer vision researchers have investigated the problem of kinship verification via facial image analysis while some encouraging results have been obtained, this problem still remains unsolved especially when face images were captured in unconstrained an environment which makes this problem extremely challenging. In our thesis, we present a kinship verification system that starts with pair of facial images of the child and parent, then as a final result is determine whether two persons have a kin relation or not. The first step in our approach is the face preprocessing with two methods Retinex filter and Elliptical mask, then feature extraction stage based on hist-Gabor wavelets that is used before the powerful dimensionality reduction method called TXQDA. Finally, decide whether there is a kinship or not. We conducted several experiments to demonstrate the effectiveness of our approach with Cornell KinFace benchmark database. Our results indicate that our system is robust compared to other existing approaches.

Keywords: Artificial Intelligence**,** Facial Kinship Verification, Machine Learning, Biometrics, Retinex Filter, Elliptical Mask, Hist-Gabor Wavelets, Computer Vision, TXQDA.

Résumé

L'apparence du visage humain est un indice important pour la mesure de la similitude génétique, car les enfants et leurs parents sont biologiquement liés et les enfants ressemblent généralement plus à leurs parents que les autres personnes. Motivés par cette découverte, les chercheurs en vision par ordinateur étudié le problème de la vérification de la parenté via l'analyse d'images faciales. Des résultats encourageants ont été obtenus. Ce problème n'est toujours pas résolu, en particulier lorsque les images de visage ont été capturées dans un environnement non contrôler, ce qui rend ce problème extrêmement difficile. Dans notre mémoire, nous présentons un système de vérification de la parenté qui commence par une paire d'images faciales de l'enfant et du parent, puis comme résultat final la décision si ces deux personnes ont une relation de la parenté ou non. La première étape de notre approche est le prétraitement du visage avec deux méthodes filtre Retinex et un masque elliptique pour les images de visages, puis l'étape d'extraction de caractéristiques basée sur les ondelettes de Hist-Gabor est l'utilisée avant méthode la puissante de la réduction de dimensionnalité appelée TXQDA. En fin, la décision s'il y a une parenté ou non. Nous avons évalués plusieurs expériences pour démontrer l'efficacité de notre approche avec la base de données de Cornell KinFace. Nos résultats indiquent que notre système est robuste et efficace par rapport aux autres approches existantes.

Mots-clés : Intelligence Artificielle, Vérification de la Parenté Faciale, Apprentissage automatique, Biométrie, Filtre Retinex, Masque Elliptique, Ondelettes Hist-Gabor, Vision par Ordinateur, TXQDA.

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List of Abbreviations

AI	Artificial intelligence.
AFIS	Automated Finger Imaging Systems
AMM	Active Appearance Model
BSIF	Binarized Statistical Image Features
DL	Deep Learning
DNA	Deoxyribonucleic Nucleic Acid
LDA	Linear Discriminant Analysis
LBP	Local Binary Patterns
LDA	Linear Discriminant Analysis
LPQ	Local Phase Quantization
ML	Machin learning
PCA	Principal Component Analysis
PIN	Personal Identification Number
RL	Reinforcement Learning
SL	Supervised Learning
SSL	Semi-Supervised Learning
SILD	Side-information Based Linear
TXQDA	Tensor Cross-View Discriminant Analysis
UNL	Unsupervised Learning

General introduction

The likeness between two people based on using the physical features of the person, including the hairstyle, pose, hand bone and facial features (nose, eye, ear, and mouth) is one of the most important factors for kinship verification. Although the results can vary comparing with analyzing using DNA sequence, the physical features can be used as an initial investigation and can quickly detect whether two people have a kinship relationship and analyzing facial images is one of the major research topics in biometrics, computer vision, and pattern analysis. In the past few decades, face verification and people recognition problems have been the focus of considerable attention.

Kinship verification through facial images in practice, it has many applications such as finding missing children, family album organization and creation of family trees. Among the difficulties found in this study is the apparent similarity of two people who have no relationship and the case when people have blood relationship and don't have a similar appearance. In addition, effect of the different conditions of images captured [1].

The researcher's attention has shifted to propose an algorithm that determines whether a pair of facial images belonging to a class is kin or non-kin. Analyzing kinship through human facial image is a challenging task and based on the literature, few attempts have been made to do this and the difficulties in recognizing kinship can be divided into the following two categories: (1) directly challenging (related to kinship itself) and (2) indirectly challenging (related to the environment of the database). Moreover, feature extraction is most sensitive and important because special features made available for discrimination straight affect the efficacy of the kinship verification and recognition tasks.

However, although many of the published algorithms have demonstrated excellent recognition results, there are still many open problems. In this paper, we propose a new system of kinship verification that is composed of five stages: starting by obtaining pairs facial images (child/parent) after the face preprocessing step, where facial images are processed by two methods Retinex filter and Elliptical mask in to correct illumination and pose and other variations, then we used the features extraction where these facial images are subject to many methods to extract useful information known as features, in this work we used Gabor wavelets model that is collection of mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. Finally, the similarity measurement stage to measure

similarity between face samples then the verification stage outputs a binary for the figures : final decision input samples, (Kin or No-Kin) [2].

The main contributions of this work to improve the performance of kinship verification are summarized as follows:

- We propose two new methods on the preprocessing stage which are
  1. The Retinex filter in which it's a powerful method for image enhancement in poor visibility conditions that simultaneously provides dynamic range compression, color consistency and lightness rendition, also its denoising process may provide good noise removal. It is markedly superior to a strong increase in local contrast and overall sharpness, especially in scenes of poor visibility.
  2. The elliptical mask it's a traditional method utilizes inherently elliptical nature of human head and fits an ellipse to the head its then used to mask out all unwanted feature point especially in complex environment.
- We use in the extraction features phase a new method named hist-Gabor wavelets in which, the images are decomposed into several blocks to encode the facial structure. The histogram features based on Gabor wavelet give more microstructure information such as plane area, spots, orientations and edges. The histograms of all blocks are extracted and concatenated creating an enhanced feature vector.
- We use new Multilinear subspace approach for kinship verification TXQDA based on multidimensional representation of data, to provide a better discrimination between samples in the dataset.
- Considerable experiments on a public database (Cornell KinFace) along with good and stable results of the proposed approach.

The rest of the paper is organized as follows: an overview of Artificial Intelligence and biometrics are presented in chapter 1. Facial kinship verification system is detailed in chapter 2. Finally, the implementation of our approach based on Retinex filter and elliptical mask using Hist-Gabor Wavelets Features are presented in chapter 3.

Chapter 1 :

Overview of artificial intelligent & machine learning &biometrics.

1.1. Introduction

Artificial Intelligence (AI) has been widely explored across the world over the past decades a rapid growth in research and development. Such areas as expert systems, machine learning, natural language processing, speech recognition, computer vision, robotics, etc. have significantly progressed, even though important problems still remain to be solved. The present success of AI results, among other approaches, from the design of new system architectures that are able to use all the knowledge, including human expertise, available in a given domain. Such knowledge-based systems thus take human expertise into account in order to improve their own performances.

A particularly emerging topic is the many important applications of AI in the real world using a biometric system as the unique (personal) physical/logical characteristics or traits of human body. These characteristics and traits are used to identify each human. This chapter aims at presenting an overview of the definition of AI and its applications also the basic methods of the Machine Learning, and A brief background about biometric systems.

1.2. What is Artificial intelligence?

Artificial Intelligence (AI) is the intelligence displayed by machines. In computer science, the field of artificial intelligence research defines itself as the study of "intelligent agents": any device that can perceive its environment and take actions to maximize the chance of success for achieving a certain goal. In layman's terms, the term "artificial intelligence" applies to a machine imitator in the following situations. Humans have "cognitive" functions related to other human thinking, such as "learning" and "problem solving." Capabilities currently classified as artificial intelligence include successful understanding of human voice, high-level competition in strategic game systems (such as chess and go), autonomous vehicles, intelligent routing in content delivery networks, military simulation, and interpretation of complex data [3].

The central problems of AI research include reasoning, knowledge, planning, learning, natural language processing (communication), perception and the ability to move and manipulate objects. General intelligence is among the field's long-term goals. Approaches include statistical methods, computational intelligence, and traditional symbolic AI. Many tools are used in AI, including versions of search and mathematical optimization, logic, methods based on probability and economics. The AI field draws upon computer

science, mathematics, psychology, linguistics, philosophy, neuroscience, artificial psychology plus many others [3].

Since then, AI has broken away from the hypothetical and into real-world business solutions. Much of them have to do with the wide availability of GPUs (graphics processing units), which make parallel processing ever faster, cheaper, and more powerful. The ascent of AI also has to do with the simultaneous of practically infinite storage and a deluge of data of every stripe, including images, video, audio, text, transactions, and geospatial data [4].

Embedding smart behaviors in code blocks cannot handle all human smart behaviors. Some simple tasks, such as sorting numbers or playing some games, can be described by humans and then processed by machines with 100% human intelligence. However, some complex tasks, such as speech-to-text, image recognition, sentiment analysis, etc., cannot be solved by code alone. Humans cannot use chess to describe these problems. It is impossible to write code to recognize image objects such as cats. This intelligent behavior of recognizing objects cannot be solved with static code at all, because there is no single object classification rule. For example, there is no rule to identify cats. Even if you successfully create a rule to identify cats in one environment, applying it in another environment will definitely fail. Here comes what is known as AI, the goal here is not to hardcode instructions into machines but to teach machines to learn by themselves and find patterns in the data then give appropriate decisions. AI application extends to many subfields, the figure 1.1 represents the applications of AI [5] :

- Machine Learning (ML).
- Data Mining.
- Deep leaning
- Information Retrieval and Semantic Web.
- Speech Recognition and Natural Language Processing.
- Image Processing/Recognition and Computer Vision.
- Robotics.
- Knowledge Representation and Knowledge Database.
- Logic Reasoning and Probabilistic Reasoning.
- Expert Systems.

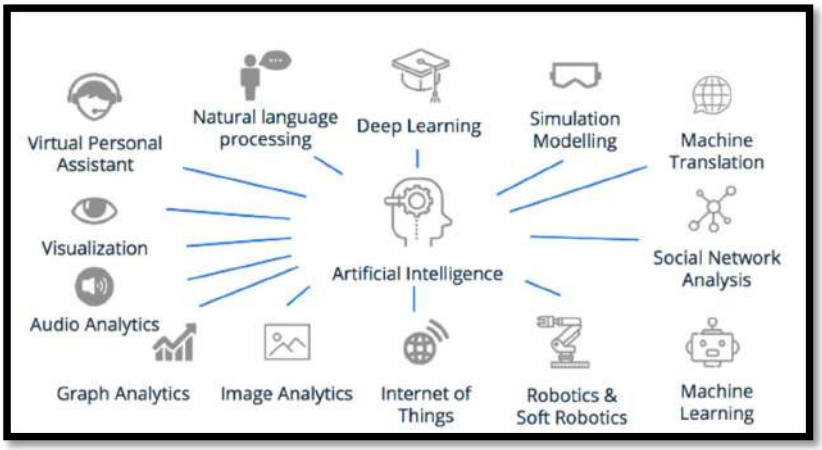


Figure 1.1 : Applications of AI.

1.3. Machine Learning

ML is a sub discipline of AI it includes various tools and methods that allow machines to learn without humans programming them. Humans input large amounts of data into an ML system. Then they give the system a desired output. The ML system tries to find the relationship between the two. The machine then produces a specific algorithm from the given output and input as illustrated in figure 1.2.

For example, social media platforms use recommendation systems. These systems choose what content to show you. The input data includes your browsing history, your likes and your friends' preferences. It also includes your personal information like age and gender. ML explores the study and construction of algorithms that can learn from and make predictions on data such algorithms overcome following strictly static program instructions by making data-driven predictions or decisions, through building a model from sample inputs [5].

Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms with good performance is difficult or unfeasible; example applications include detection of network intruders or malicious insiders working towards a data breach, optical character recognition (OCR), learning to rank and computer vision.

Machine learning is closely related to computational statistics, which also focuses on prediction making through the use of computers. It has strong ties to mathematical optimization, which delivers methods, theory and application domains to the field. Machine learning is sometimes conflated with data mining, where the latter subfield focuses more on exploratory data analysis and is known as unsupervised learning. Machine learning can also

be unsupervised and be used to learn and establish baseline behavioral profiles for various entities and then used to find meaningful anomalies [6].

We are encircled by a machine learning based-technology, web search tools figure out how to present to us the best outcomes, anti-spam software learns to filter our email messages, and credit card transactions are figures out how to distinguish fakes. Advanced cameras figure out how to detect faces and intelligent personal assistance applications on smart-phones learn to recognize voice commands. Vehicles are equipped with accident prevention systems that are built using machine learning algorithms. ML is likewise broadly utilized in scientific applications such as medicine, astronomy, biometrics and bioinformatics [7].

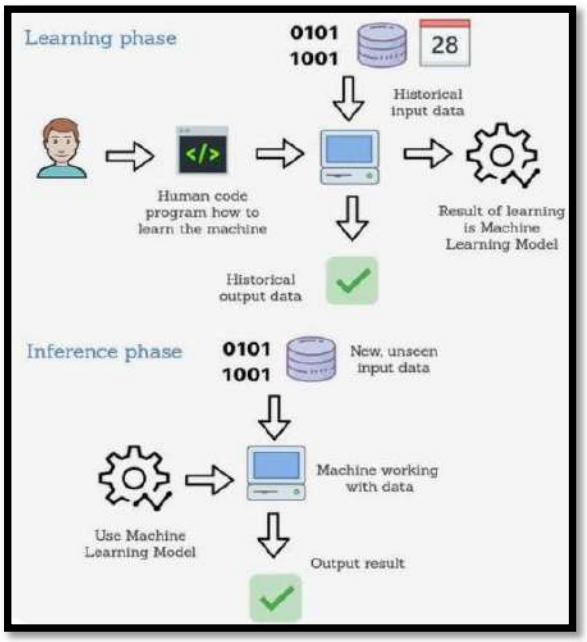


Figure 1.2 : the way of machine learning works.

1.4. The Types of Machine Learning

Machine Learning algorithms are mainly divided into four categories: Supervised learning, Unsupervised learning, Semi-supervised learning, and Reinforcement learning, as shown in Figure 1.3. In the following, we briefly discuss each type of learning technique with the scope of their applicability to solve real-world problems and examples of their algorithms [8].

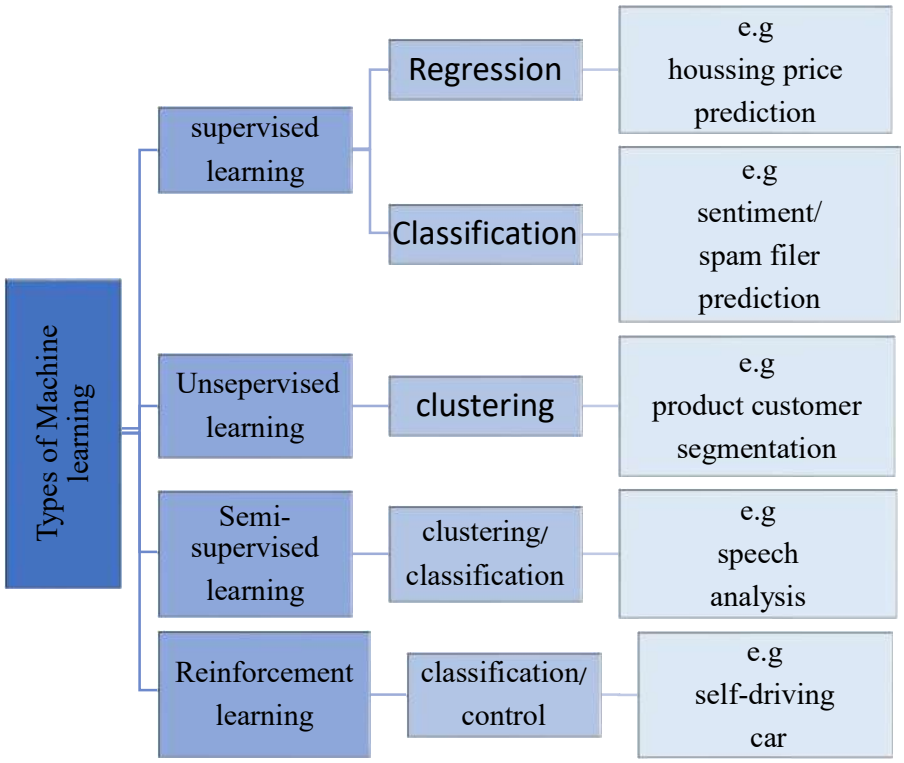


Figure 1.3 : categories of machine learning.

1.4.1. Supervised learning

SL algorithms are trained using labeled examples, such as an input where the desired output is known. For example, a piece of equipment could have data points labeled either "F" (failed) or "R" (runs). The learning algorithm receives a set of inputs along with the corresponding correct outputs, and the algorithm learns by comparing its actual output with correct outputs to find errors. It then modifies the model accordingly. Figure 1.4 illustrate the supervised learning way of work Through several methods like classification, regression, prediction and gradient boosting, supervised learning uses patterns to predict the values of the label on additional unlabeled data. Supervised learning is commonly used in applications where historical data predicts likely future events. For example, it can anticipate when credit card transactions are likely to be fraudulent or which insurance customer is likely to file a claim.

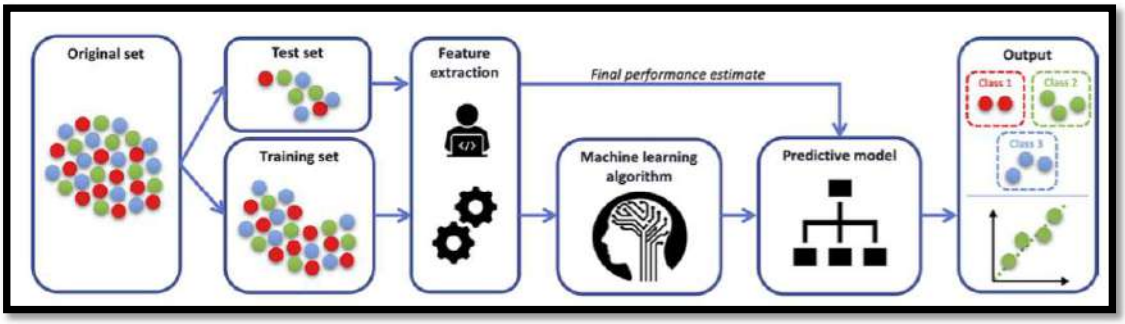


Figure 1.4 : Illustration of supervised learning method.

Linear Discriminant Analysis

LDA is a supervised dimensionality reduction algorithm It is a fundamental data analysis method originally proposed by R. Fisher for discriminating between different types of flowers. used as a pre-processing step in ML and applications of pattern classification, dimension reduction, and data visualization. It has been around for quite some time now. Despite its simplicity, LDA often produces robust, decent, and interpretable classification results [9]. The intuition behind the method is to determine a subspace of lower dimension, compared to the original data sample dimension, in which the data points of the original problem are "separable" (Figure 1.5). Separability is defined in terms of statistical measures of mean value and variance. One of the advantages of LDA is that the solution can be obtained by solving a generalized eigenvalue system. This allows for fast and massive processing of data samples in order to avoid the curse of dimensionality and also reduce resources and dimensional costs [10].

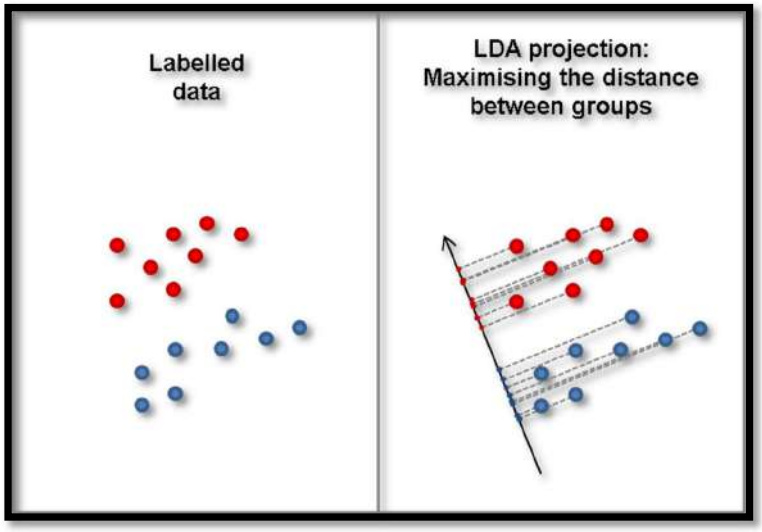


Figure 1.5 : LDA projection.

1.4.2. Unsupervised learning

USL is used against data that has no historical labels. The system is not told the "right answer." The algorithm must figure out what is being shown. The goal is to explore the data and find some structure within. Unsupervised learning works well on transactional data. For example, it can identify segments of customers with similar attributes who can then be treated similarly in marketing campaigns. Or it can find the main attributes that separate customer segments from each other. Popular techniques include self-organizing maps, nearest-neighbor mapping, means clustering and singular value decomposition. These algorithms are also used to segment text topics, recommend items and identify data outliers Figure 1.6 illustrate the pipeline of unsupervised learning works [11].

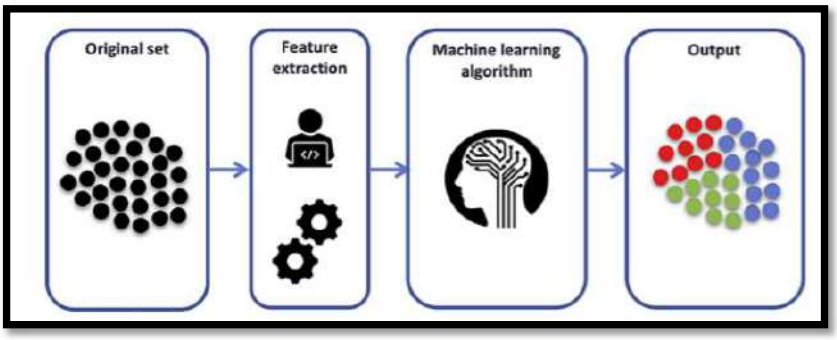


Figure 1.6 : Illustration of unsupervised learning method.

- **Principal component analysis (PCA)** is an unsupervised algorithm The concept of PCA is based on the objective of reduction in dimensionality of a data set consisting of multiple variables which are correlated with each other while retaining maximum variability in the data set figure 1.7 The algorithm transforms the variables in the data set to a new set of orthogonal principal components ordered in a manner such that the retention of variation in the original variables decreases while traversing down the order. The principal component is defined as a "linear combination of optimally weighted observed variables". The output generated from PCA are such principal components whose numbers are either lesser or equal to the original variables. The concept of dimensionality reduction in PCA pitches its use in facial recognition, computer vision and image compression. It has also wide spectrum of applications in pattern identification of high dimensional data pertaining to the field of finance, datamining, bio-informatics and psychology [12].

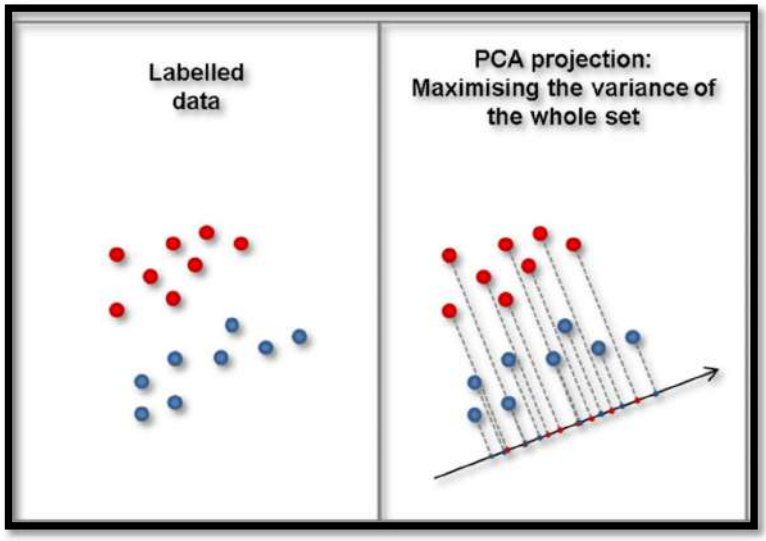


Figure 1.7 : PCA projection.

1.4.3. Semi-supervised learning

SSL in this type of learning, the given data are a mixture of classified and unclassified data. This combination of labeled and unlabeled data is used to generate an appropriate model for the classification of data. In most of the situations, labeled data is scarce and unlabeled data is in abundance (as discussed previously in unsupervised learning description). The target of semi-supervised classification is to learn a model that will predict classes of future test data better than that from the model generated by using the labeled data alone. The way we learn is similar to the process of semi-supervised learning (Figure 1.8). A child is supplied with: unlabeled data provided by the environment. The surroundings of a child are full of unlabeled data in the beginning. Labeled data from the supervisor. For example, a father teaches his children about the names (labels) of objects by pointing toward them and uttering their names [8].

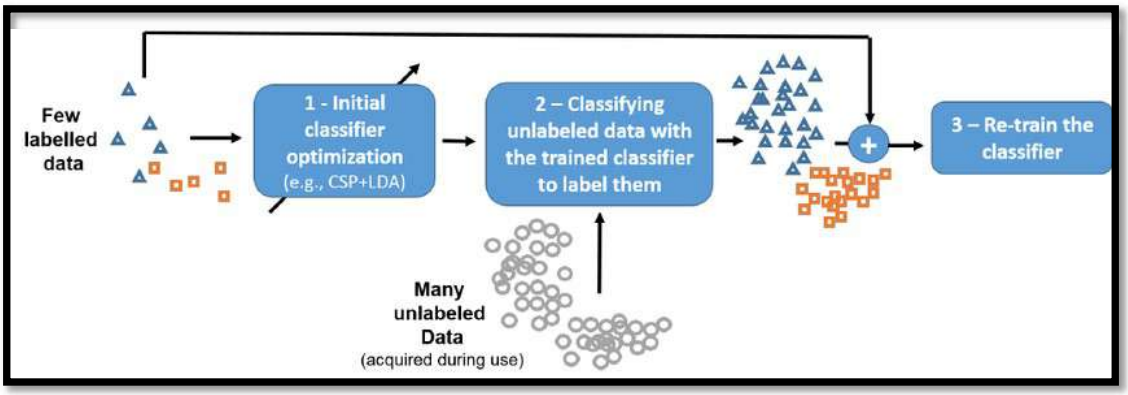


Figure 1.8 : Semi-supervised learning.

- **Side-Information based Linear (SILD**) is a semi-supervised learning algorithm It is a discriminative dimensionality reduction SILD directly calculates the within-class and between-class scatter matrices using the side-information it is mainly used in kinship verification. SILD In many situations, determining the exact full class labels of the data samples is a hard task. Instead, collecting a kind of weak labels of the samples is easier to achieve. An example of this case includes face verification under unconstrained conditions, where the only known information is whether pairs of face images belong the same persons or not. Such weak labels (pair match/non match) are referred to as side information. In this case, In SILD, the positive pairs (match) are used to calculate the within scatter matrix $S_w$and the negative pairs (non match) are used to calculate the between scatter matrix S_b.

Let P = { (u_i, u_j): I(u_i) = I (u_i) } be the set of match images pairs and Q ={ (u_a, u_b): I(u_a) ≠ I (u_i) } be the set of non-match images pairs, with I denotes the side information. The SILD with in class and between-class scatter matrices are estimated as follows:

$$S_w^{sild} = \sum_{(u_i,u_j)\in P} (u_i, u_j)\,(u_i, u_j)^T \quad (1.1)$$

$$S_b^{sild} = \sum_{(u_i,u_j)\in Q} (u_a, u_b)\,(u_a, u_b)^T \quad (1.2)$$

Thus, the scatter matrices computation does not require knowing the full class label of every sample. Instead, the side information is exploited to calculate the two matrices. the projection matrix in SILD is obtained by solving the following optimization problem:

$$H_{opt}^{sild} = \underset{H}{\operatorname{argmax}} \frac{\|H^T S_b^{sild} H\|}{\|H^T S_w^{sild} H\|} \quad (1.3)$$

1.4.4. Reinforcement learning

RL is a type of learning which makes decisions based on which actions to take such that the outcome is more positive. The learner has no knowledge which actions to take until it's been given a situation. The action which is taken by the learner may affect situations and their actions in the future. Reinforcement learning solely depends on two criteria: trial and error search and delayed outcome [13].

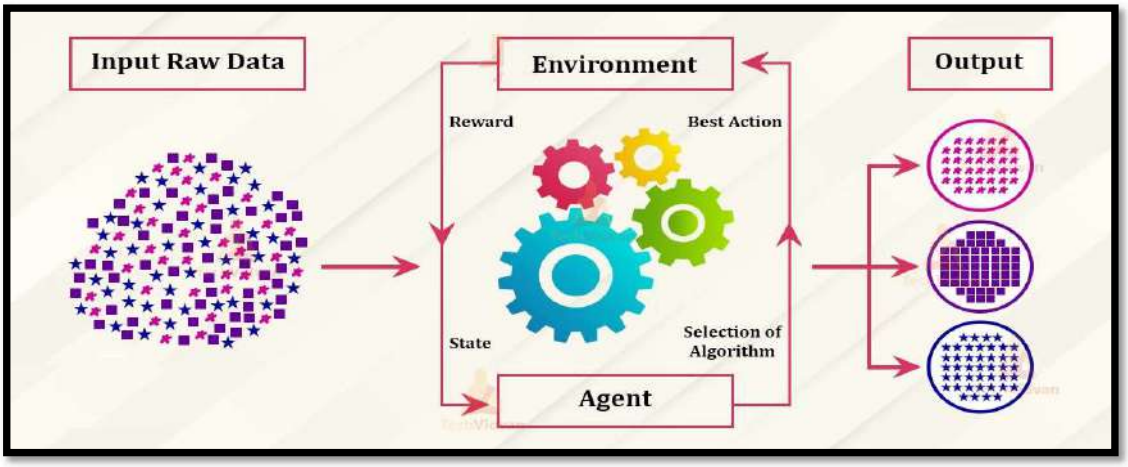


Figure 1.9 : The Reinforcement Learning Model.

In the Figure 1.9 the agent receives an input, current state, state transition and input function from the environment. Based on these inputs, the agent generates a behavior B and takes an action at which generates an output, the goal in reinforcement learning is to learn the best policy [13].

1.5. Deep learning

Deep learning is a subset of machine learning (Figure 1.10). It is a neural network with a large number of layers and parameters. Most deep learning methods use neural network architectures. Therefore, it is also referred to as deep neural networks. In short, deep learning uses a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. The lower layers close to the data input learn simple features, while higher layers learn more complex features derived from lower layer features. The architecture forms a hierarchical and powerful feature representation. It means that deep learning is suited for analyzing and extracting useful knowledge from both large huge amounts of data and data collected from different sources [14].

1.5.1. Deep learning application

While surveying through we arrived at various application domains and sub-domains of machine learning applications:

• **Computer Vision** object recognition, object detection, and object processing are sub-domains in computer vision domain.

• **Prediction** the various sub-domains here are classification, analysis, and recommendation. Text classification, document classification, image analysis, medical diagnosis, prediction of network intrusion detection and predicting denial of service attack have been successfully implemented using machine learning.

• **Semantic Analysis and Natural Language Processing and Information Retrieval** Semantic analysis is the process of relating syntactic structures from paragraphs, sentences, words to the level of writing as a whole. Natural language processing is how to program computers to correctly process natural language data. Information retrieval is the science of searching for information in a document, searching for documents and searching for metadata that describe the data and for databases of sounds and images. These are three domains in which machine learning techniques have been explored in the past.

An attempt to classify all machine learning applications found in the past is summarized here. The following depicts the same as application domains at first level, sub-domains at second level and few applications at last level which have been implemented by researchers [14].

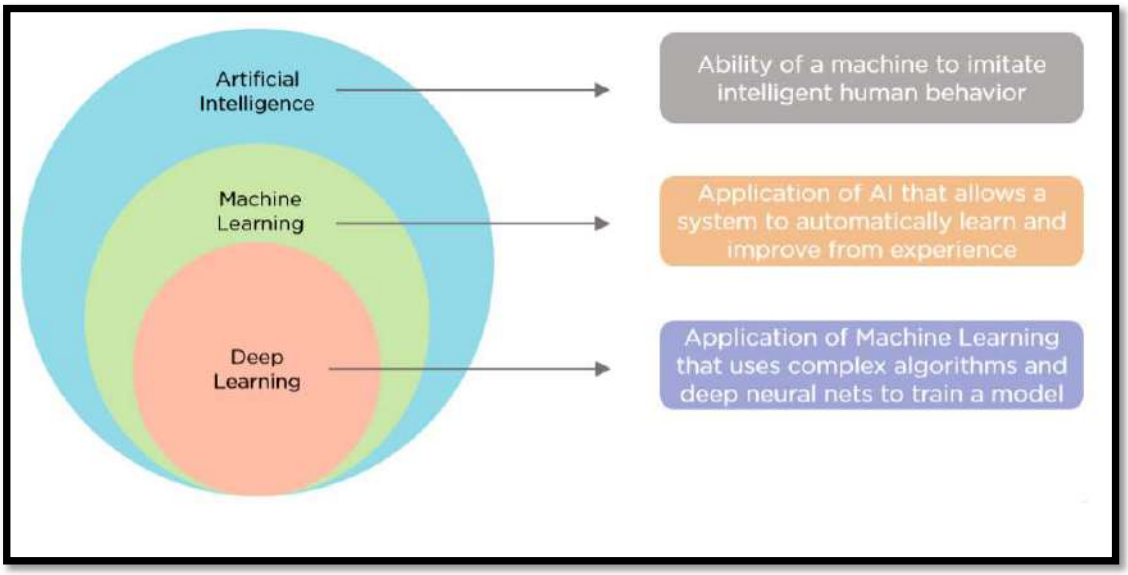


Figure 1.10 : How deep learning is a subset of machine learning.

1.6. Biometrics

The word biometrics is a combination of the Greek word's bio and metric. When combined, it means "life measurement." Biometric technology refers to any technique that reliably uses measurable physiological or behavioral characteristics to distinguish one person from another. Common physiological biometric traits include: fingerprints, hand

geometry, retina, iris, and facial images. Whereas, common behavioral biometric traits include: signature, voice recordings, and keystroke rhythms. It should be noted that behavioral biometrics generally include a physiological component as well [15]. What biological measurements qualify to be a biometric? Any human physiological and/or behavioral characteristic can be used as a biometric characteristic as long as it satisfies the following requirements [16]:

- Universality: each person should have the characteristic.
- Distinctiveness: any two persons should be sufficiently different in terms of the characteristic.
- Permanence: the characteristic should be sufficiently invariant (with respect to the matching criterion) over a period of time.
- Collectability: the characteristic can be measured quantitatively. However, in a practical biometric system (i.e., a system that employs biometrics for person recognition).
- Performance: which refers to the achievable recognition accuracy and speed, the resources required to achieve the desired performance, as well as the operational and environmental factors that affect the performance.
- Acceptability: which indicates the extent to which people are willing to accept the use of a particular biometric identifier in their daily lives.
- Circumvention: which reflects how easily the system can be fooled using fraudulent methods.

1.6.1. Working of a biometric system

A biometric system is a system that allows the recognition of a certain characteristic of an individual using mathematical algorithms and biometric data and Figure 1.11 represents the biometric system description. There are several uses of biometric systems. There are systems that require enrollment upstream of users. Other identification systems do not require this phase [17].

- The enrollment module is responsible for training the system to identify a given person. During the enrollment stage, a biometric sensor scans the person's physiognomy to create a digital representation. A feature extractor processes this representation to generate a more compact and expressive representation called a template. For a facial image, these features may include the size and relative positions of the eye, nose, and mouth. The template for each user is stored in a biometric system database; the database

can be a central or distributed database, such as the one in which each user's template is stored on a smart card and issued to the user [18].

- The verification or authentication mode is a "one-to-one" comparison, in which the system validates the identity of a person by comparing the biometric data entered with the biometric template of that person stored in the system's database. In such a mode, the system must then answer the question related to the identity of the user. Currently the verification is carried out via a personal identification number, a user name, or a smart card.

- The identification mode is a "one-to-N" comparison, in which the system recognizes an individual by matching it with one of the models in the database. The person may not be in the database. This mode consists of associating an identity with a person.

- Capture module that represents the entry point of the biometric system and consists in acquiring the biometric data in order to extract a digital representation. This representation is used later in the following phases.

- Signal processing module makes it possible to optimize the processing time and the digital representation acquired in the enrollment phase in order to optimize the processing time of the verification phase and the identification.

- Storage module that contains the biometric templates of the system enrollees.

- Matching module that compares the data extracted by the extraction module with the data of the registered models and determines the degree of similarity between the two biometric data.

- Decision module that determines whether the similarity index returns through the matching module is sufficient to make a decision about the identity of an individual [17].

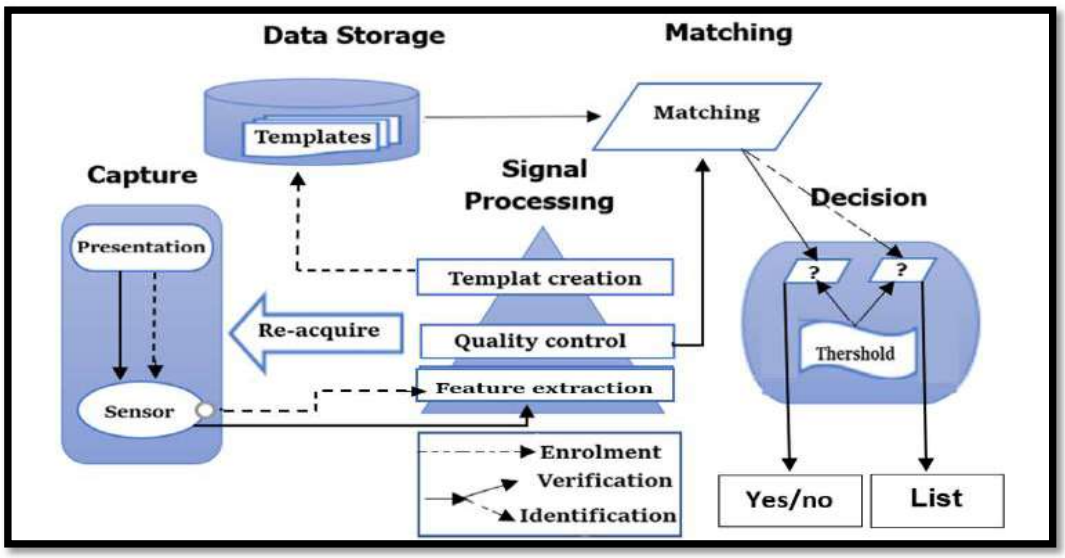


Figure 1.11 : Biometric System Description.

1.6.2. Biometric application

Most biometric applications fall into one of nine general categories [19]:

1. Financial services (e.g., ATMs and kiosks).
2. Immigration and border control (e.g., points of entry, precleared frequent travelers, passport and visa issuance, asylum cases).
3. Social services (e.g., fraud prevention in entitlement programs).
4. Health care (e.g., security measure for privacy of medical records).
5. Physical access control (e.g., institutional, government, and residential).
6. Time and attendance (e.g., replacement of time punch card).
7. Computer security (e.g., personal computer access, network access, Internet use, e-commerce, e-mail, encryption).
8. Telecommunications (e.g., mobile phones, call center technology, phone cards, televised shopping).
9. Law enforcement (e.g., criminal investigation, national ID, driver's License, correctional institutions/prisons, home confinement, smart gun).

1.6.3. Biometric technologies

The function of a biometric technologies authentication system is to facilitate controlled access to applications, networks, personal computers (PCs), and physical facilities. A biometric authentication system is essentially a method of establishing a person's identity by comparing the binary code of a uniquely specific biological or physical

characteristic to the binary code of an electronically stored characteristic called a biometric [19]. A number of biometric characteristics exist and are in use in various applications (see Figure 1.12) Each biometric has its strengths and weaknesses, and the choice depends on the application. No single biometric is expected to effectively meet the requirements of all the applications. In other words, no biometric is "optimal". The match between a specific biometric and an application is determined depending upon the operational mode of the application and the properties of the biometric characteristic. A brief introduction of the common used biometrics is given below[20]:

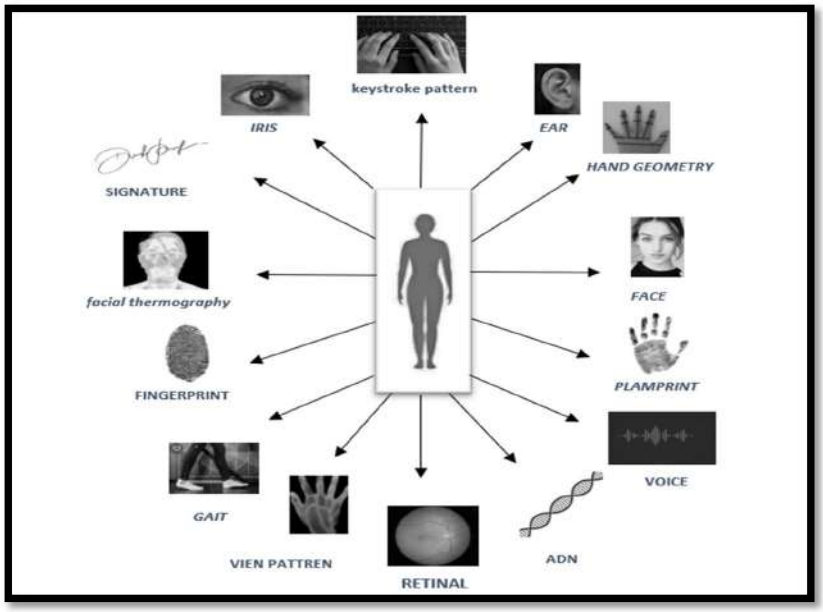


Figure 1.12 : commonly used biometrics.

DNA

Deoxyribose Nucleic Acid (DNA) is the one-dimensional ultimate unique code for one's individuality - except for the fact that identical twins have identical DNA patterns. It is, however, currently used mostly in the context of forensic applications for person recognition [20].

Retinal scan

The retinal vasculature is rich in structure and is supposed to be a characteristic of each individual and each eye. Retina-scan technology makes use of the retina, which is the surface on the back of the eye that processes light entering through the pupil. Retinal Scan technology is based on the blood vessel pattern in the retina of the eye. The principle behind the technology is that the blood vessels at the retina provide a unique pattern, which may be

used as a tamperproof personal identifier. Since infrared energy is absorbed faster by blood vessels in the retina than by surrounding tissue, it is used to illuminate the eye retina. Analysis of the enhanced retinal blood vessel image then takes place to find characteristic patterns , It is claimed to be the most secure biometric since it is not easy to change or replicate the retinal vasculature [20].

Iris Scan

The human iris is a thin circular structure in the eyes which is responsible for controlling the diameter and size of the pupils. It also controls the amount of light which is allowed through to retinal in order to protect the eye's retina. Iris scanning measures the iris pattern in the colored part of the eye (figure 1.13), although the iris color has nothing to do with the biometric. Iris patterns are formed randomly. As a result, the iris patterns in a person's left and right eyes are different, and so are the iris patterns of identical twins. Iris scanning can be used quickly for both identification and verification applications because the iris is highly distinctive and robust [21]. It is unique and easy to identify a user. Even though the system requires installation equipment and expensive fees, it is still the easiest and fastest method to identify a user. There should be no physical contact between the user and the system during the verification process. During the verification process, if the users are wearing accessories such as glasses and contact lenses, the system will work as normal because it does not change any characteristics of the user's iris[22].

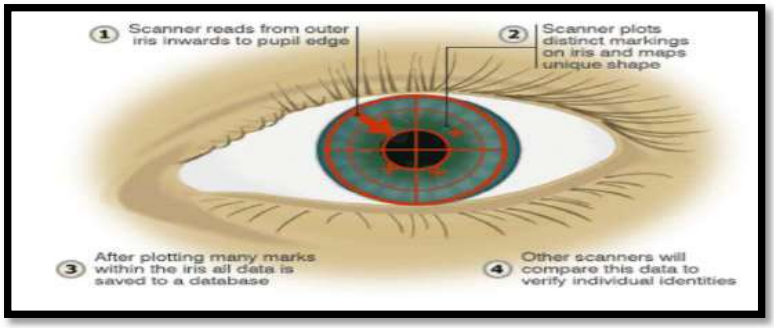


Figure 1.13 : How Iris scanners record identities.

Facial Recognition

Facial recognition records the spatial geometry of distinguishing features of the face. Different vendors use different methods of facial recognition, however, all focus on measures of key features of the face. Because a person's 3 face can be captured by a camera from some distance away, facial recognition has a clandestine or covert capability (i.e., the subject does not necessarily know he has been observed). For this reason, facial recognition has been used in projects to identify card counters or other undesirables in casinos,

shoplifters in stores, criminals and terrorists in urban areas [21].

Voice Recognition

Voice or speaker recognition uses vocal characteristics to identify individuals using a pass-phrase. A telephone or microphone can serve as a sensor, which makes it a relatively cheap and easily deployable technology. However, voice recognition can be affected by environmental factors such as background noise. This technology has been the focus of considerable efforts on the part of the telecommunications industry and the U.S. government's intelligence community, which continue to work on improving reliability [21].

Fingerprint reader

The fingerprint biometric is an automated digital version of the old ink and-paper method used for more than a century for identification, primarily by law enforcement agencies. The biometric device involves users placing their finger on a platen for the print to be electronically read. The minutiae are then extracted by the vendor's algorithm, which also makes a fingerprint pattern analysis. Fingerprint biometrics currently have three main application arenas: large-scale Automated Finger Imaging Systems (AFIS) generally used for law enforcement purposes, fraud prevention in entitlement programs, and physical and computer access [21].

Hand/Finger Geometry

Hand or finger geometry is an automated measurement of many dimensions of the hand and fingers. Neither of these methods takes actual prints of the palm or fingers. Spatial geometry is examined as the user puts his hand on the sensor's surface and uses guiding poles between the fingers to properly place the hand and initiate the reading. Finger geometry usually measures two or three fingers. Hand geometry is a well-developed technology that has been thoroughly field-tested and is easily accepted by users. Because hand and finger geometry have a low degree of distinctiveness, the technology is not well-suited for identification applications [21].

Signature Verification

We have long used a written signature as a means to acknowledge our identity. Dynamic signature verification is an automated method of measuring an individual's signature. This technology examines such dynamics as speed, direction, and pressure of writing; the time that the stylus is in and out of contact with the "paper," the total time taken to make the signature; and where the stylus is raised from and lowered onto the "paper" [21].

Keystroke Dynamics

Keystroke dynamics is an automated method of examining an individual's

keystrokes on a keyboard. This technology examines such dynamics as speed and pressure, the total time taken to type particular words, and the time elapsed between hitting certain keys. This technology's algorithms are still being developed to improve robustness and distinctiveness. One potentially useful application that may emerge is computer access, where this biometric could be used to verify the computer user's identity continuously [21].

Palm print

Palm print recognition is a biometric technology which recognizes a person based on his/her palm print pattern. Palm print serves as a reliable human identifier because the print patterns are not duplicated in other people, even in monozygotic twins. More importantly, the details of these ridges are permanent [23]. In 3-dimensional image of the hand is collected and the feature vectors are extracted and compared with the database feature vectors. These devices are bulky but identification is done in a short time [24].

Vein pattern

The pattern of blood vessels hidden underneath the skin is quite distinct in individuals, even among identical twins and stable over long period of time. The primary function of veins is to carry blood from one part of the body to another and therefore vascular pattern is spread throughout the body. The veins that are present in hands are easy to acquire (using near infrared illumination) and have been employed for the biometric identification [25].

Gait

Gait is a person's manner of walking. Biometric gait recognition refers to verifying and/or identifying persons using their walking style [26]. The sensor for a gait-based biometric system is a video camera capturing videos of human subjects walking within its field-of view. The raw sensor video is then processed to extract relevant features which can then be used for recognition. Gait as a biometric has several advantages compared to traditional biometrics such as fingerprint in that gait is non-intrusive, does not require cooperation from the individual, and can function at moderate distances from the subject [27].

Ear shape recognition

The ear is made up of standard features including the helix, the antihelix, the lobe, and the u-shaped intertrack notch between the ear hole and the lobe [28].Researchers have suggested that the shape and appearance of the human ear is unique to each individual and relatively unchanging during the lifetime of an adult. Therefore, the ear has been proposed for use in biometrics. In fact, the ear may already be used informally as a biometric [29].

1.7. Issues of biometrics

While biometric systems can offer greater levels of security, various attacks exist to gain unauthorized access to a system that is protected by biometric authentication. The various issues of the biometric system are dealt here [19].

1.7.1. System design issues

Biometrics is invariably associated with security; hence the biometric system itself should be reasonably secure and trustworthy. Some of the biometric security issues are [19]:

- Rogue sensors and unauthorized acquisition of biometric samples
- Communications security between sensors, matchers and biometric databases
- Accuracy
- Speed
- Scalability
- Resilience
- Cost
- Privacy

1.8. Checklist of things to consider when choosing a biometric

Physical contact and durability - Usage and durability - Flexible packaging - Infrastructure and interoperability - Enrolment - Standards - Security - Proven technology - Reliability - Accuracy - Capture - Liveness - User friendliness -Intrusiveness - Context of application - Convenience - Cost.

1.9. Disadvantages of biometrics technologies

Some people, especially those with disabilities may have problems with contact biometrics. Not because they do not want to use it, but because they endure a disability that either prevents them from maneuvering into a position that will allow them to make use the biometric or because the biometric authentication system (solution) is not adaptable to the user. For example, if the user is blind a voice biometric may be more appropriate. Some of the disadvantages are listed below [19]:

- Biometric systems are very expensive So, people are not ready to pool in so much money to utilize the latest technology that is available in the market.
- Like every new technology, Biometrics has a low user acceptance rate.
- People consider it to be an invasion of their privacy and thus, it hasn’t been exploited to its full potential.
- Biometric system is not fool proof and has its own flaws and can sometimes allow

a person who has assumed a fake identity into the network.

- Biometric template data consume more space than the conventional user ID/password combinations.

1.10. Advantages of biometrics

After the initial implementation and setup of the database Biometrics is an easy and convenient method to authenticate a user. Passwords can be forgotten or stolen, keys can be misplaced, and PIN numbers can be difficult to remember. Biometrics on the other hand cannot be stolen or misplaced it is unique to every individual [27].

1.11. Conclusion

We are entering the era of artificial intelligence and big data, and thus, systems are becoming more intelligent with performance even to a human level in limited applications. At the core of artificial intelligence, machine learning algorithms contribute to semiautomatically or automatically develop highly intelligent systems by overcoming existing difficulties for various fields and biometrics are emerging as essential technologies for Internet-era intelligent systems to ensure both computer and network securities as well as security for stand-alone equipment. in this chapter, we introduce some representative of AL, ML and discuss their effective methods and descriptors and major characteristics of samples from corresponding algorithms, we also introduce the well-known biometrics and its way of functioning, application and its advantages and advantage.

Chapter 2 :

Face Kinship Verification.

2.1. Introduction

Human faces have abundant features that explicitly or implicitly indicate the family linkage, giving rich information about genealogical relations It is a common and an easy practice for humans to identify their relatives from faces. Relatives usually wonder which facial attributes does a new born baby inherit from which family member. Automatic kinship verification from faces aims at determining whether two persons have a biological kin relation or not by comparing their facial attributes. In this chapter we are going to focus on the kinship term and its degrees types challenges and all about kinship verification.

2.2. Definition

Kinship is a term that distinguishes each person and his relationship with a group of individuals or communities. It is the basic principle which links individuals who belong to the same family and classify them and social groups. showing us how we are associated with eachother and with our family. Kinship can be a complex system of social groups. It is a universal system as everyone has a family. Some small and large societies use kinship not only for humanreproduction but for "economic transactions, the political system, and their religious beliefs"[30].

Kinship is conventionally defined as relationships between persons based on descent ormarriage. If the relationship between one person and another is considered by them to involve descent, the two are blood relatives. If the relationship has been established through marriage, so it is affinal [31].Encyclopedia Britannica said "Kinship is the socially recognized relationship between people in a culture, who are either held to be biologically related or given the status of relatives by marriage, adoption, or other rituals. Kinship is a broad-ranging term for all the relationships that people are born into or create later in life that is considered binding in the eyes of their society. Although customs vary as to which bonds are accorded more weight, their very acknowledgment defines individuals and roles that society expects them to pay" [32]. Figure 2.1 illustrated an example of kin-relationships.

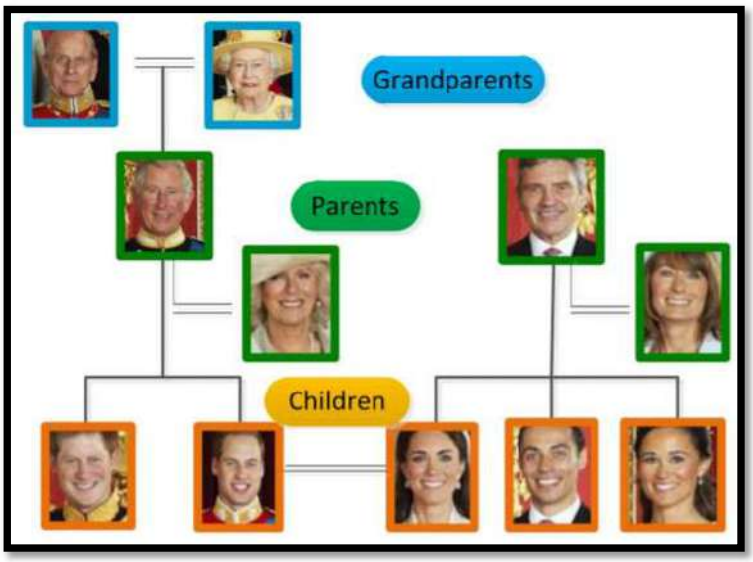


Figure 2.1 : A family tree (bottom) can be extracted from a family photo (top) if kin relationships among people in the photo are known. The double horizontal line shown in the figure represents the couple relationship.

2.2.1. 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 [33].

2.3. Kinship types

Kinship is one of the universals in human society. In any society, kinship systems establish relationships between individuals and groups on the model of biological relationships between parents and children, between siblings, and between marital partners. By contrast, the adoptive child is excluded from this relationship. “Adoption” is the term that is often used to describe a person who has no biological link with the parents.

Relationships established by marriage form alliances between groups of persons related by blood (or consanguineous ties). These two aspects of human life are the basis for the following two main types of kinships in society [33] :

– **Blood ties (consanguineal):** Relationships or connections based on blood or genetic ties, that is, the relationship between parents and children and between siblings are the most basic and universal kin relationships.

– **Marriage ties (affinal):** Relationships formed on the basis of marriage. The most basic relationship that results from marriage is that between husband and wife.

2.4. Degree of kinship

Primary kinship This degree refers to kin that are closely and directly related to one another. The eight types of primary kinship include mother-son, husband-wife, father-son, mother-daughter, father-daughter, sister-brother, younger sister-elder sister and younger brother-elder brother.

Secondary kinship: This degree refers to the primary kin of the first-degree kin (also known as secondary kin), such as father's brother, sister's husband, and brother's wife.

Tertiary kinship: This degree refers to the secondary kin of the primary kin (also known as tertiary kin), such as brother of sister's husband and wife of brother-in-law[33] .the (figure 2.2) represents the degree and types of kinship .

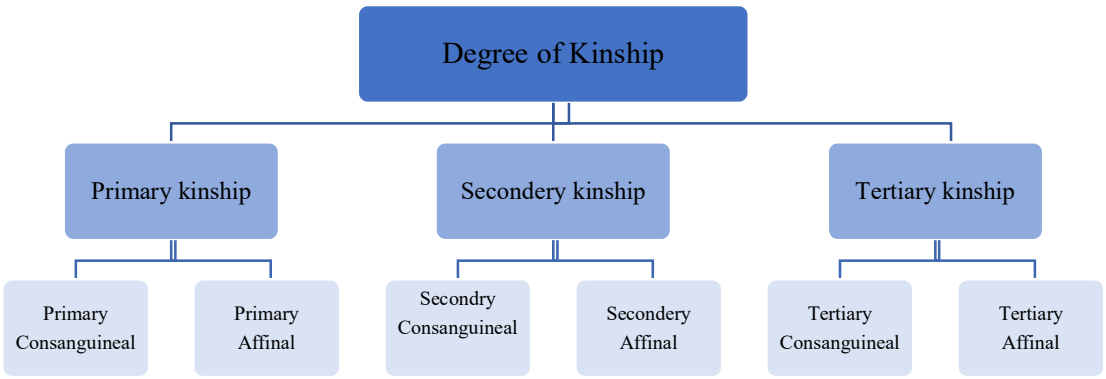


Figure 2.2 : degree and types of kinship.

2.4.1. Importance of kinship

- The kinship system maintains unity, harmony, and cooperation among relationships.
- Kinship sets guidelines for communication and interactions among people.

- Where marital taboo exists decides who can marry whom.
- Kinship act as a watchdog of social life.
- It helps people to better understand their relationship with each other.
- It builds and develops and helps better relate to one another in society.
- Kinship regulates the behavior of different kin.

2.5. Kinship in computer vision

kinship is a genetic relationship between two family members, including parent-child, sibling-sibling, and grandparent-grandchild. Therefore, in automatic kinship recognition using computer vision techniques, the machine is able to distinguish parents from unrelated persons and determine the degree of kinship based on an inspection of their images.

Kinship verification has also gained interest in machine learning communities. Therefore, in automatic kinship recognition using computer vision techniques, the machine is able to distinguish parents from unrelated persons and determine the degree of kinship based on an inspection of their images. the first dataset containing kin pairs was collected for performing kinship verification, the authors proposed an algorithm for facial feature extraction and forward selection methodology. Since then, the algorithms for verifying kin have increased in complexity and provides a review of algorithms recently published in this area along with the databases used.

The problem of kinship verification is particularly challenging because of the large intra-class variations among different kin pairs. At the same time, look-alikes decrease the inter-class variation among the facial images of kin. While existing algorithms have achieved reasonable accuracies, there is a scope of further improving the performance. For instance, deep learning algorithms can be utilized [34].

2.6. Challenges of kinship verification

Kinship verification is a challenging research problem due to the lack of standardized experimental protocol in classifying kin in the published literature. In summary, the following two factors have significant influence on problem-solving: Unique challenges which appear only in the kinship verifications systems, and common challenges which already exist in the automatic face recognition systems, both challenges are discussed in details below [35].

2.6.1. Unique Challenges

Humans inherit traits from their ancestors. We often hear phrases such as "Mohamed has his father's nose" or "Ahmed has his mother's eyes''. A "familial trait" is defined as a trait shared by a pair of family members, e.g., father and son. Given that information, Kinship verification is different from face recognition or verification. In face recognition, the problem is to recognize the same individual by matching the probe face image with gallery images. The measure is about the "facial identity." In kinship verification, we are dealing with different individuals, i.e., to extract similar features but from different persons that share some traits in common. We identify three major challenges in kinship verification which are considered to be unique (only for kinship verification tasks). This will help to understand the problem deeply and provide a general guide to develop a computational system [35].

- **Trait Similarities Are Measured Across Age and gender**

Familial traits (features) are measured for people at different ages (e.g., father-son), with different gender (e.g., brother-sister), or who are different in both (e.g., father - daughter).

- **Familial Traits Are "Special" for Each Family Pair**

Familial traits have "special" properties for each specific pair of family members. In a family, sons or daughters (with the same sex) may inherit traits from their parents differently. Kinship has a stochastic combination of traits as stated above, familial traits are "special" for each pair of faces. The shared traits between fathers and daughters (or other relations) can be stochastic. As a result, the kinship has to be measured by a "stochastic" (rather than a fixed) combination of familial traits. In sum, kinship verification has its own challenges. Familial traits are the building blocks for kinship measure. While some recent approaches, e.g., have processed kinship similar to an automatic face verification problem.

2.6.2. Common challenges

kinship verification through facial images is challenging due to the high degree of appearance variability of influences, a as the challenges in face verification, the appearance of kin faces is sensitive to the change of various factors, in addition, some common influencing factors in real scenes, such as lighting, blur or low resolution, may also change the appearance of relatives-faces in different ways [36].

Image resolution and modality Other usual factors influencing face recognition performance are related to the quality and resolution of the face image and/or to the set-up

and modalities of the digital equipment capturing the face. real-world situations of face image acquisition imply the use of different photographic hardware, in which could include, e.g., wide-field sensors, photometric stereo, etc. Cameras could work in the range of the visible light or use infra-red sensors, leading to multiple modalities for face recognition [27].

Illumination variations When the image is formed, factors such as lighting (spectra, source distribution and intensity) and camera characteristics (sensor response and lenses) affect to some degree the appearance of the human face. Illumination variations can also do this because of skin reflectance properties and because of the internal camera control [36].

Orientations Humans do not have obvious problems recognizing the same object with different orientation, but many algorithms do. invariance to this possibility is often crucial [35].

Pose/viewpoint the images of a face vary because of the relative camera face pose (frontal, 45°, profile, upside down), and some facial features such as the eyes or nose may become partially or wholly occluded. In fact, pose changes affect the recognition process because of introducing projective deformations and self-occlusion. Thus, pose-tolerance becomes even more critical for face recognition systems that rely on a single view of a subject [36].

Ageing and wrinkles Ageing can be natural (because of age progression) and artificial (using makeup tools). In both cases, ageing and wrinkles can severely affect the performance of face recognition methods. In general, the effect of age variation or age factor is not commonly considered in face recognition research [36].

Facial expression/facial style the appearance of faces is directly affected by a person's facial expression, Facial hair such as beard and moustache can alter facial appearance and features in the lower half of the face, specifically near the mouth and chin regions. Moreover, hair style can be changed to alter the appearance of the face image or hide facial features [36].

Occlusion Faces may be partially occluded by other objects. In an image with a group of people, some faces or other objects may partially occlude other faces, which in turn results in only a small part of the face is available in many situations. However, this makes the face (face detection) by the system location a difficult task, and even if the face is found, recognition itself might be difficult because of some hidden facial parts, making features difficult to recognize [36].

2.7. Facial kinship verification process

kinship verification by facial images is a modern method associated with advanced technologies and has a huge impact on many real-world applications. To verify the kinship

between two people using the face image, we must go through components including face image pairs preprocessing, local facial feature extraction, projection per feature dimensionality reduction, similarity measurement, score level and decision. In the following, we describe the details of each component [37].

2.7.1. Preprocessing stage

The preprocessing stage is responsible for preparing the facial images. In the following stage the prepressing steps are explained then images are supplied to the local feature representation stage to extract the main features from the processed faces.

2.7.1.1. Face detection

Face detection is defined as the process of detecting and extracting face sub-regions from an image as shown in (figure 2.3). It is a fundamental component of fully automated kinship verification system. An efficient face detection algorithm is robust to orientation, position and lighting, and other conditions; these considerations are the challenges to face detection. Certain techniques are used in detecting the face from an image, including Active Appearance Model (AAM), Boosted Cascade of Simple Ad boost Face Detector, and Fiducial Points Detection. All of these techniques have been used in earlier studies of kinship [38].



Figure 2.3 : Sample images of face detection.

2.7.1.2. Normalization phase

Preprocessing is also called normalization. A face is normalized after it is detected. The purpose of this phase is to make the condition of the processing face as close as possible with ones stored in the database. Besides identities, other factors can make two faces look

different. Among such factors are illumination, scale, and color intensity. Normalization reduces these types of differences to improve recognition rate. Preprocessing is an important component in kinship verification. This process was first aimed at aligning images and delimiting the same section for face, including the most significant facial features. Moreover, it is aimed at reducing the influence of different illumination, background, image size, and orientation. It also converts images to grayscale, equalizes histograms, and extracts key points or landmarks of the faces. Several image preprocessing techniques were implemented to mitigate image quality factors. Figure 2.4 shows examples of Weber normalized faces without the illumination factor [8].

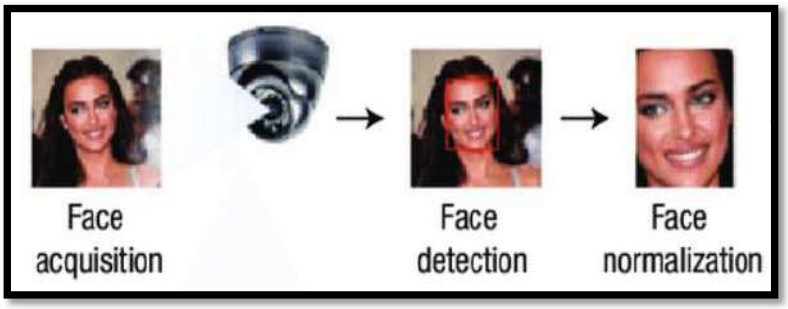


Figure 2.4 : face normalization.

2.7.2. Feature extraction phase

Feature extraction from a face can be defined as the process of locating and extracting useful features as shown in figure 2.5 and relevant information for distinguishing between faces of different persons, especially in the case of kinship. Feature extraction greatly affects the design and performance of the classification. Accuracy achieved by combining facial parts is higher than when considering the full face. Genetics studies show that resembling regions on faces among immediate family members are mostly concentrated on eyes, nose, and mouth. The features that can distinguish true pairs from the false ones are facial visual attributes, facial appearance, geometry, color and texture, contextual information, or a mixture of those features and most common descriptors are Local Binary Patterns (LBP), Local Phase Quantization (LPQ), Binarized Statistical Image Features (BSIF), Hist-Gabor wavelets… etc. The features can be typed as low-level, high, mild-level, high-level features [39].

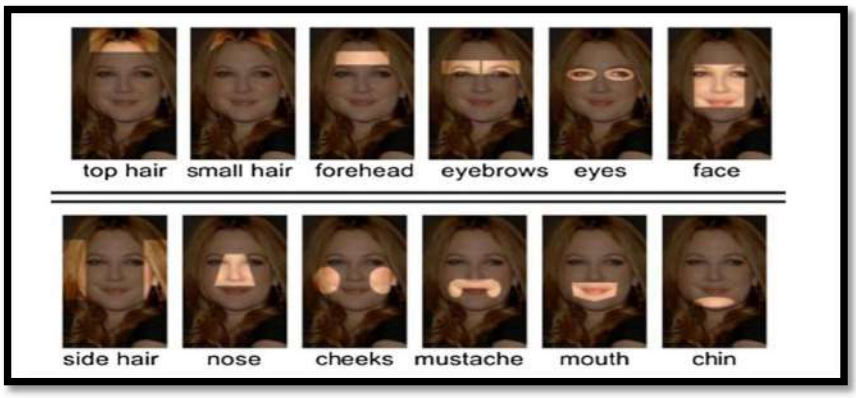


Figure 2.5 : twelve parts represents the facial feature extraction.

2.7.3. Classification and Matching

The phase after the feature extraction, the next step is image classification and matching. Generally, image classification is performed by calculating the similarity between a target discriminating vector of feature and a query discriminating vector of feature. In addition, the similar facial components (features) are placed into one class and the others in different classes. In a kinship system, the outline of the classification algorithm is as follows. The database is used to train the system and from the training, important feature vectors extracted from facial features such as nose, eyes, forehead, cheek and mouth, construct discriminating sets of features to generate a model which is then used to recognize facial characteristic similarities and in ship in a query image In order to compare two face pairs to configure out if there is a kinship or not as illustrated.in Figure 2.6 below we show the general structure of the steps to verify kinship [40].

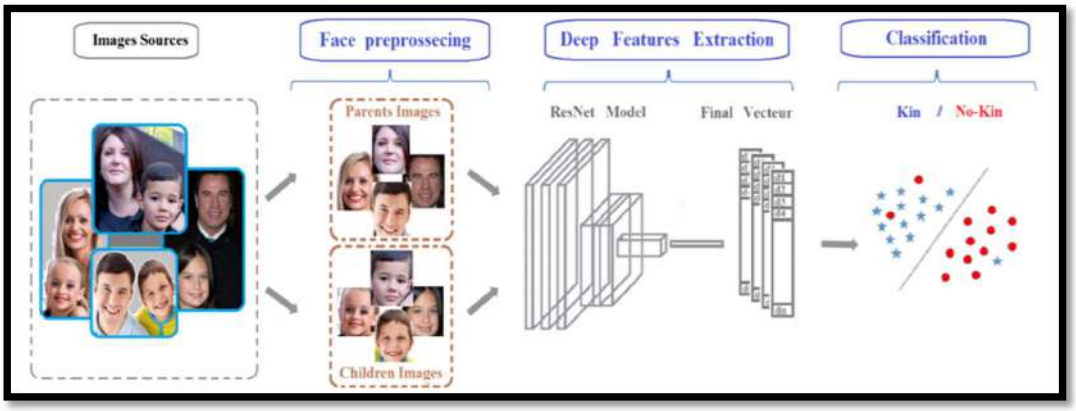


Figure 2.6 : General structure of the proposed kinship verification approach.

2.8. Benchmark Databases for kinship verification

An Important factor in stimulating research in kinship verification is the availability of databases, Figure 2.7 represents samples of facial images in different kinship databases, the details of the databases are presented below [35]:

Cornell Kinship: It consists of 286 images pertaining to 143 subject pairs. The facial images in this database are frontal pose and have a neutral expression.

KinFaceW-I: This database consists of 1066 images corresponding to 533 kin pairs. It has 156 Father-Son, 134 Father-Daughter, 116 Mother-Son, and 127 Mother-Daughter kin pair images.

KinFaceW-II: This database has been created such that images belongingto the kin pair subjects are acquired from the same photograph. It consists of 1000 kin pair images with an equal number of images belonging to the four kinship relationships: Father-Son, Father-Daughter, Mother-Son, and Mother- Daughter.

UB KinFace: This database consists of 200 groups consisting of 600 images. Each group has one image of the child and one image belonging to the core- spending parent when they were young and when they were old. The database has 91 Father-Son, 79Father-Daughter,15 Mother-Son, and 21 Mother-Daughter kin pair images.

WVU Kinship: All the above kinship datasets contain only one image per kin-pair and hence are not suitable for face recognition experiments. It was developed as part of this research. It consists of 113 pairs of individuals from Caucasian and Indian ethnicity. The dataset has four images per person, which introduces intra-class variations for a specific kin-pair. These multiple images per kin-pair include variations in pose, illumination, and occlusion.

Family 101: The Family 101 dataset contains 101 different families with dis- tinct family names, including 206 nuclear families, 607 individuals, with 14,816 images. The database is particularly useful for family classification where the problem is identifying which family a particular image belongs to.

TSKinFace: The Tri-subject kinship face database consist of images be- longing to the child, mother, and father. The database consists of 513 images of Father, Mother and Son group and 502 images of Father, Mother and Daughter group.

FIW: the families in the wild dataset consist of 10,700 images belonging to 1000 families.

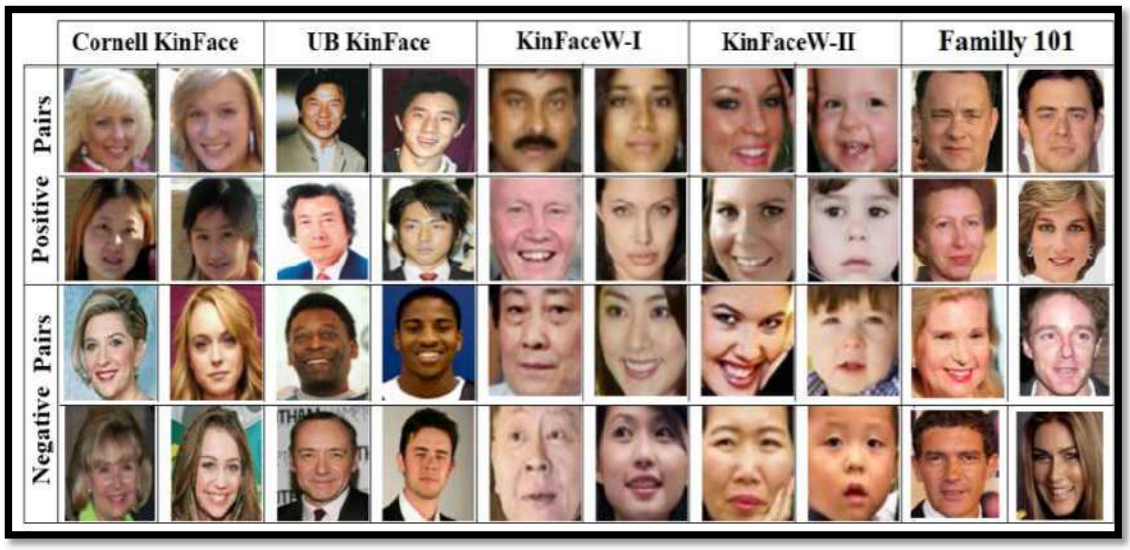


Figure 2.7 : Samples of facial images in different kinship databases.

2.9. Application of kinship verification

We can use kinship in many different fields for example [9]:

Finding missing children: Currently, Deoxyribonucleic acid (DNA) testing is the dominant approach to verify the kin relation of two persons, which is effective to find missing children. However, there are two limitations for the DNA testing: (1) the privacy of DNA testing is very high, which may make it restricted in some applications; (2) the cost of DNA testing is higher. However, kinship verification from facial images can remedy these weaknesses because verifying kinship relations from facial images is very convenient and its cost is very low. For example, if we want to find a missing child from thousands of children, it is difficult to use DNA testing to verify their kin relation due to privacy concerns. However, if our kinship verification method is used, we can quickly first identify some possible candidates who have high similarity from facial images. Then, DNA testing is applied to get the exact search result [9].

Entertainment: Visual effects that age or rejuvenate the actors are already being used in the film making industry. These effects are not limited to movies but are also widely applied to photo editing. The imminent integration of such tools into popular design soft-ware will make for a more realistic retouching of photos. Make-up artists that specializein transforming the face can leverage the construction of person, age, and kin specific morphable models. Guided by those models, the artists will transform the face of the actor for roles that demand sibling-like similarity between actors [10].

Social media analysis: For example, there are tens of billion images on the popular Face-

book website, and more than 2.5 billion images are added to the website each month. How to automatically organize such large-scale data remains a challenging problem in computer vision and multimedia.

2.10. Conclusion

Kinship is defending as coefficient of relationship or degree of genetic relatedness between individuals of the same species. The process of finding this kinship relation through correlated visual resemblance is called kinship verification. Initial hypothesis that kinship verification could be performed using facial images Eccentricity based kinship verification from facial images. In this chapter, the emphasis is to measure the degree of genetic similarity between children-parents. The outcome showed that children resemble their parents more than other persons due to the genetic overlapping. we have discussed kinship definition, its different types and degree. We also investigated the face-kinship verification its challenges, application, and its stages through the process (preprocessing, feature extraction and classification), finally we mentioned the various benchmark databases for kinship verification.

Chapter 3 :

Kinship verification using Retinex filter & Elliptical mask based on Hist-Gabor wavelets.

3.1. Introduction

There are many studies have been conducted on kinship verification from facial images which can be categorized based on the type of feature extraction and the similarity algorithms .In this chapter we are going to run a set of experiments with different settings and parameters on Cornell KinFace dataset with a kinship verification system based on Retinex filter and elliptical mask during the preprocessing stage then using Hist-Gabor wavelets during the feature extraction phase also We add a new dimensionality reduction and classification method called Tensor Cross-View Quadratic Discriminant Analysis to improve the performing for kinship verification.

3.2. Environment used and work outline

The experiments were carried out using MATLAB R2018a on a PC with an Intel (R) Core (TM) i5-8256U CPU at 1.80 GHz with 12.0 GB of RAM. Figure 3.1 represents our architecture for kinship matching system. It consists of three major parts: Preprocessing, Feature Extraction and Dimensionality reduction with Matching. Each part is discussed in details in the next sections.

The preprocessing stage consists of setting the images to be ready for use in the verification system by performing a filter and a mask. The feature extraction stage consists of extracting a certain number of features from face images by certain method explained later in this chapter. The dimensionality reduction stage is about reducing the dimensions of the collected data (i.e., features) to be used without complications inside the learning algorithm.

Our system contains two phases off-line and on-line. The training phase (off-line) is responsible for learning the discriminative features for each pair of images in the dataset. The testing phase (on-line) estimates the performance of the training stage by testing face image pairs randomly via kin-fold cross validation technique. The Matching stage determines if the pair of face images are kin related or not by comparing their feature vectors using cosine similarity metric. Each stage is explained in details in the following sections.

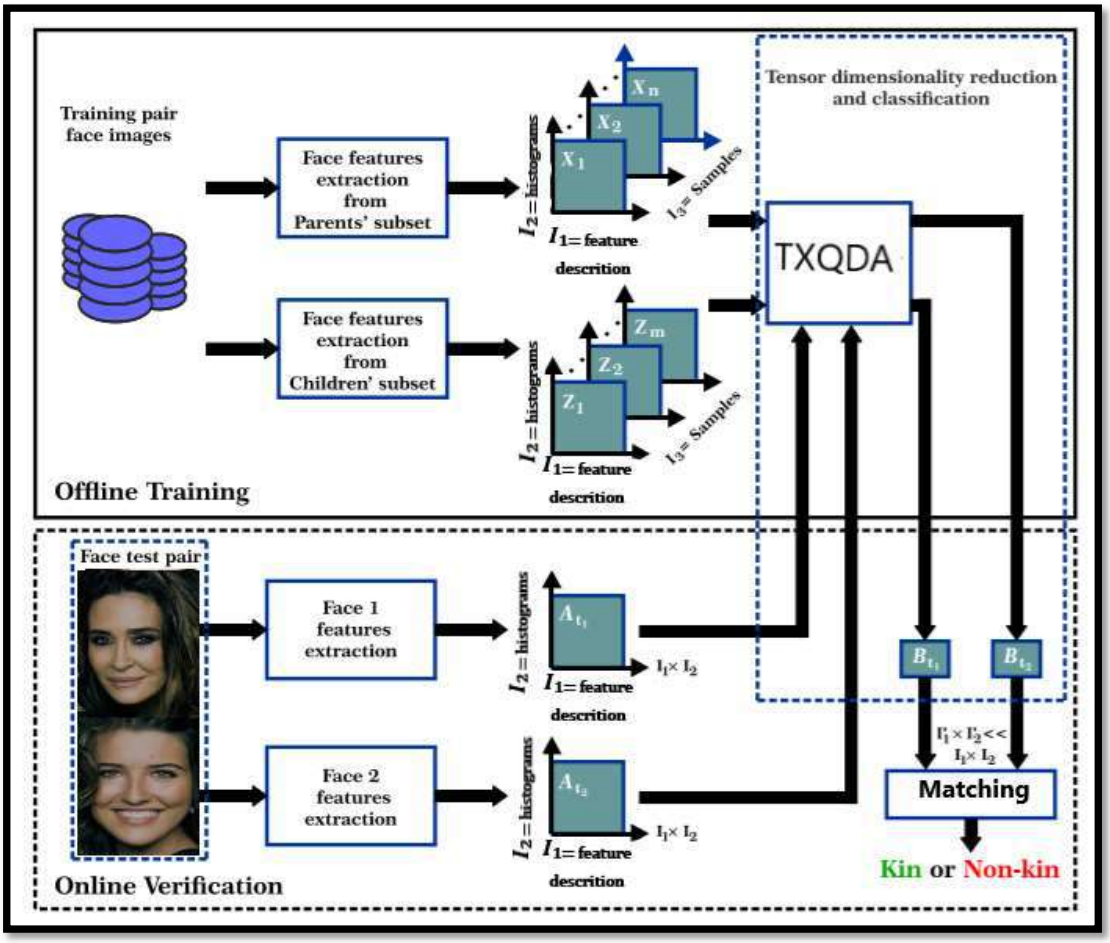


Figure 3.1 : block diagram of the proposed face pair matching system.

3.3. Preprocessing stage

The preprocessing stage is responsible for preparing the facial images to the training stage. The processed images for Cornell KinFace dataset are resized to 200 × 200 pixels and cropped to identify the face region between pixel number 55 to 180 along the *X* axis and from pixel number 43 to 157 along the *Y* axis. then the images will pass two stages: **The Retinex filter and the elliptical mask.**

After that the images are supplied to the local feature representation and extraction stage to extract the main features from the processed faces, each method is explained in details in the following sections.

3.3.1. The Retinex filter

As one of the effective methods to improve the quality of image, color image enhancement can make the image more vivid and more colorful while enhancing the

image details and improving the quality of image. It will not lead to the distortion of image's color so that it is better to make human observation and later-period machine treatment.

At present, color image enhancement mainly has two tasks: research of gray image enhancement algorithm and color information processing of color space. The conventional enhancement algorithm mostly includes non-linear conversion techniques, histogram equalization techniques, and homomorphic filtering techniques and so on. These algorithms have limitation in practice, whose effects are not satisfactory. In recent years, with the development of color constancy theory, enhancement algorithm based on the Retinex theory has reached a better effect in dealing with the problem arose from the uneven illumination (see figure 3.2). It has currently become the hot spot of research [41].

The Retinex theory developed by Land and McCann in 1971 [42], models the color perception of human vision on natural scenes. It can be viewed as a fundamental theory for intrinsic image decomposition problem, which aims at decomposing an image into illumination and reflectance (or shading) components [43].

The Retinex theory is proposed to simulate the human retina system and assumes that the color of the object is determined by its reflection ability of light of different wavelengths, which is independent of the illumination on the object. The source image S (x, y) can be separated into the reflectance image R (x, y) and the illumination image L (x, y), given by Eq 3.1 where x and y are image pixel coordinates.

$$S(x, y) = R(x, y) \cdot L(x, y) \tag{3.1}$$

The Retinex Theory is to remove the illumination impact from the source image and gets the reflectance image which can reflect the surface characteristics of the object. To compute the reflectance image, logarithmic transformation deployed on both sides of the Eq1. So, the estimation of R (x, y) can be implemented as follow:

$$\text{Log}\,[S(x,y)] = \log[R(x,y)] + \log[L(x,y)] \tag{3.2}$$

where log [S (x, y)], log [R (x, y)], and log [L (x, y)] are represented by s (x, y), r (x, y), and l (x, y) for convenience. From Eq 3.2 we can see, the most vital step of Retinex algorithm is to estimate the illumination image. The traditional Retinex based algorithms, such as Single-scale Retinex (SSR) and multi-scale Retinex (MSR), utilize the Gaussian filter for illumination estimation, shown in Eq 3.3:

$$R(x,y) = s(x,y) - \log[S(x,y) * G(x,y)] \quad (3.3)$$

Symbol'*' is the convolution operation, G (x, y) is Gaussian filter, given as follow:

$$G(x,y) = K - (x2 + y2)/c \quad (3.4)$$

where c is the scale parameter of Gaussian surround function. The value of c is empirically determined. K is selected to satisfy:

$$\iint F(x,y)dxdy = 1 \quad (3.5)$$



Figure 3.2 : Results of Retinex algorithms for images.

3.3.2. The Elliptical mask

The outline of the human head can be generally as being elliptic in nature to segment the face region from the rest of the image we have tried the approach of fitting the best ellipse to the outline of the head The basis of the elliptical mask is the use of a parameter domain this means, given a point (x; y) in the plane, find the parameters of an ellipse passing through that point. The parameters are the center point (x_0; y_0), the semi-major axis a, and the semi-minor axis b of the ellipse, the method of finding them is in the equation of ellipse below.

$$\frac{(x - x_0)^2}{a^2} + \frac{(y - y_0)^2}{b^2} = 1 \quad (3.6)$$

let $X = x - x_0$ and $Y = y - y_0$ then

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1 \tag{3.7}$$

Differentiate with respect to x:

$$\frac{2X}{a^2} + \frac{2Y}{b^2}\frac{dY}{dX} = 0 \tag{3.8}$$

Using (6) and (7) and the added information of the gradient $\frac{dY}{dX}$ at each point (x, y) we can solve for x_0 ,y_0 over a range of values for a, b.

This technique utilizes the information present in the image and tries to find the best ellipse given all the edge pixels and their gradient information. It can also handle rotation of the ellipse, i.e., the axes of the ellipse need not coincide with the axes of the image, when this approach was tried on real images, even with uniform backgrounds, the com- mutational complexity increased with the size of the parameter range for every edge pixel, a majority of them relating to features inside the face region. To limit the computation to a reasonable level, the edge map was constrained to contain only the outer shell of the face [44].

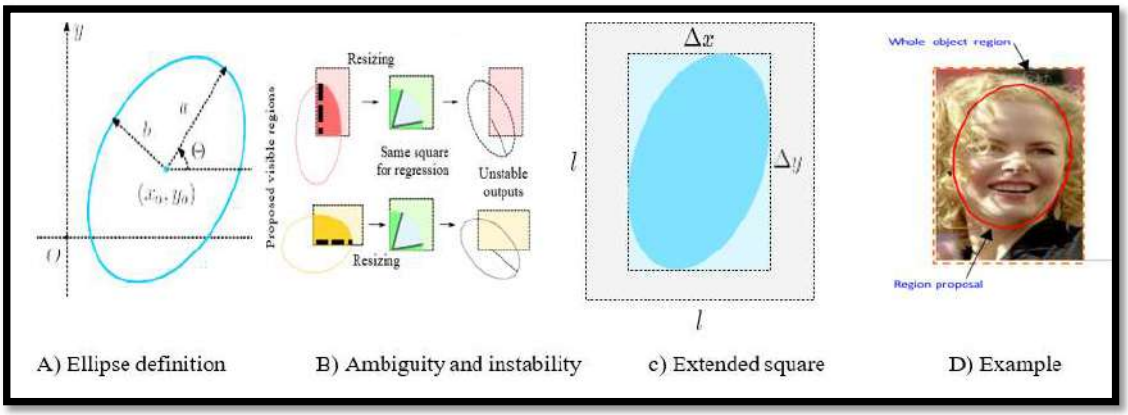


Figure 3.3 : steps of elliptical mask working.

Figure 3.3 represents: A) Definition of parameters for a general ellipse. B) Directly resizing proposed ellipse regions (red and yellow) as squares (green) has two drawbacks: (1) proposed visible regions of different ellipses may end up with the same resized feature region, which brings orientation ambiguity; (2) original ellipses are distorted and resized close to circular shapes, where the information of orientation and two axes is not salient for regression. If the resizing direction is tracked, the orientation in (1) can be uniquely determined by the ellipse implicit equation that is transformed from the resized square) Our ex- tended feature square of an ellipse region. D) example of the elliptical mask on a real image [45].

3.4. Feature Extraction

Facial feature extraction is an essential step in the face detection. The extracted features contain meaningful information of the face that describes the face behavior. To develop a better face recognition system, a good feature extraction method is needed so that the system can successful. In this research area, feature extraction is the most difficult and challenging task. Many researchers have proposed variety of techniques for feature extraction, and have tried to solve the problems that exist in this stage we are using Gabor Wavelet for the feature extraction.

3.4.1. Feature Extraction using Hist-Gabor Wavelets

Gabor filters has been found to be particularly appropriate for texture representation and discrimination. From information theoretic view-point. derived Gabor functions as solutions for a certain mutual information maximization problem. It shows that the Gabor receptive field can extract the maximum information from local image regions. Researchers have also shown that Gabor features, when appropriately designed, are invariant against translation, rotation, and scale. Gabor filter is a linear filter used for edge detection in the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually (see figure 3.4) [46].

Real

$$g(x, y; \lambda, \theta, \psi, \sigma\gamma) = \exp\left(-\frac{x'^2 + y^2 y'^2}{2\sigma^2}\right)\cos(2\pi\frac{x'}{\lambda} + \psi) \tag{3.9}$$

Imaginary

$$g(x, y; \lambda, \theta, \psi, \sigma\gamma) = \exp\left(-\frac{x'^2+y^2y'^2}{2\sigma^2}\right)\sin(2\pi\frac{x'}{\lambda} + \psi)(10) \tag{3.10}$$

Were

$$x' = x\cos\theta + x\sin\theta \tag{3.11}$$

$$y' = -x\sin\theta + y\cos\theta \tag{3.12}$$

and λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the sigma of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function.

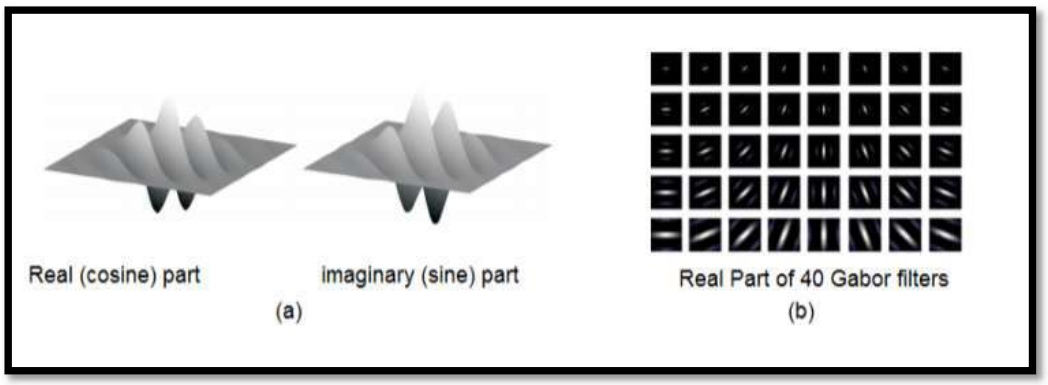


Figure 3.4 : the real part of the Gabor filters with 5 frequencies and 8 orientations for w_{max}=π/2, the row corresponds to different frequency w_m, the column corresponds to different orientation θ_n.

When exploited for feature extraction, a filter bank with several filters is usually created and used to extract multi-orientation and multi-scale features from the given face image. This filter bank commonly consists of Gabor filters of 5 different scales and 8 orientations. Gabor features representation of the face image is the result of image I (x, y) convolution with the bank of Gabor filters $g_{u,v}(x, y)$. The convolution result is complex value which can be decomposed to real and imaginary part:

$$G_{u,v}(X, y) = I(x, y) * g_{u,v}(x, y). \quad (3.13)$$

$$E_{u,v}(X, y) = Re[G_{u,v}(x, y)]. \quad (3.14)$$

$$O_{u,v}(X, y) = Im[G_{u,v}(x, y)] \quad (3.15)$$

Based on the decomposed filtering result both the phase $\varphi_{u,v}$ (x, y) as well as the magnitude $A_{u,v}(x, y)$ filter responses can be computed as:

$$A_{u,v}(X, y) = \sqrt{E^2{}_{u,v}(x, y) + O^2{}_{u,v}(x, y)} \quad (3.16)$$

$$\phi_{u,v}(X, y) = \arctan\left(\frac{O_{u,v}(x, y)}{E_{u,v}(x, y)}\right) \quad (3.17)$$

Since the computed phase responses vary significantly even for spatial locations only a few pixels apart, Gabor phase features are considered unstable and are usually discarded (see Figure 3.5). The magnitude responses, on the other hand, varying slowly with the spatial position, and are thus the preferred choice when deriving Gabor filter-based features. We use Gabor filter with different scales by changing the settings the following settings repeatedly:

Orientations ($\boldsymbol{\theta}$): 45°, 67.5°, 360°, 112.5°.

Wavelength ($\boldsymbol{\lambda}$): 16, 22.63.

Gaussian's variance: we set it equal to wavelength.

Phase offsets ($\boldsymbol{\varphi}$): = 0, 90°.

The process goes as follows:

- Each face image from our datasets is subdivided into a certain number of blocs $M \times N$, where N= $\frac{X}{P1}$ and M = $\frac{Y}{P2}$, $P2$ and $P1$ denote the number of pixels corresponding to the number of blocks along X and Y respectively.
- The resulted matrix is arranged into another matrix of size $(P2 \times P2) \times (M \times N)$.
- Histograms of 256 bins are applied to aggregate the features from each bloc to get a matrix of size $(256) \times (M \times N)$.
- The resulted feature matrix is reshaped to a set of vectors where each vector represents one scale of the features, we get $(Scales) \times (256) \times (M \times N)$). Scales are set to: 4, 6, 8, 10. e. Finally, these features are concatenated (flattened) into a one-dimensional vector of length $Scales \times 256 \times M \times N$.

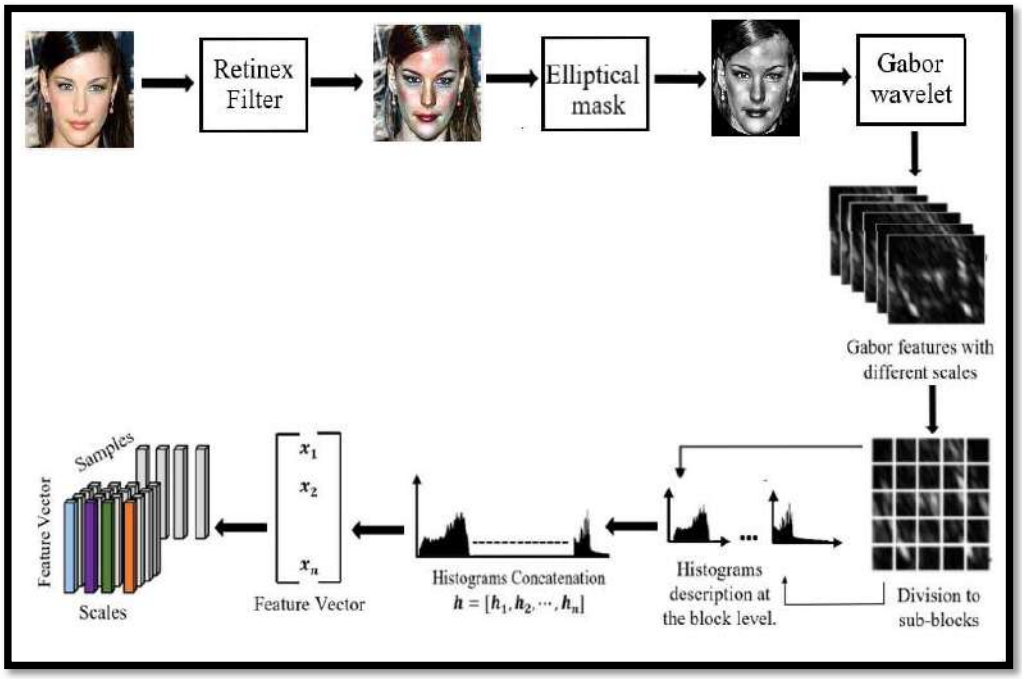


Figure 3.5 : Feature extraction using Hist-Gabor wavelets.

3.5. Tensor dimensionality reduction and classification

Let a Tensor cross-view training set of c classes where[47]:

$X \in R\ R^{I_1 \times I_2 \times \ldots \times I_N \times n}$ contains n samples of one view (Parents samples) and $Z \in R^{I_1 \times I_2 \times \ldots \times I_N \times m}$ contains m samples of other view (Children samples). The goal of our TXQDA is the calculation of N projection matrices ($W_1 \in R^{I_1 \times I'_1}$, $W_2 \in R^{I_2 \times I'_{12}}$, …,$W_N \in R^{I_N \times I'_N}$) [47].

$$\Sigma_E^K \, k \, W_K = \Lambda_K \Sigma_I^K \, k \, W_K \tag{3.18}$$

Where, $W_K$is the eigenvectors matrix and Λ_K the eigenvalues matrix. The iterative process of TXQDA breaks up on the recognition of one of the following situations:

i) The number of iterations reaches a predefined maximum;

ii) the difference of the estimated projection between two consecutive iterations is less than a threshold

$$||W_k^{iter} - w_k^{iter-1} < I_K \, I_K||(\tag{3.19}$$

where I_K is the k mode dimension of W_k^{iter} . The number of iterations, for our TXQDA algorithm, is empirically tuned and the better value is Iteration_{max}= 2.

3.5.1. TXQDA algorithm

The entire procedure for the proposed Tensor Cross-view Quadratic Discriminant Analysis (TXQDA) is provided in Algorithm 1. The input of this algorithm is defined as follow[47]:

- The tensor $X \in X \in R\ R^{I_1 \times I_2 \times \ldots \times I_N \times n}$ contains n samples of one view (Parents samples).
- The tensor $Z \in R^{I_1 \times I_2 \times \ldots \times I_N \times m}$ contains m samples of other view (Children samples).
- $\text{Iteration}_{max}$is the maximal number of iterations.
- The final lower dimensions: $I'_1 \times I'_2 \times \cdots \times I'_N$.

Whereas the output can define as follow:

- The projection matrices $W_K = W_k^{iter} \in R^{I_k \times I'_k}$, k=1…, N.

Algorithm of Tensor Cross-view Quadratic Discriminant Analysis (TXQDA)

Input:

- $X \in R^{I_1 \times I_2 \times \ldots \times I_N \times n}$
- $Z \in R^{I_1 \times I_2 \times \ldots \times I_N \times m}$
- $I_{teration_{max}}$
- $I'_1 \times I'_2 \times \ldots \times I'_N$

Output:

- $W_k = W_k^{iter} \in R^{I_k \times I'_k}, k = 1, \ldots, N$

Algorithm:

1. **Initialization:** $W_I^0 = I_{I_1}, W_2^0 = I_{I_2}, \ldots, W_{!N}^0 = I_{I_N}$
2. **For** iter; 1 to Iteration$_{max}$

- $U = X \times 1W_I^{iter-1} \ldots \times 1W_{k-1}^{iter-1} \times 1W_{k+1}^{iter-1} \times \ldots NW_N^{iter-1}$
- $U^k \Rightarrow kU$
- $Y = Z \times 1W_I^{iter-1} \ldots \times 1W_{k-1}^{iter-1} \times 1W_{k+1}^{iter-1} \times \ldots NW_N^{iter-1}$
- $Y^k \Rightarrow kY$
- $n_1\sum_{I=} \sum_{p=1}^{\prod_{0 \neq k} I_0} n_1\sum_I^p, n_1\sum_I^p = \breve{U}^{k,p}(\breve{U}^{k,p})^T + \breve{Y}^{k,p}(\breve{Y}^{k,p})^T - \breve{S}^{k,p}(\breve{R}^{k,p})^T - \breve{R}^{k,p}(\breve{S}^{k,p})^T$
- $n_E\sum_{E=} \sum_{p=1}^{\prod_{0 \neq k} I_0} n_1\sum_E^p, n_1\sum_E^p = m\breve{U}^{k,p}(\breve{U}^{k,p})^T + n\breve{Y}^{k,p}(\breve{Y}^{k,p})^T - \breve{s}^{k,p}(\breve{r}^{k,p})^T - \breve{r}^{k,p}(\breve{s}^{k,p})^T - n_I\sum_I^p$
- **Compute** $\sum_E^k W_k^{iter} = \wedge_k \sum_I^k W_k^{iter}$, **obtain** W_k^{iter}

if $iter > 2$ and $\| W_k^{iter} - W_k^{iter-1} \| < I_k I_k, k = 1, \ldots N,$ **break**;

3. sort I'_N the eigenvectors $W_k^{iter} \in R^{I_k I_k}$according to$\wedge_k$ in decreasing order, k=1, N

3.6. Parameter Settings

cross-validation is one of the most popular methods for model and tuning parameter selection in statistics and machine learning, due to its conceptual simplicity and wide applicability (see figure3.6)[48]. in which five-fold cross-validation for kin verification is performed by keeping the same number of pairs images for each fold. This protocol is considered to make sure that our results are directly comparable to the state of the art. The negative pairs for kinship are generated randomly such that each image appears only once in the test set. The number of positive pairs and negative pairs is the same in the test stages [47].

	Data				
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5
Iteration-1	Test	Train	Train	Train	Train
Iteration-2	Train	Test	Train	Train	Train
Iteration-3	Train	Train	Test	Train	Train
Iteration-4	Train	Train	Train	Test	Train
Iteration-5	Train	Train	Train	Train	Test

Figure 3.6 : Fold cross validation.

3.7. Matching

In order to compare two face pairs, we use simplified features projected through TXQDA space. These features are connected to form a feature vector. Then, we apply cosine similarity to each pair of tests of the two face images to complete the matching score. After the discriminant analysis method, the use of cosine similarity distance has advantages, which comes from its connection with Bayesian decision rules (see figure 3.7). The cosine similarity between two vectors b_t1 and b_t2 is defined as follows:

$$cos(b_{t1}, b_{t2}) = \frac{b1_{t1}^{T} . b_{t2}}{||b_{t1}||.||b_{t2}||} \quad (3.20)$$

Where$||.||$ is the Euclidean norm A high value of the produced score means a high probability that b_{t1} andb_{t2}belong to the same family [47].

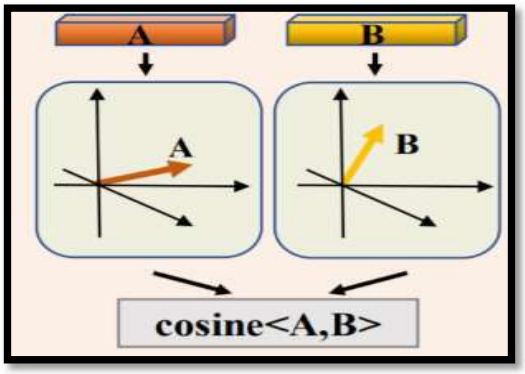


Figure 3.7 : The cosine similarity.

3.8. Cornell kinship database

To evaluate the performance of the proposed kinship verification approach, we considered one kinship database (Cornell KinFace). This database consists of four kinds of parent-child relationships. The face images are with various ages and ethnicities, and captured under uncontrolled environments and no restriction in terms of pose.

The Cornell KinFace dataset consists of 150 pairs of parent-child images, which is collected through an on-line search. The face images are chosen to be frontal and a neutral facial expression to ensure image quality. The database includes 40% father-son pairs, 22% father-daughter pairs, 13% mother-son pairs, and 26% mother-daughter pairs. Due to privacy issues, 7 families are removed from the original dataset and the remaining 143 pairs of kinship images are used for validation. Figure 3.8 shows some example images from Cornell KinFace dataset, respectively. In the experiments, Naturally, the feature dimension D was equal to 512. Data augmentation is a crucial step to improve performance. Specifically, random cropping and flipping were utilized to augment data [49].

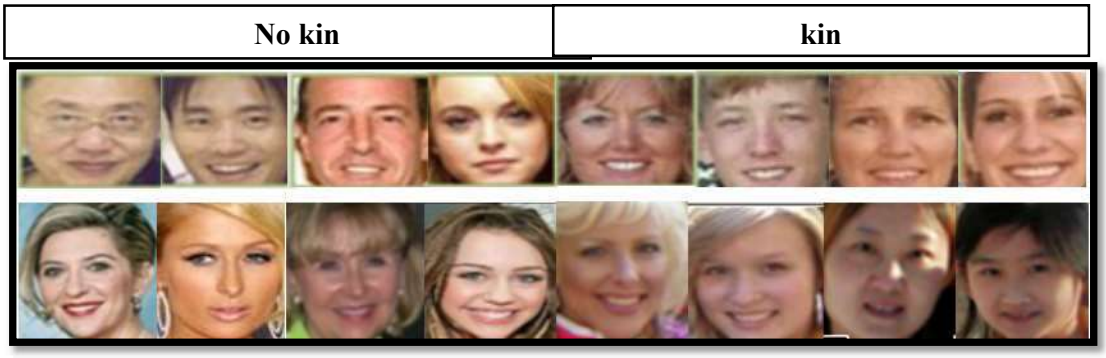


Figure 3.8 : Examples from the Cornell KinFace dataset.

3.9. Implementation and results

We perform a number of experiments to discover the best results for kinship verification and we fixed the parameters of the Gabor wavelets with best performing number of scales and number of blocs, the number of features projection is changed iteratively with the step of 10 as shown in the table 3.1:

Table 3.1 : The best sittings we used in Gabor wavelets

Number of scales	*Number of blocs*	*Number of features projection*
6	**12 / 16**	**150-200**

Here we present the results of our experiments on Cornell KinFace dataset with three methods:

- Basic system (without retinex and elliptical mask)
- Retinex filter
- Elliptical mask
- Retinex filter & elliptical mask combined

In which Tables 3.2, 3.3, 3.4, 3.5 illustrate the mean accuracy folds of our simple basic, elliptical mask, Retinex filter, Elliptical mask & Retinex filter combined and the Figure 3.9 represents the accuracies in histograms.

Table 3.2 : The accuracy for the simple basic method of kinship verification for TXQDA using our Hist-Gabor wavelets. on Cornell Kin Face database defining 6 scales, (table down): defining 12 blocs.

Method	**Number of features projection**	**ACCURACY FOLD1**	**ACCURACY FOLD2**	**ACCURACY FOLD3**	**ACCURACY FOLD4**	**ACCURACY FOLD5**	**MEAN ACCURACY %**
Basic system	150	0.9630	0.9286	0.9286	0.9500	0.8500	92.40%
	160	0.9630	0.9286	0.9286	0.9500	0.8500	92.40%
	170	0.9630	0.9286	0.9286	0.9500	0.8500	92.40%
	180	0.9630	0.9286	0.9286	0.9500	0.8500	92.40%
	190	0.9630	0.9286	0.9286	0.9500	0.8500	92.40%
	200	0.9630	0.9286	0.9286	0.9500	0.8500	92.76%

Table 3.3 : The accuracy for the Retinex filter method of kinship verification for TXQDA using our Hist-Gabor wavelets. on Cornell Kin Face database defining 6 scales, (table down): defining 12 blocs.

Method	Number of features projection	ACCURACY FOLD1	ACCURACY FOLD2	ACCURACY FOLD3	ACCURACY FOLD4	ACCURACY FOLD5	MEAN ACCURACY %
Retinex	150	0.9630	0.9286	0.9464	0.9500	0.8500	92.76%
	160	0.9630	0.9286	0.9286	0.9500	0.8500	92.40%
Filter	170	0.9630	0.9286	0.9464	0.9500	0.8500	92.76%
	180	0.9630	0.9286	0.9264	0.9500	0.8500	92.76%
	190	0.9630	0.9286	0.9286	0.9500	0.8500	92.40%
	200	0.9630	0.9286	0.9464	0.9500	0.8500	92.76%

Table 3.4 : The accuracy for Elliptical mask method the of kinship verification for TXQDA using our Hist-Gabor wavelets. on Cornell Kin Face database defining 6 scales, (table down): defining 12 blocs.

Method	Number of features projection	ACCURACY FOLD1	ACCURACY FOLD2	ACCURACY FOLD3	ACCURACY FOLD4	ACCURACY FOLD5	MEAN ACCURACY %
Elliptical	150	0.9630	0.9107	0.9107	0.9500	0.8533	92.35%
	160	0.9630	0.9107	0.9107	0.9500	0.8533	92.35%
Mask	170	0.9630	0.9107	0.9107	0.9500	0.8533	92.35%
	180	0.9630	0.8929	0.9107	0.9500	0.8533	92.00%
	190	0.9630	0.8929	0.9107	0.9500	0.8533	92.00%
	200	0.9630	0.8929	0.9107	0.9500	0.8533	92.00%

Table 3.5 : The accuracy for the Retinex filter and elliptical mask method of kinship verification for TXQDA using our Hist-Gabor wavelets. On Cornell Kin Face database defining 6 scales, (table down): defining 16 blocs.

Method	Number of features projection	ACCURACY FOLD1	ACCURACY FOLD2	ACCURACY FOLD3	ACCURACY FOLD4	ACCURACY FOLD5	MEAN ACCURACY %
Retinex	150	0.9815	0.9107	0.9464	0.9500	0.8533	93.44%
Filter	160	0.9815	0.9107	0.9643	0.9500	0.8833	93.80%
+	170	0.9630	0.9107	0.9643	0.9500	0.8833	93.43%
Elliptical	180	0.9815	0.8929	0.9464	0.9500	0.8833	93.08%
Mask	190	0.9815	0.9107	0.9643	0.9500	0.8833	93.80%
	200	0.9630	0.9107	0.9643	0.9500	0.9000	93.76%

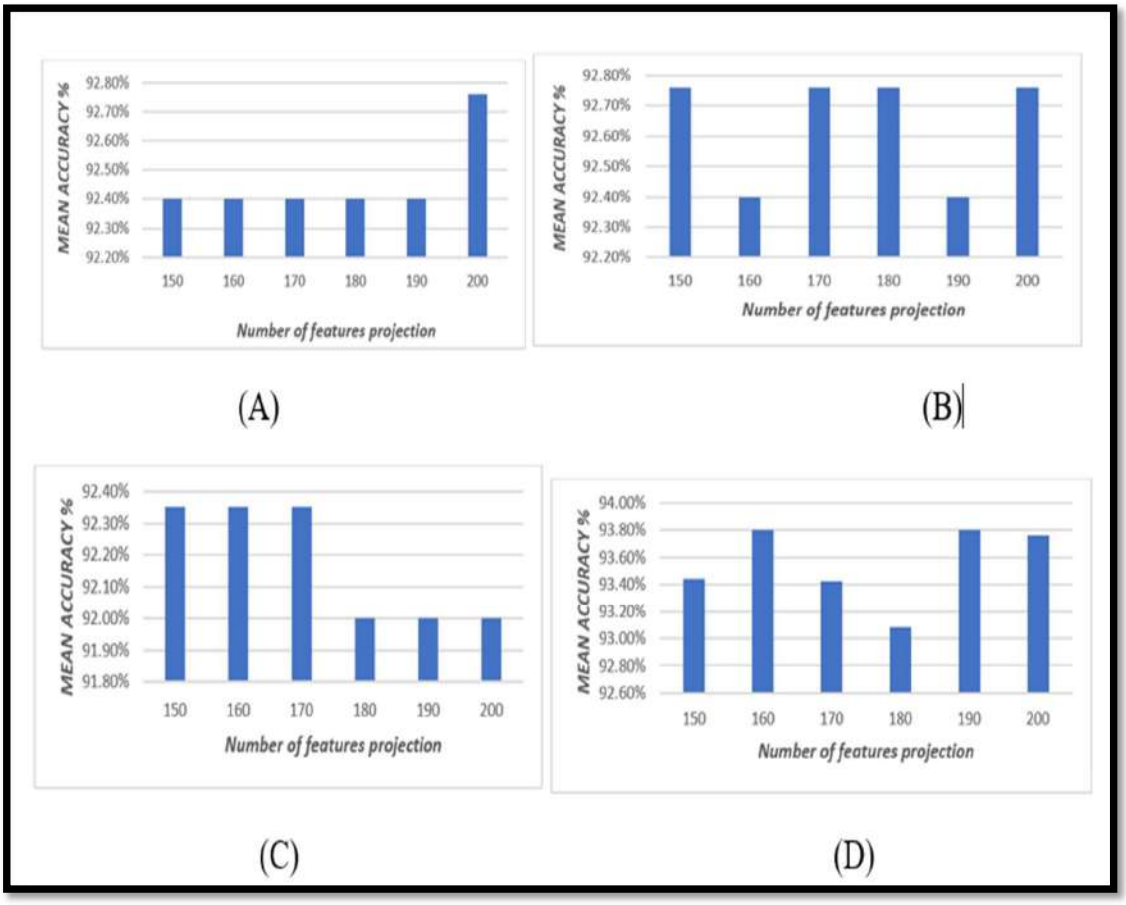


Figure 3.9 : histograms of the accuracy for all methods That we used (A) basic method (B) Retinex filter (C) elliptical mask (D) Retinex+Elliptical.

Table 3.6 : The best accuracy (%) for all methods performance of kinship verification for TXQDA using our Hist-Gabor. on Cornell Kin Face database defining 6 scales, (table down): defining 12 or 16 blocs on Cornell KinFace database.

Methods	**Number of features projection**	**Accuracy**
SIMPLE BASIC	180	92.76%
Retinex filter	200	92.76%
Elliptical mask	170	92.35%
Elliptical mask + Retinex function	**190**	**93.80%**

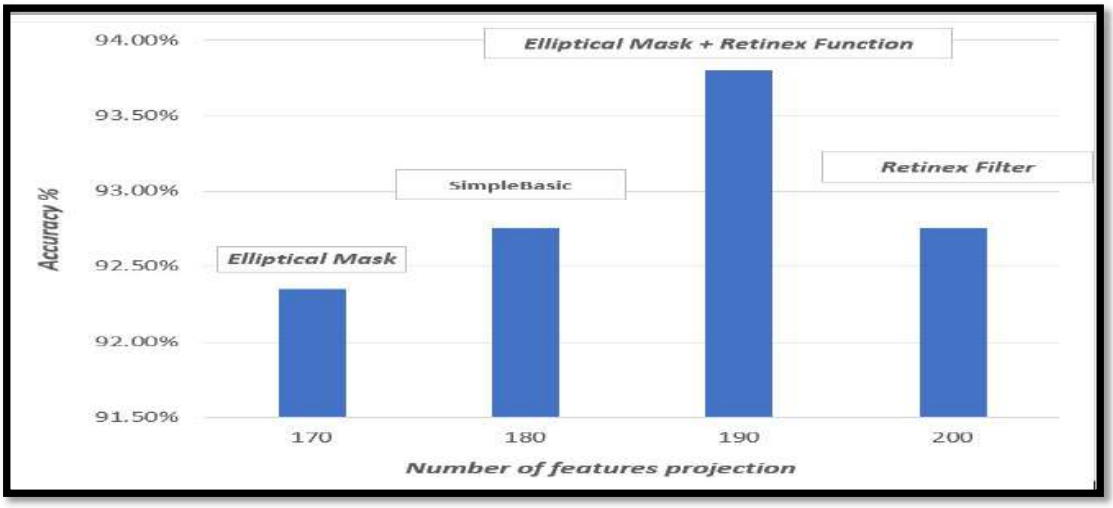


Figure 3.10 : histogram of the best accuracy (%) for the whole methods performance of kinship verification.

3.10. Discussion

The experiments that we conducted using two types of preprocessing (Retinex filter & Elliptical mask) and the evaluation results of the proposed TXQDA using (Hist-Gabor wavelets) and cosine similarity and their combinations are shown in figure 3.10 on benchmark kinship datasets (Cornell KinFace). These results outline three principal observations which are detailed in the following*:*

1. **The power of Retinex filter and Elliptical mask:**

Retinex filter has shown itself to be a very versatile automatic image enhancement algorithm that simultaneously provides dynamic range compression, color constancy, and color rendition and good image quality It was shown in figure 3.2 that for a wide range of the involved parameters, For better illustration of the performances of different features.

Elliptical mask is our key idea to infer relative offset parameters directly from visible parts so as to maintain key benefits described in Second. And by further leaning occluded patterns, the confidence score of visible parts of an occluded object is leveraged from incorporated informationof its estimated ellipse.

we apply those two methods in our images from the dataset and it is remarkable that Retinex filter and Elliptical mask shows a high performance with in the Cornell KinFace dataset (see table 3.6) we can observe from the increase in the accuracy.

2. **The Performance of Gabor wavelets:**

In order to extract features from our kinship dataset, we used Gabor wavelets , this model was trained for face recognition tasks, on different dataset, the experimental results on Cornell KinFace show a quite satisfactory results, in fact, it outperforms some

other approaches in different Chapter 3 Kinship Verification Based on Gabor Features , since it was trained for face recognition in a large dataset, the weights of this model are tuned in favor of facial recognition which is useful for kinship verification. But the performance of Gabor wavelets can still be improved by combining it with other deep metric learning methods.

3. **The advantage of using TXQDA for dimensionality reduction:**

TXQDA preserves the data structure, where these data stacked in a tensor mode providing the maximum extraction of information also helps lightening the small sample size problem and It can obviate the curse of dimensionality dilemma by using higher order tensors and k-mode optimization approach, where the latter is performed in a much lower-dimension feature space than the traditional vector-based methods and Many more feature dimensions are available in TXQDA than the traditional vector-based methods [47].

3.11. Comparison with state-of-the-art methods:

The best performance of the proposed methods of the preprocessing stage (the Retinex filter & the Elliptical mask) and the Hist-Gabor wavelets of the extraction phase TXQDA tensor design of Gabor wavelets and compared with recent techniques in Table 3.7 for Cornell database. The related works are cited according to the type of learning used, metric, multi-metric and multilinear learning approaches. The comparison shows that our proposed method outperforms the recent state of the art on the Cornell KinFace database and showed a remarkable **Increase** in the mean accuracy (see table 3.8**)**.

Table 3.7 : Comparison of realized performance against existing methods in Cornell KinFace dataset.

Approach type	Author	Year	Mean Accuracy%
Metric learning	Lu and al[50].	2014	69.50%
	Zhou et al [51]	2018	81.40%
	Laiadi et al [52]	2018	77.60%
Multi Metric Learning	Lu et"eet al.	2014	71.60%
	Yan and al [53].	2014	73.50%
	Mahpod and Keller [54].	2017	76.60%
Multilinear Subspace Learning	Bessaoudi and al [49].	2019	86.87%
	Laiadi and al [50].	2019	93.04%
	Proposed	**2021**	**93.80%**

Table 3.8 : Increase in mean accuracy of propose approach against state-of-the art methods.

Database	Approach type	Best method	Year	Increase Mean Accuracy%
Cornell Kinface	**Metric learning**	Zhou and al.[51]	2018	12.36
	MultiMetric Learning	Mahpod and Keller.[54]	2017	17.16
	Multilinear Subspace Learning	Laiadi and al.[50]	2019	**0.76**

3.12. Conclusion

The kinship verification through facial image is an active research topic due to its potential application, in this chapter we described a novel approach with highly efficient methods in which takes two as input then give kinship result (kin/ no kin) as an output. our approach based on 2 methods for preprocessing stage which are Retinex filter and Elliptical mask and the Hist-Gabor wavelets for the feature extraction step that consists of dividing sample images into a number of blocks, extracting histogram features from each block and then concatenating these features into one feature vector representing each sample image, alongside with TXQDA the new dimensionality reduction and classification method to classify for the decision of kinship verification. The approach contains three steps which are: (1) face preprocessing, (2) deep features extraction (3) Classification. Experiments are conducted on one public database Cornell KinFace. Furthermore, our work achieves an impressive verification accuracy of **93.80%** which is better than all the state-of-the-art results n kinship verification literature.

General conclusion

Automatic kinship verification aims to determine whether some individuals belong to the same family. generally, four main types of kinship relationships were used in most studies which are: father-daughter relationship (F-D), mother-son (M-S), father-son (FS) and mother-daughter (M-D). Although, there are other types of kinship relationships such as siblings and grandparents, and these types are rarely studied. Kinship verification verifies a classical Boolean problem. it is used to predict whether given face images have kin relations. It is of great research significance to help missing persons reunite with their families It is essential in various real-world applications such as genealogical studies, social-media analysis, and tracking missing persons. The use of facial images in the kinship verification is a challenging research problem in soft biometrics and computer vision. Our study proposes a novel kinship verification system for better accuracy based on the Retinex filter and elliptical mask on the preprocessing stage and for the KinFace features extraction Gabor wavelets. In our work we mainly explored as blows:

- An overview about Artificial intelligent and machine learning and deep learning and biometrics and their definitions and applications. And in details about kinship verification and how it works and its challenges.
- Considerable experiments on one public databases (Cornell KinFace) along with good and stable results of the proposed approach.
- The preprocessing phase includes two methods Retinex filter and elliptical mask combined
- The feature extraction phase method based on Gabor wavelets, consists of extracting the histogram features for each block of the sample image, and the matching stage.
- The use of a powerful dimensionality reduction technique called Tensor Cross View Quadratic Discriminant Analysis (TXQDA).
- The matching level to verify kin or non-kin.
- The Retinex filter and the elliptical mask and The Gabor wavelets to improve the classification accuracy.

In our future work, we intend to explore new methods on the level of feature extraction, and more datasets for pre-training. So that we can deal with the obstacles and difficulties and analyze them in an exemplary manner and create a simple short program and with distinguished and effective performance.

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