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Thème

DEEP LEARNING FOR FACE KINSHIP VERIFICATION SYSTEM

Before the jury composed of:

Mr. Khelil Abdellatif	**....**	**Président**
Mr. Touhami Ridha	**....**	**Examiner**
Ms. Tidjani Amina	**....**	**Framer**

2020-2021

بسم الله الرحمن الرحيم

Dedication

I dedicate this modest work:

To those who have given me everything without expecting anything in return Apart from my success, to those who taught me to follow my ambitions, to those who have always believed in me: to my dear parents.

*To my beloved wife**: Salemi Ibtihadj***

*To my dear children: **Iyed**, **Adem** and my little angel **Djana***

My dear brothers and sisters

To all the professors that initially made me successful in my academics

To all my friends

To all those who are dear to me.

BENNACEUR MED LAID

Dedication

We dedicate this work at the end of the study for success and taught me patience, my dear parents' mom and dad

Those who condemned them a lot of love and constant support throughout my studies.

This work is a testament to the honest and deep love of gratitude that we have done everything for me.

And to my brothers and all my family.

To all my colleagues

MEFTAH TAREK

Dedication

I dedicate this modest work:

To those who have given me everything without expecting anything in return Apart from my success, to those who taught me to follow my ambitions, to those who have always believed in me: to my dear parents.

To my beloved wife

To my dear children

My dear brothers and sisters

To all the professors that initially made me successful in my academics

To all my friends

To all those who are dear to me.

TALBI Med Sadok

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His availability, his patience throughout this work has been beneficial to us. We also thank the President and the members of the Jury who do us the honor of accepting to judge our work.
Without forgetting of course all the teachers who have contributed by their knowledge and their encouragement along our journeys.

Abstract

Kinship verification from face images is a new and challenging problem in pattern recognition and computer vision, and it has many potential real-world applications including social media analysis and children adoptions.

The focus is on providing novel solutions for challenges of family verification from faces with an efficient system with the aim of providing enhancement to the accuracy of kinship verification.

In our work, we analyzed the facial kinship verification systems in two modes the Hand crafted Features and No Hand Crafted. The feature extraction is a crucial step in the kinship recognition system. For this reason, we used an efficient feature learning extraction algorithm called discrete cosine transform network (**DCTNet**).

Besides, the experimental results demonstrated that these methods achieved competitive results compared with other state-of-the-art.

Index Terms Biometrics, Kinship, Verification, DCTNet, KinFaceW-II

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Abbreviations

BSIF	Binarized Statistical Image Features
CNN	Convolutional Neural Networks
COALBP	Co-Occurrence of Adjacent LBP
DCT	Discrete Cosine Transform
DCTNet	Discrete Cosine Transform Network
FPLBP	Four Patch Local Binary Patterns
F-D	Father-Daughter
F-S	Father-Son
HOG	Histograms of Oriented Gradient
KML	Kinship Metric Learning
LBP	Local Binary Patterns
LDA	Linear Discriminant Analysis
LPQ	Local Phase Quantization
M-D	Mother-Daughter
M-S	Mother-Son
NRML	Neighborhood Repulsed Metric Learning
PCA	Principal Component Analysis
ROC	Receiver Operating Characteristic
SIFT	Scale Invariant Feature Transform
SILD	Side-Information based Linear Discriminant
SSML	Sparse Similarity Metric Learning
SVM	Support vector machines
TOP	Three Orthogonal Planes
WLD	Weber Local Descriptor

General Introduction

General Introduction

Technological progress, particularly in new techniques for treating information and the impending revolution of microprocessor systems have made it possible to develop artificial solutions for the resolution and demystification of a great number of problems caused by insecurity and unauthorized access in various sectors: embezzlement, forgery and use of forgeries, alteration or loss of information confidential, computer crimes, etc. Biometric verification and identification are solutions that are used to reduce (or even eliminate) the risks of such criminal situations. Indeed, authentication is the procedure, which aims to verify and to validate the authenticity of a person or a machine so that it can access controlled locations or an information system. While identification consists of determining in a manner that is both efficient and accurate the identity of an individual. Currently, authentication of individuals is widely used in all areas requiring controlled or secure access such as banking applications, access to locations highly secure such as government offices, connection to a computer or a computer network, electronic commerce… etc. On the other hand, forensic scientists to find out about a potential criminal and the services immigration at airports… etc. often use identification

In addition, among all the biometric technologies that exist, the recognition of faces and one of the most used and suitable technologies. In this brief, we let’s highlight some basic concepts related to face recognition. We give the operating principle of facial recognition systems, the various technologies and tools used to measure their performance as well as the areas applications. Several face recognition methods were proposed during these thirty years, following two main axes: recognition from still images and recognition from image sequence (video).Face recognition based on video is preferable to that based on still images, since the simultaneous use of temporal and spatial information helps in recognition. In our study we are interested in recognition based on still images, since it represents the basis of all work The analysis of facial images is one of the main research topics in the image processing, computer vision and model analysis. During the last decades, face verification and people recognition issues have made the subject of considerable attention. The big data boom in recent times years is testament to the digital photo being shared across many platforms media. Potential relationships in the photos include those of parents, colleagues and friends. Kinship verification and recognition are new areas of computer vision research that have received increasing attention these last years. Motivated by the psychological results, several scientists have studied the ability human evaluators or the perception of recognizing kinship from facial images human. In addition, the biological relationships and similarities between the traits found in the same family encourage us to exploit this fact to develop a computer system that will be able to recognize kinship and apply it in a variety of applications. Simply, kinship systems establish relationships between individuals and groups on the model of biological relationships between parents and children, between siblings and between marital partners. Once again, due to advances in psychology, the unique biological development and other factors, researchers' attention has shifted to propose an algorithm, which determines whether a pair of facial images belonging to a class is kin or not kin. The analysis of kinship by the image of the human face is a task difficult and based on the literature, few attempts have been made to do so .For this reason in this research we have highlighted the verification of kinship automatically, as we explained previously, Some of the concepts and basic principles in the kinship system and other methods we have studied and applied in order to give the best results in the relations between the two images different.

Our dissertation is divided as following:

Chapter I: Details the verification procedure for facial kinship. By presenting a number of theories, definitions and terminology needed to explain this issue, we offer an overview of automatic kinship verification. Next, we discuss the facial kinship verification system design. Some applications as well as the issues associated with checking parent’s ship.

Chapter II: we introduce the hand-crafted features extraction techniques including global and local features. Next, we present a deep learning method based on learned (No Hand-Crafted) features learning.

Chapter III: In this chapter a discussion about the extraction characteristics and classification approach for kinship verification. Next we talk about the learning approach, which is based on DCTNet (no Hand-crafted) characteristics.

Chapter IV: Experimental data are given and discussed in the face kinship verification analysis. We examined the kinship verification employing a novel solution using the 2D-DCT filter bank via a DCTNet. A discriminatory biological information is employed to improve the performance of kin verification. Biological views suggest that face color is linked to hereditary features such as eye color or skin tone.

Chapter I

Facial Kinship Verification

I.1 Introduction:

Kinship authentication is a process that uses facial features to validate a person's relationship. Recognizing people in pictures is a good example of this capacity. The background information and concepts needed to understand the kinship verification topic are discussed in this chapter. We also offer an overview of the problems associated with kinship verification using human facial images, as well as the key solutions suggested by state-of-the-art study.

The definition of kinship verification in computer vision is introduced first, followed by a discussion of kinship terms. The disparity between a facial verification system and a kinship verification system was highlighted. We also concentrated on device design and implementation. A few current databases are also summarized in this chapter.

I.2 Kinship Thermology (theory) :

Before digging into the essence of the issue and possible solutions, it's important to consider the numerous kinship concepts that will form the reach and direction of this research. On the basis of any or all of the basic traits or characteristics, kinship may imply similarity, familiarity, or closeness between individuals. Kinship is a general concept that takes on various meanings depending on the context or system in which it operates [1].

Kinship systems create relationships between individuals and groups in every culture, based on biological relationships such as those between parents and children, siblings, and married partners. The adoptive boy, on the other hand, is not included in this relationship. The word "adoption" is sometimes used to describe a person who has no biological ties to the parents. Marriage establishes alliances between groups of people who are linked by blood (or consanguineous ties) [2] [3]. These two facets of human life function as the base for society's two dominant forms of kinships [4]:

– Blood ties (consanguine): The most fundamental and universal kin relationships are those based on blood or genetic ties, such as the relationship between parents and children and siblings.

– Marital bonds (affine): Relationships that have developed as a result of a marriage. The most fundamental relationship established by marriage is that between husband and wife.

I.3 Kinship Verification in computer Vision:

Kinship is a genetic relationship between two family members, including parent-child, sibling-sibling, and grandparent-grandchild, this is the application of kinship in computer vision so far. Therefore, in automatic kinship recognition using computer vision techniques, the machine is able to discriminate kin from unrelated people and determine the degree of kin relationship based on an inspection of their images. [5] In other words, it is a task of training a machine to recognize the blood relation between a pair of kin and non-kin faces (verification) based on features extracted from facial images and to determine the exact type or degree of that relation (recognition). A biometric system is a pattern-recognition system that recognizes an individual based on a feature vector derived from a physiological or behavioral characteristic (also known as modalities) [6].

These modalities provide a high degree of fraud security and have many key features such as non-transferability, non-repudiation, and non-guess ability. The technology has been successfully applied in forensics, government departments, banking and financial institutions, and enterprise identity management, among other real-world applications. According to its potentiality and capacity to differentiate between individuals, the face is one of the most commonly used biometric modalities; it has many advantages over other biometric modalities such as fingerprints [7] [8], palm-prints [9], [10] speech [11] [12], or iris[13] [14]. It is more widely known because of its major benefit: it is the only physiological biometric that can be reliably tested remotely, and it can also be used to authenticate users without their awareness or clear contact with the sensor. Age estimation [15], for example, is one of the fields that is gaining momentum. Anti-spoofing of the face [16], facial cosmetics [17], beauty study for surgical/orthodontic preparation [18]. In recent years, kinship authentication has become one of the newest fields of biometric application that utilizes face modalities.

The automated kinship verification method uses only photos of people's faces to attempt to identify their relationships. Kin recognition is the job of teaching a computer to identify genetic kin and non-kin based on features extracted from digital images and attempting to decide whether or not kinship occurs between a pair of faces [19]. Kinship verification is a difficult problem in computer vision since it faces many obstacles similar to face recognition issues, such as low-resolution images, lighting shifts, pose variations, aging effects, mixed ethnicities, and different age groups. Furthermore, the kinship system is a classification system for people who are related by kinship based on patterns such as their faces (see Figure 1). For example, the inputs may be two faces (Face A and Face B), with the expected output being a determination of whether Person A is Person B's father, sister, mother, or brother.

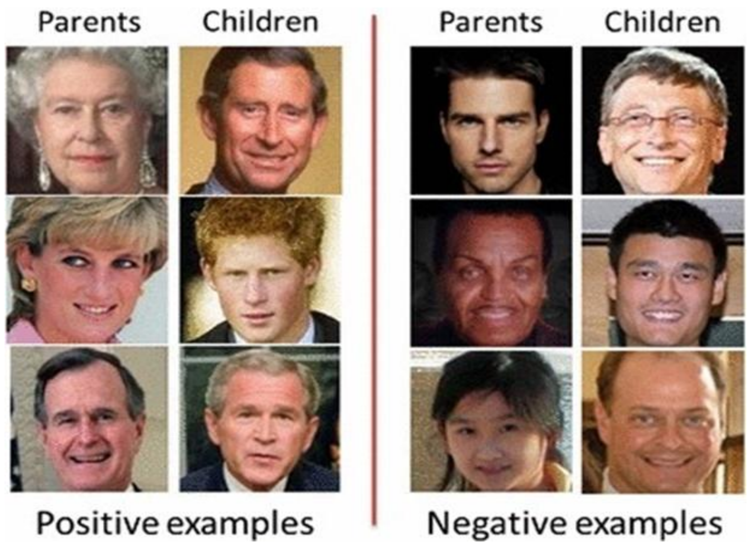


Figure 1*: An example of kinship verification via face images.*

I.4 Face recognition and Kinship recognition:

Face verification and recognition may appear to be similar to kinship verification and recognition at first glance. Face verification and recognition and kinship verification and recognition are two distinct processes. The highest degree of face verification and recognition may be said to be kinship verification and recognition. At the same time, we can't overlook the fact that they have certain things in common, such as obstacles or even techniques. The following table compares and contrasts facial and kinship recognition based on seven criteria: meaning and aim, mode, challenges, implementations, features, and others, processes, and accuracy.

Kinship Recognition	Facial Recognition
Extract features from different person	Extract features from same person
Verify the relationships	Verify or identity
Different trait of query image1 and query image 2	Same trait of query image1 and query image 2

Highest level system	Height level system
Studying the biological relationship and utilizes by people and less by government agencie	The most common application is the security, monitoring and extensively by government a agencies
In decision stage Kin or not kin	In decision stage Matched or not matched
Accuracy is around 90%	Performance of the machine is very roughly as accurate as human

Table 1: Difference between kinship and face Recognition system.

I.4.1 Definition:

The concept of an image-based face recognition system can be calculated as follows: Given the input facial image and the database of facial images of known individuals, it is the duty of the system to differentiate between the facial features of the input facial image and the facial image of a known individual from the database and to check or identify whether the image belongs to the same person (intra-personal or intra-pair) or not (extra-personal or extra-pair) [20] [21]. On the other hand, in the parent recognition scheme, extract the analog Characteristics but from different persons who have certain characteristics or traits in common (the computer examines whether the subjects (the person) share or are unrelated to a parent-child or sibling relationship, and then determines the family class of two persons from their facial images) [22] [23] It should be remembered that the face could be used in several different ways, as proof of identification, gender and race discrimination, and to identify gestures and feelings and to understand their meanings and purposes. It is therefore advisable to re-formulate the word "facial recognition" to "identity recognition" since the former term may have many meanings due to the details found in the face, that lead a variety of tasks, as we just mentioned.

We can see that the role of defining the relationship has been allocated to the face. As we know, there are a variety of biometric characteristics that are not compatible and cannot be relied on in terms of discrimination against blood relations, except DNA, facial and odor. That's why we're trying to use the face to check the relationship, and it seems that the face is the best option of those biometrics, and that's because the face has triggers or characteristics that are suited to performing this role. These attributes can be summarized as follows;

- (1) Face is the most commonly used method of identifying individuals, and many of our daily social interactions rely on our ability to recognize people's faces.

- (2) Often, it does not involve user cooperation.

- (3) It is cheap to introduce due to the availability of camera devices.

- (4) It is useful for automated real-time recognition.

- (5) It can function in various environments and conditions.

The common element between facial recognition (identity) and parenthood is that the fundamental structure and the catalyst for both systems is characteristic of the face. In the other hand, the foundation and the significant variation between the two schemes are the objectives. Where identity recognition is intended for "the same person" while "multiple individuals and a network of relationships" are used in the family.

I.4.2 Modes :

Both systems encompassing the mode of verification and identification, with a discrepancy
in the style of implementation. Figure 2 shows identity (face) and kinship modes.
– Face verification: Is this same person? (1:1)

– Face identification: Who is this person? (1:N)

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

– Kinship identification: identifies the degree of kin relationship (1:N).

In kinship, we observe the existence of a link between verification and identification mode, which means that the system cannot proceed in determining the degree of kinship without resorting to verify the existence of kinship. This leads us to declare that the mode of identification adopt on verification. In contrast, identity or face recognition, verification and identification modes are uncorrelated practically. In other words, the verification mode does not depend or adopt on the identification and vice versa.

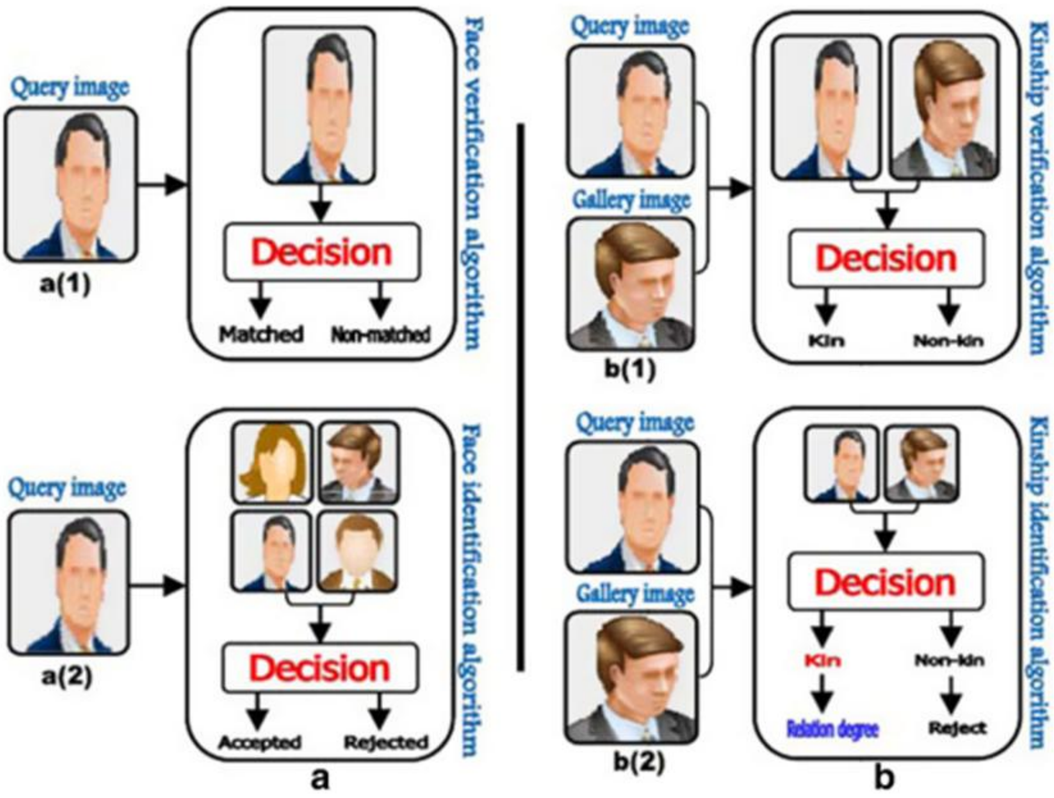


Figure. 2 *Modes of identity (face) and kinship.* ***a*** *identity (face verification a(1) and face identification a(2)), and* ***b*** *kinship (kinship verification b(1) and kinship identification b(2))*

I.4.3 Challenges:

In reality, we may argue that these issues are things shared by identity recognition and parenthood. These structures can be influenced by effects such as lighting, lack and presence of structural elements, occlusions, emotions, facial expression, makeup, cosmetic surgery, ageing, rotations, pose changes, noise, size, cluttering and resolution, twins, and so on[24] [25] [26] [27] [28]. These are the most critical and popular problems in these two areas.

I.4.4 Applications:

Nowadays, we can find that there are familiar applications for face recognition in various fields. The most common applications are surveillance, security, entertainment, access control, suspect tracking, and forensic [29]. Kinship recognition is the most interesting aspect related to the relationship of people in the images, and has a significant influence on real applications and many areas.

The difference that we can observe in this regard is the security and monitoring which is a concern and dominates most of the facial recognition applications, and is also used extensively by government agencies. While the kinship is concerned with studying the biological relationship between people and is also utilized more broadly by the people and less by government agencies.

I.4.5 Features:

The best way to identify, emphasize the resemblance, and realize a person is to have face imprinted in the memory, by understanding the physical structure of face and features which are not affected by deformed other features. This matter is different for kinship; an image of the face of a relative person should be printed already in memory. The purpose of features extraction is to find a distinctive representation of data that can shed light on the relevant information. In fact, the facial features are the most important and sensitive, and directly impact the effectiveness of verification and identification for both face and kinship.

The circumstance surrounding the design of facial recognition and kinship systems, such as expressions, pose, twins, and so on, have contributed to the complexity of choosing and extracting the most appropriate features. In the coming few lines we will seek to answer the following question, Can the features or cues that have been used in facial recognition to succeed in determining kinship, or vice versa? In other words, Is there a difference between the features? Probably, the answer to this question is not as easy as expected, due to the lack of experiments and researches on kinship. Regardless, we will strive to give the reader a brief overview to some extent our current understanding. We wonder whether all regions (features) of face are in the same of importance when we attempt to discriminate faces? Indeed, facial features are not on the same rank of recognize face and kinship [30] [31]. So, do we concentrate deeply on some features than others? Some studies have shown that the most important features in face recognition are eye, nose, and mouth, respectively [32]. In another study, reported that hair, face outline, eyes, and mouth are the important features [33]. Moreover, the performance accuracy of the eyebrows has great importance compared to the eye and the rest of the above-mentioned features [34]. With regard to kinship, genetics studies-like areas on the faces of the immediate family members are limited to certain parts, eyes, nose, and mouth [35]. However, the idea of restricting specific features to determine kinship is a sensitive matter. In addition, the feature found in the upper part of the face is considered more useful and more accurate than the bottom in both systems [36] [37]. There are studies showed that the distinctive faces and odd features (such as large eyes, twisting the nose, the parts of the basic facial features, etc.) are better and faster for recognition than regular faces in both face or kinship [38] [33]. There are experiments (both in the face or kinship) reported that the movement of faces (dynamic features) provides useful information to facilitate identification [39] [30] [33]. Moreover, we want to note that most of the features that have been used in facial recognition has been utilized in determining kinship, such as PCA, LBP, geometric, textures, SIFT, and others. The obvious question that deserves to answer is: Is it possible for features, algorithms, and techniques designed for facial recognition used to address the problem of kinship? The answer to this question may be unavailable at this time due to lack of studies and experiments.

I.4.6 Processes:

The process of the identity or face recognition and kinship is carried out by examining of critical and dominant features found in facial features and comparing them with those that have been derived from another faces, this also is one of the obvious things in common between the two concepts. Moreover, there is almost a clear convergence between the successive steps in order to achieve the purpose of two different goals. In addition, the processes of verification and identification mode steps for both systems are almost equal. The essential stages for both systems can be pass through: (1) acquiring the images, next (2) pre-processing and face detection, then (3) extracting the inspiring face features, followed by (4) comparing between the targeted image and the rest of the images located in the database as a prelude to classify, concluded with (5) presenting the consequence of comparison which will be either:

– Identity recognition: matched or non-matched when the context is in the verification mode, or accepted or rejected when the context is in the identification mode.
– Kinship recognition: kin or non kin when the context is in the verification mode, or identifies relation degree or rejected (non-kin) when the context is in the identification mode.

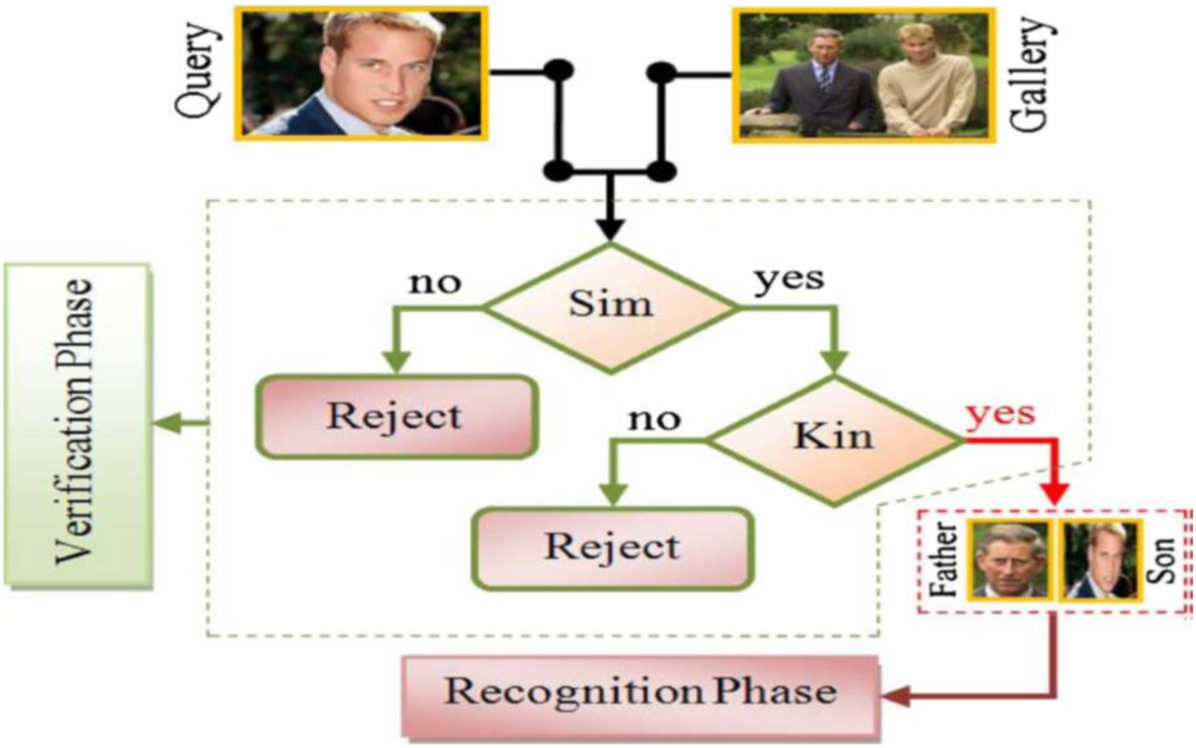


Figure.3 *Flowchart to understand the difference between kinship verification and identification*

I.4.7 Kinship recognition methods:

According to the taxonomy shown in Figure. 4, the methods of kinship recognition can be roughly divided into two groups: feature-based [40] [41] [42] and learning-based[43] [44] [35].

In addition, it worked either based-image or based-video [40].

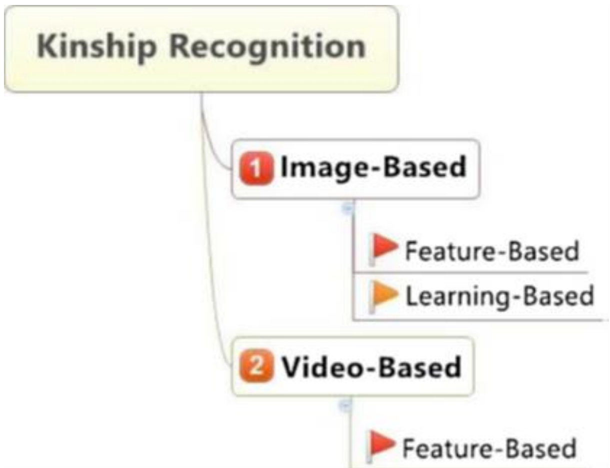


Figure.4 *Taxonomy of kinship*

I.5 Motivations and applications:

In today's real-world contexts, face recognition has become more relevant, active, and widely used. Digital photographs are becoming a modern identity marker for people because of technological advancements such as high-quality digital cameras, mobile devices, and the Internet. As a result, the study of kinship through faces has increased in popularity and scientific significance. The relationship between the people in the pictures is the most fascinating feature of people-centered photography.

The ability to recognize people and their relationships from photographs has important social and commercial implications. Furthermore, the parameters, methodology, and algorithm used in kinship recognition studies vary from those used in other studies from one program to the next As a result, selecting a real-world application, such as family album organization, might be a good place to start To resolve the issue of kinship, this is a starting point and a fundamental foundation. This inspiration is close to what finds in his work [45] [46].

Modern biological measures are available, but the majority of them are ineffective on a large scale. For example, DNA testing is commonly used in fatherhood identification and crime scene investigations, but the time-consuming process takes days to complete and is costly.

Computer vision techniques may provide a new dimension to the quest for family kinship in a timely and cost-effective manner [40].

We intend to use the biological relationship and similarities between traits found in the same family to build a computer framework that can identify kinship and apply it to a variety of applications [47] [35]. Other possible projects in this domain include information/image retrieval and social media research, all of which depend on the findings and results in terms of kinship solutions.

Such programs should devise methods for overcoming the difficulties that emerge from kinship.

Most digital cameras can currently focus on and capture human faces at a camera lens focus point in the consumer market; in the future, a camera that can focus on family faces rather than other faces in the background in-group images could be created.

In addition, albumin apps and social robots might be able to tell the difference between family members and impostors [40]. When attempting to recognize a person whose face sample was captured a long time ago or when no sample is available, kinship recognition becomes more difficult [40].

Because of the above motivations and the rapid growth of multimedia, kinship verification has a major influence on real-world applications and a wide variety of fields. The following are some examples of future applications:

- ✓Historical and genealogical studies
- ✓Forensic science
- ✓Finding lost relatives
- ✓Child trafficking and smuggling
- ✓Social media review
- ✓Creating a dynamic connection tree from images and family album organization
- ✓Automated management and labeling/annotation of image databases
- ✓Recognizing relatives from a photo set and image retrieval

Finally and going back to where we started, the study of kin relationship is a subject of great scientific interest. Several applications in this area, such as social media analysis or finding missing family members, can be improved with the significant developments in computer vision techniques. However, research on this subject remains complex and challenging. To achieve the goal of kinship verification and recognition, analyzing kinship through human faces must be conducted comprehensively. The aforementioned motives and

applications attract a significant number of researchers to present their contributions in this area. Evidently, research in this domain is still active.

I.6 Kinship problems and challenges:

In reality, in order to develop an effective solution to the kinship problem, we must first recognize the issues and obstacles that obstruct the achievement of the ultimate goal, which will help us, understand the issues and provide a roadmap for developing a framework that can automatically identify kinship relationships. Age, gender, and other factors all contribute to complications illumination, pose, or even a passing resemblance between distant relatives Automatic kinship recognition is a wider and more complex issue than conventional face verification and identification because of these complications.

The issues are divided into two categories: (1) specifically challenging (related to kinship) and (2) indirectly challenging (not related to kinship) (related to the environment of the database). Many previous studies have established four major issues in terms of the directly challenging problems [47] [43] [48] [35], namely I confirming feature similarity between kin, (ii) confirming the presence of kinship, (iii) defining the exact form of kin relationship, and (iv) differences in age and gender.

I.6.1 Verifying feature resemblance between kin :

This problem can also be called distinctive feature extraction. The features can be considered as a major problem in determining kinship. Feature extraction is most sensitive and important, and directly influence the effectiveness of the verification and recognition tasks.

The idea of selecting and utilizing specific features is considered extremely complicated [49] [47] [43] [50] [51] [35] [38]. Familial features have particular properties for each certain pair of family members [41]. For instance, sons or daughters may inherit features from their parents in a different way. In other words, when relying on genetics to solve the kinship problem, the laws and principles of heredity pose another challenge. Therefore, we have to be familiar with the traits or features that can be attributed to genetics and the transition

between generations as well as the traits or features that are non-inherited and acquired from the environment. In addition, the extent and point of similarities (kin can have similar eyes, nose shape, and forehead) vary from person to person, which causes difficulty in establishing kinship using facial images only [52]. Therefore, we may resort to the use of contextual information and metadata [35]. To illustrate this problem, given two images of two persons, we must initially determine the situations or challenges in distinguishing the resemblance of features between images. This step will assist us to comprehend the problem extensively and to develop a system to better recognize kinship automatically. Previous studies lack investigation and analysis of these challenges.

Based on the aforementioned finding regarding feature-based methods for kinship verification, the following conclusions can be made. First, most of the results of the feature-based method are unsatisfactory even if more than one feature was used to get more efficient results. Second, the highest result we have acquired does not prove that the features used can address the problem of kinship most effectively. Third, the approach may not be well designed to take advantage and exploit these features in term of age adaptation and gender variations. Finally, a set of three questions have to be considered and placed side by side to address the feature-based problems in kinship recognition and verification.

To the best of our knowledge, previous studies have not discussed the following questions.

i What is the difference between using the features extracted for face verification and using them for kinship verification?

ii Which facial features are most likely or crucial to provide significant kinship verification clues and kinship identification clues? Is there a difference between these two kinds of clues?

iii What is the best method or approach to represent the features?

I.6.2 Verification of existence of kinship:

The second direct main problem related to kinship is discussed in this section. The use of facial images for kinship verification is used to determine whether two people are related by blood. The method of kinship verification is used to quickly classify certain potential candidates that have high similarities based on facial images while looking for missing family members, such as identifying a missing child among thousands of children. The backbone of kinship authentication and kinship recognition is the discovery of discriminative facial features.

As a result, we must first solve the problem of locating these distinguishing characteristics. To solve this problem, we need to build a system that can properly use these features as proof in detecting the presence of a relationship. Many previous studies, such as those by, have concentrated on how to resolve or solve the problem of kinship verification [47] [41] [43] [35].

1.6.3 Identification of the degrees or classes of kin relation:

This section discusses the third direct main problem related to kinship. Kinship identification through facial images is intended to identify the degrees or classes of kin relation. Solving the problem of kinship verification is a prerequisite to this step. The applications related to kinship are different in terms of requirements. For instance, when kinship relation exists and the type of this relation is known, building a family photo album from social media websites is possible. Moreover, the treatment of this problem differs depending on the classes or degrees of kinship, such as family relationships (4-relations and 7-relations) and siblings. Unlike kinship verification, kinship identification received modest attention in previous studies [45].

I.7 Architecture of automated kinship recognition:

The mechanisms underlying kinship recognition are likely to vary from one application to the next at first. There has been a lot of effort put into resolving kinship problems. Furthermore, the scientific group has adopted convergent methods to some degree. As shown in Figure. 5, automated kinship recognition on facial images usually consists of six main steps, beginning with preprocessing and ending with verification and recognition. Most of the time, a still image is often used as the input to the kinship verification and recognition scheme. Two photos are used as inputs: one is a family photo of family members, and the other is a question or test photo of a single person. The automated kinship verification and recognition system goes through six phases to verify any kinship connection between any family member and the person, as well as recognize the relation's class. Each step/phase of the process/phase is briefly described below.

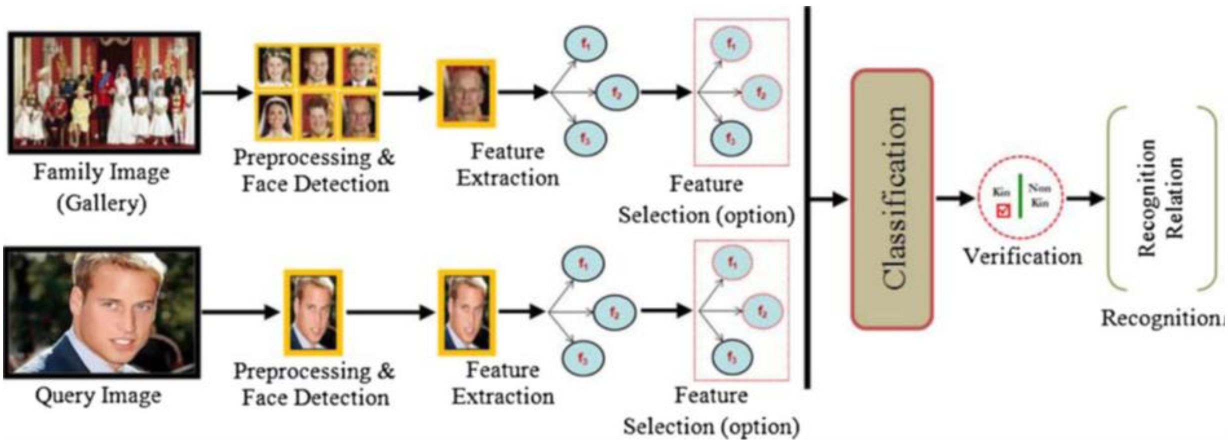


Figure. 5 *General automated kinship verification and recognition system*

1. Input (face datasets): includes public Figure face images of family members. Therefore, the face images are captured under uncontrolled environments with no constraints.

2. Pre-processing: is an important component. In order to localize the face of the image, this latter is then cropped, such that the non-facial regions such as the background and hairs were removed and only facial region was used for kinship verification. If those are color images, they converted into gray-scale images. For each cropped image, histogram equalization was applied to mitigate the illumination.

3. Face describing: the best way to learn kinship analysis is first to learn how to recognize the different facial features for children, and then learn how to relate them to their corresponding parents. Facial features must be described in a way that enables them to be efficiently descriptors.

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

I.8 Conclusion:

In this dissertation, we provided a comprehensive discussion of the important concepts needed to understand kinship recognition through still facial images. We have assessed former approaches to the kinship problem in most aspects. Through the presentation of literature, we explored the problems and issues that affect the efficiency of a kinship recognition model performance. In addition, we showed technologies and features that have been used in previous studies. We also explained the distinctive features that are commonly utilized to serve as yardsticks in measuring efficiency of kinship verification and identification that may have increased or reduced the severity of problems and challenges. Moreover, we presented common benchmark databases that have been widely used by many researchers.

The performance of a recognition system largely relies on representations of feature. For this, we recommend taking advantage of the Deep Learning (DL) technique in order to addressing this problem. Because, deep learning recognition methods automatically learn and understand features from a massive amount of data like text and image, rather than designing features manually. Accordingly, we can gain useful features to perform tasks without much effort and request expertise. In this, that automatically features derived from learning algorithms can provide highly informative representations for a classification task and thus lead to improved accuracy. Finally, we can conclude from the foregoing that in some certain cases the overall rate of the machine ability to recognize the kinship is better than human ability. In addition, there are problems, issues and challenges related to kinship, which has not yet been solved. Moreover, verification and recognition of kinship has a significant impact on real applications and many areas. Nevertheless, in computer vision, the number of studies and researches in automated kinship is very limited. The aforementioned points motivate researchers to explore in depth the automated kinship verification and identification and contribute in the improvement and development of methods and algorithms. Research in kinship domain is still new and further exploration will definitely open up to new more interesting direction. In the foreseeable future, the products of this research will bring advantages to various domain area and benefit to mankind.

Chapter II

Related Studies on Kinship Verification

II.1. Introduction:

Google Scholar automatically attests to the extent of interest in kinship identification. Since the beginning of 2010, a search for the words "kinship identification by facial images automatically" yielded less than 50 papers. To our knowledge, Fang et al. (2010) published the first machine study of kinship. These articles concentrated on kinship authentication rather than kinship recognition or both, despite the fact that automated kinship has a number of issues. Furthermore, researchers use a variety of methods and algorithms to automatically extract kinship features and solve kinship problems. The automated kinship system is being investigated the majority of these papers don't go into great detail about the issues, which is possibly due to the topic's novelty in the field of computer vision.

However, as a result of developments in psychology, specific biological growth, and other factors, researchers' emphasis has shifted to developing algorithms that decide whether a pair of facial images belonging to the same class are kin or not. Analyzing kinship through human facial images is a difficult job, and only a few attempts have been made, according to the literature. The research on kinship classification and verification is still in its early stages, with the aim of improving the accuracy of kinship system performance by improving facial feature extraction and classification techniques and overcoming influencing challenges.

Many previous researches used the K-fold and leave-one-out validation procedures. Although there are several different types of classifiers, the support vector machine (SVM) is the most widely used. Furthermore, despite the significance of the feature selection (FS) mechanism in identifying the most discriminative features, only a few previous studies have used it. In reality, a few studies used a feature selection technique to obtain good features, with the minimum redundancy-maximum-relevance (mRMR) feature being the most common. In addition, the degree of kinship connections varies. It may be a sibling relationship (brother sister, brother-brother, or sister-sister) or a 4-, 7-, or 9-relationship between parents and children (previously mentioned). There were only three studies that looked at sibling relationships. The highest classification rate in these studies was 81.9 percent. A total of thirteen studies looked at parent-child 4-relationships. Using ground reality, the best accuracy score was 82.50 percent. Three research looked at seven-relations, with the highest classification rate of 75.2 percent. It is demonstrated that no research has looked into 9-relations.

When it comes to achieving high results, age gap is both a challenge and a benefit. When it comes to sibling relationships, age gap has a minor impact, but it has a significant impact on child-parent relationships. Our research into the impact of age differences between siblings and in 4- or 7-child-parent relationships was prompted by this finding.

Deep Learning (DL) has become relevant and commonly used in recent studies due to some drawbacks suffered by the features. Many applications that use deep learning technologies to increase kinship recognition classification rates have been observed. Many real-world apps, such as Microsoft, Google, Facebook, and others, have taken note of this trend.

We agree that deep learning has a lot of potential for enhancing and improving kinship recognition intelligence.

Furthermore, we observe that the lack of large databases can have a negative impact on the evaluation of kinship recognition algorithms. We believe that creating a standard repository of kinship datasets would promote further research into algorithm testing and act as a benchmark for future research.

II.2. Kinship Verification:

The person's facial appearance is a primary source of knowledge about their identity, gender, race, emotional state, head pose, age, and kinship relationships. As a result, facial perception influences individual perception, interpersonal attraction, and, as a result, pro-social and social activity [53] [54], and [55] Automatic kinship recognition from facial appearance is a difficult issue that has been extensively explored across many fields, including psychology [56] [57] [58] medicine anthropometry .Human Behavior and Evolution Society and more recently in computer vision and machine learning and recently in computer vision and machine learning [59] [60].

We use computer vision techniques to automatically detect relationships between two people based on their faces in this dissertation. Facial kinship verification is a module that examines pedigree construction and computes similarity indices for various facial traits. While this issue has many fascinating applications, such as organizing family albums, locating lost children, and using social media, it is still difficult to use in real life because there are often significant variations in posture, voice, lighting, age, and ethnicity, particularly when face images are captured in unconstrained environments.

The findings of kinship verification studies in psychology and sociology are as follows [59] [60]:

1. Humans are capable of recognizing kinship relationships between strangers.

2. Human faces provide important cues for determining kinship relationships between people.

3. Because facial appearance has been found to be a useful cue for genetic similarities, previous research has attempted to classify which facial features humans use to recognize relationships between individuals.

Researchers explored the kinship verification problem from facial images, seeking to create computational models and algorithms to automatically verify kin relationships between people, inspired by the findings and results of psychological studies and capitalizing on recent developments in computer vision and machine learning. Father son (F-S), father-daughter (F-D), mother-son (M-S), and mother-daughter (M-D) are the four forms of kinship relationships that are usually considered (M-D).

The challenge of kinship verification has attracted various levels of study in recent years. The first researchers to take on the kinship verification challenge were Fang et al., who extracted low-level features from facial parts in 2010 [61]. Researchers began looking into this issue in 2011 with many mid-level features. Some researchers have recently used high-level feature representations [62].

Fundamentally, two major kinship verification problems are discussed. The first is concerned with the database's environment, including age, lighting, facial expression, pose variations, resolution, and rotations. The second is about kinship itself, and it is focused on determining the nature of kinship by comparing feature similarities between kin. Furthermore, feature extraction is critical and responsive because special features have a visible effect on the recognition system's performance.

The task of kinship verification-based feature extraction is the subject of this study. We present an original investigation into detecting the most significant characteristic features of human faces, which should aid in improved kinship verification results.

II.3 The newest technology, ideas, and features in kinship verification:

Face recognition is the automatic identification or authentication of an individual based on their facial physiological characteristics. Over the last few years, face recognition has become a common research subject in image processing, computer vision, and biometrics, and one of the most promising applications in image analysis. Face recognition technologies are becoming more popular in the enterprise and security screening markets, making them a viable alternative to traditional methods. Family (kinship) authentication is the name for this technology. This idea is focused on the study of family relationships.

Automatic kinship verification aims to recognize the degree of kinship of two individuals (e.g. parents and children) from their facial images.

Researchers have been paying close attention to the issue of kinship verification in recent years. The topic's potential applications, especially in social data mining, have piqued people's interest.

Fang et al. were among the first to investigate kinship authentication [61]. As seen, the database used included 150 pairs of images taken from the Internet. They used the Pictorial Structures Model, which represents an entity as a series of parts organized in a deformable pattern, to locate facial parts (eyes, nose, mouth, and so on). Then, from these pieces, they extracted a collection of 22 low-level functions, including:

- ✓ **Color parts:** the central location of the facial part is determined, and the color at this stage, such as eye and hair color, is used. The middle of the nose was used to represent skin tone. To obtain the most frequently occurring color in this area, a sub window of the top of the image was taken, and a mode filter was added to this sub-window.
- ✓ Facial parts (geometry): they detected the central position and the boundaries of each part. With these image coordinates, they extracted the sub-window for each face.
- ✓ Facial Distances: distances between parts are calculated using the Euclidean distance.
- ✓ Histogram of Gradients feature (HoG).

Several scientists have investigated kinship verification using facial pictures, and various approaches have been suggested as a result of the preliminary findings. This techniques can be classified into two categories. The first is focused on techniques based on Hand-Crafted Features. The second is focused on Deep Learning Feature-based algorithms.

Various metric learning methods, on the other hand, have been investigated for tackling the facial kinship verification issue. In addition, several protocols are suggested. Some of the other key features used in facial automated kinship authentication are described in Tables 2.1 and 2.2.

Paper	Year	Database	Features
[20]	2010	CornellKinFace	Face appearance & geometry
[21]	2011	UBKin Face	Gabor
[41] [44] [48]	2012 2012 2012	UBKin Face IITD Kin UBKin Face	Gabor DoG salient points Binary, Relative attributes
[40] [13] [49]	2013 2013 2013	Family 101 UvA-NEMO Smile CornellKinFace	SIFT Dynamic features, CLBP-TOP, CLBP Geometric, WLD
[42] [50] [51] [52]	2014 2014 2014 2014	KinFaceW-I & II KinFaceW-I & II CornellKinFace UBKin Face KinFaceW-I & II Family101	LBP, LE, SIFT, TPLBP LBP, SIFT, SPLE LE, LBP, TPLBP, SIFT LBP, Grassman Manifold
[53] [54] [43] [55]	2015 2015 2015 2015	KinFaceW-I & II KinFaceW-I & II TSKinFace KinFaceW-I & II CornellKinFace UBKin Face	LBP, SIFT, SPLE LPQ, TPLBP, FPLBP, WLD SIFT LBP, SIFT
[56] [57] [58] [59]	2016 2016 2016 2016	KinFaceW-I & II KinFaceW-I & II KinFaceW-I & II KinFaceW-I & II	LBP, HOG LBP, HOG HOG, SIFT SIFT
[60]	2017	KinFaceW-I & II	LBP, DSIFT, HOG, LPQ

[61]	2017	UvA-NEMO	BSIFTOP, LBPTOP, LPQTOP
[62]	2017	KinFaceW-I & II	LE
[63]	2017	KinFaceW-I & II	LTP
		KFVW	
[46]	2018	KinFaceW-I & II	LBP, HOG
[64]	2018	CornellKinFace	BSIF, LPQ, CoALBP
[65]	2018	TSKinFace	LBP, HOG
[66]	2018	KinFaceW-I & II	LBP, HOG, SIFT, LPQ, WLD
		KinFaceW-I & II	

Table 2.1: *Summary of the Hand-Crafted features.*

II.4 Features extractions based on Hand-Crafted Features:

Traditional handcrafted features became the most common tool for assessing facial kinship (shallow structure). Hand-crafted features descriptors include the Histogram of Oriented Gradients (HOG) [63], Scale-Invariant Function Transform (SIFT) [64], Gabor Filter [65], Local Binary Pattern (LBP) [66], Local Phase Quantization (LPQ) [67], and others. These characteristics, on the other hand, are determined by an object's surface properties and shape, which are determined by the form, size, composition, density, and proportion of its elementary components.

II.4.1 Features based on the overall appearance

This section presents several methods for facial kinship verification. In the following, we detail the steps of the methods. The schematic diagram of this system is shown in Figure.6.

Global appearance based methods try to find a suitable representation of the whole image, all pixels are regarded, by approximating (reduce the dimension) the original data and keeping as much information as possible. Therefore, the features are represented by the vector containing the weights of a linear combination of the basis vectors. The main feature of the global appearance based is that they capture both facial texture and geometry information.

II.4.2 Features based on local texture:

Local texture descriptors represent certain region properties by multi-dimensional histograms. Very often geometric properties (e.g. location, distance) of interest points in the region (corners, edges) and local orientation information (gradients) are used.

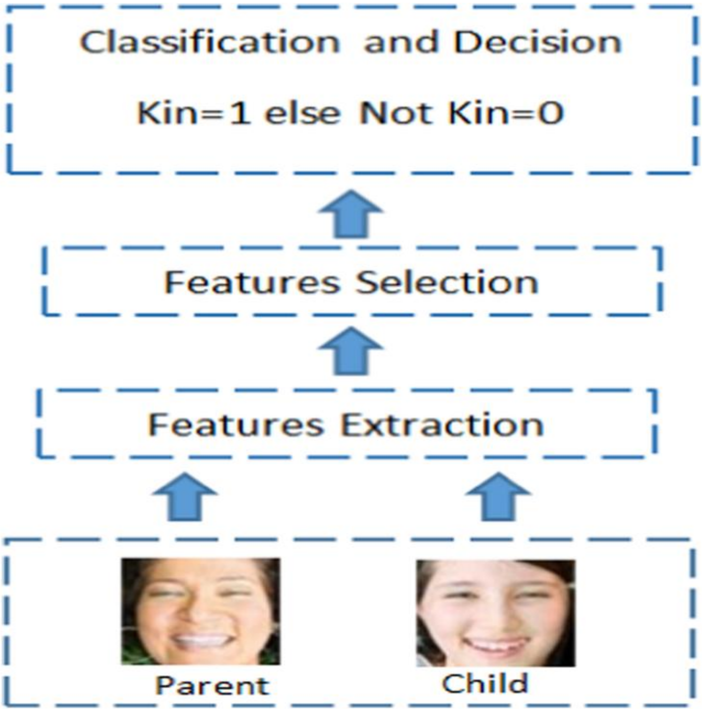


Figure. 6 *Block diagram of the kinship verification system using face images*

II.5 Features extractions based on learned (No Hand-Crafted) features:

II.5.1 Deep learning based features:

Deep learning is proposed to eliminate the dependence on handcrafted features and learn features from pixels directly. Deep learning has been recently outperforming state-of-the-art in various applications in general and faces recognition in particular [68–69]. However, deep learning recognition methods automatically learn, understand, and design features from an image manually. It requires recognizing visual patterns from pixels directly with minimal pre-processing [69], and it provides robustness to geometric distortions and transformations, and other 2D shape variations, such as illumination, pose, and scale.

Paper	Year	Database	Approach
[77]	2014	KinFaceW-I & II	Discriminative neural network layer
[79]	2015	KinFaceW-I & II	Deep Convolutional Neural Networks (CNN)
[78]	2016	KinFaceW-I & II	Similarity Metric Based Convolutional Neural Network (CNN)
[61]	2017	UvA-NEMO Smile	Deep Convolutional Neural (CNN)
[80]	2018	KinFaceW-I & IIe CornellKinFace TSKinFace	Deep Convolutional Neural (CNN)
[81]	2019	KinFaceW-I & II CornellKinFace UBKin Face	Deep Neural Network (DNN)

Table 2.2: Summary of some proposed deep learning methods

II.6 Kinship Verification Setting:

To evaluate the performance of different kinship verification algorithms three setting has been proposed in the FG kinship competition. (The 2015 IEEE International Conference onAutomatic Face and Gesture Recognition, Ljubljana, Slovenia.).

The unsupervised setting, image-restricted setting and image-unrestricted setting. For each face image, they extracted two different feature descriptors: the LBP and HOG.

• Unsupervised setting: No labeled kin relation information is used. Given a face pair, the cosine similarity of their features is used to compute their similarity directly.

• Image-restricted setting: Only the given kin relation information is used in the training splits. For each face image, we first apply PCA to project feature into a low-dimensional feature vector and then Side-Information based Linear Discriminant analysis (SILD) is employed to learn a distance metric. Specifically, the positive pairs and negative pairs in the training set were used to estimate the within-class and between-class variations of LDA. Finally, the cosine similarity of each test pair in the learned LDA space is computed.

• Image-unrestricted setting: The identity information of the person is available to potentially form additional negative pairs in the training splits. For each face image, PCA is first used to project feature into a low dimensional feature vector and then neighborhood repulsed metric learning (NRML) is employed to learn a discriminative distance metric. Specifically, the label of training sample is used to seek the most similar intra-class neighbors to learn the distance metric.

Finally, the cosine similarity of each test pair in the learned NRML space is computed.

II.7 Conclusion:

We provided an outline of automated kinship verification from faces in this chapter. We gave several ideas as well as a few definitions. The design of the facial kinship verification system is explained. We also listed a number of practical issues that affect facial kinship verification and described the current databases. In addition, we provided the major state of the art as well as an overview of automatic kinship verification techniques. We covered various commonly used approaches, which were classified as Hand-Crafted Feature-Based Methods and Deep Learning Feature-Based Methods. In kinship verification problem, deep learning approaches are proposed were numerous layers of information processing stages are exploited, and deep learning was implemented by convolutional neural network to feature extraction based and classification based. Also, different kinship verification setting has been checked to evaluate the performance of the system.

Chapter III

Kinship Verification Methods

III.1 Introduction:

The methods for extracting features and classifying them are covered in this chapter. A face picture is a vital hint that provides a lot of info about a person's identity, race, gender, age, expression, ethnicity, and so on. As a result, determining what types of traits help to identify ties and how those features are represented to determine the relation becomes a huge difficulty and a significant hurdle in kinship estimation. The features extraction step must be prioritized since it has a significant influence on the recognition system's performance. This chapter begins by introducing the features extractions based on No Hand-Crafted feature (Deep Learning) an important cues are used such as ***DCTNet***

Secondly, we focus the research on kinship classification and techniques used to improve the accuracy of system performance. Kinship Verification is bi-classification problem where the pair of input faces are classified as positive (the true pairs of parents and children) or negative (the false pairs of parents and children).

III.2 Deep Learning for Features Extraction:

Feature extraction from a face can be defined as the process of locating and extracting useful features 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 [70, 40]. Genetics studies show that resembling regions on faces among immediate family members are mostly concentrated on eyes, nose, and mouth [35]. The features that can distinguish true pairs from the false ones are facial visual attributes [38], facial appearance [35], geometry, color and texture [47, 51], contextual information [18, 35], or a mixture of those features [35]. Figure 7 represents facial features based on parts instead of the full face to address the kinship classification problem.

Through the features that have been used in previous studies, we observe that the highest percentage of accuracy [38], was obtained using a group of features, including mid-level features, binary attributes (e.g., “male,” “has glasses”), relative attributes (e.g.,“bigger” eyes, “heavier” eyebrows), and Multi-Label Learning with Label-Specific Features (LIFT) to extract binary attributes with ground truth attributes in the UB KinFace database [35].

The lowest percentage, 55.3 % [35], was obtained using salient or key points and difference of Gaussian (DoG) features in the UB KinFace database [35]. In addition, a study using a group of geometric and textural features, and a previous work using a group of geometric (NPOS, SEGS, ANGLES, and DTR), textural (RIC-LBP, RIGF, and LID), and holistic (PCA) features achieved between 81.2 and 84.8 % in the HQ faces and LQ faces database [70]. This give information that facial region information is more effective than the whole face.

It is also known that feature-based (local) and holistic-based (appearance) features are useful to determine kinship. Nevertheless, according to the study carried out by [74], they found, that the facial region features is more efficient than the whole face. However, from our perspective, it cannot be determined the features because the problem of kinship are addressing is more than just perspective. Therefore, this matter needs to be investigated more deeply. Furthermore, the former studies of kinship recognition mostly dependant on the supplied information i.e. (a user will select the features which best describe the kinship facial characteristics).

This approach however contradicts with the way deep learning handle the kinship problem. Deep Learning (DL) considered the best choice to verify and identify kinship, because it learns, extract and represent features automatically instead of selected manually. Thus, such method leads to improved accuracy performance.

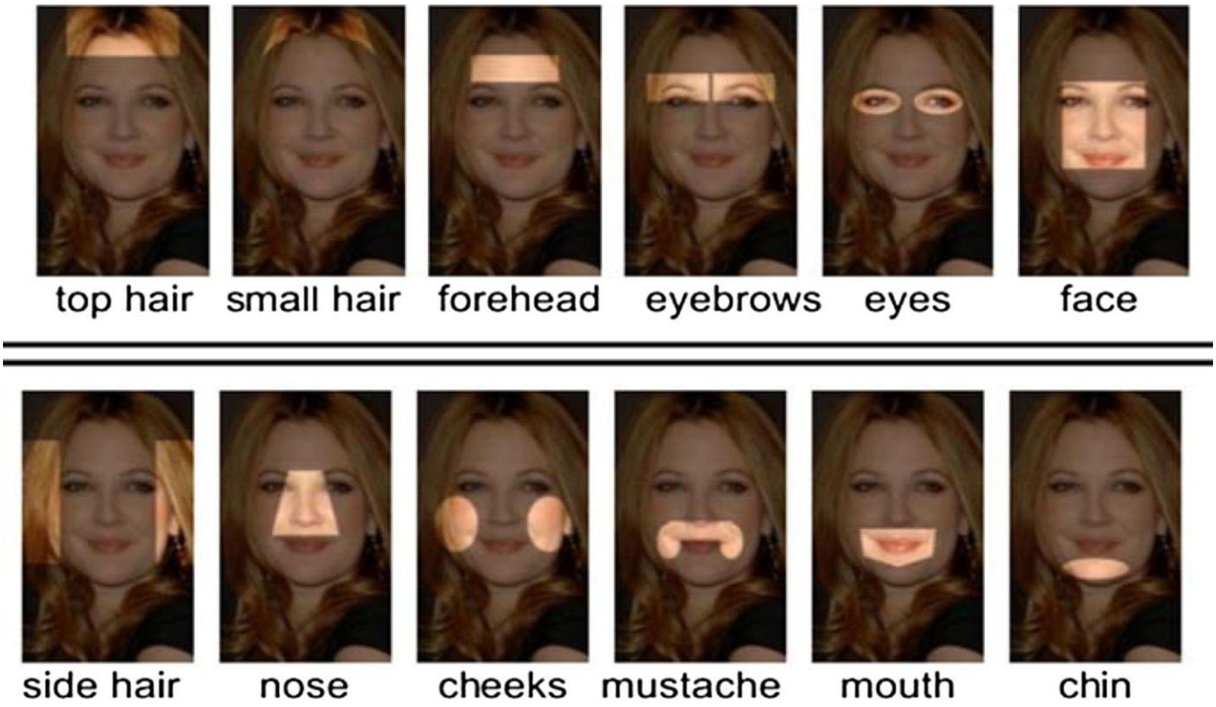


Figure 7. *Twelve parts represents the facial features*

III.2.1 Discrete Cosine Transform Network (DCTNet):

Deep learning has been proposed as a way to remove the need for handcrafted features and learn features directly from pixels. Deep learning has recently outperformed the state-of-the-art in a variety of applications, including face recognition. Deep learning recognition methods, on the other hand, automatically learn, understand, and build features from an image. It necessitates directly identifying visual patterns from pixels with minimal pre-processing, and it ensures that geometric distortions and transformations, as well as other 2-D shape variations like lighting, pose, and scale, are not affected. The steps in our approach using the Discrete Cosine Transform Network (DCTNet) are as follows:

1. Filter Banks: Discrete Cosine Transform (DCT) filter banks based on 2D-DCT. The fact that a 2D DCT basis is a good approximation for high-ranked eigenvectors motivates this. From 1D-DCT, the transformation of 2D-DCT can be expanded as follows:

$$f(x,y,u,v) = C(u)C(v)\cos\left(\frac{(2x+1)u\pi}{2N}\right)\cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (3.1)$$

Where:

$$C(u) = \begin{cases} \sqrt{\frac{1}{N}}, \text{ for} \quad \mathrm{u} = 0 \\ \sqrt{\frac{2}{N}}, \text{ for} \quad \mathrm{u} = 1,2, \ldots . \mathrm{N} - 1. \end{cases} \quad (3.2)$$

2. Convolution layers: There are two convolution layers in the network. Since each layer's DCT basis can be combined to create a single layer network. The real-valued outputs are formed by DCTNet's final convolution layer. The following is the output of an input image Id of size nm with D channels:

$$O_d^p = \{I_d * W_p^l\}_{p=1}^{p_l} \quad (3.3)$$

where $*$ denotes the discrete convolution and the size of output O_d^p is same as I_d and $W_p^l \in R^{k\times k}, p = 1,2,\ldots,P_l$ is 2D-DCT bases from P_l filters at layer l. Of each layer, we have d outputs.

3. Binarization and Block-wise Histogramming: Each set is binarized separately by first binarising the responses with a threshold of zero. By thresholding to zero (value 1 for a positive answer, zero otherwise), the real value of the last convolution layer is converted to a binary format, denoted by BIN:

$$BIN(O_d^p) = \begin{cases} 1 & \text{if } O_d^p \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.4)$$

Where BIN(Op d) is a binary image. Then, each of these binarized images is partitioned into non-overlapping blocks. The characteristics of these images are obtained by concatenating all the histograms of each block B such as:

$$H = \{H_b^d\}_{b=1,d=1}^{B,D} \quad (3.5)$$

Where: $b = 1; 2; :::; B; d = 1; 2; :::; D$

The combination of binarization and block-wise histogramming is expected to be able to extract discriminative features.

4. Histogram Tied Rank Normalization (TR normalization): TR normalization is used to minimize histogram vector disparity. Intra-normalization and robust statistics use the tied rank theory. TR normalization takes H, the image's extracted block-wise histogram, and produces v, the TR normalized histogram function vector. Given H as the extracted histogram where

$$H = \{H_b^d\}_{b=1,d=1}^{B,D}$$

The histogram TR normalization is presented in Algorithm 1.

Data: Extracted block-wise histogram or an image. Result: TR normalized histogram feature vector: v Compute $\overline{H_b^d}$:

Calculate v_b^d; Normalize v_b^d :

Concatenated al l $v_b^d . v = \left[\hat{v}_1^1, \hat{v}_2^1, \ldots, \hat{v}_B^1, \hat{v}_1^2, \ldots, \hat{v}_B^D \parallel \epsilon R^{(2^P L)BD}\right.$

Algorithm 1: Histogram TR Normalization

We detail each step of the previous algorithm in order to provide a full overview of the histogram TR normalization methodology:

(a) We compute tied rank without bin with zero occurrence for each Hd b, yielding Hd b. This is because in a histogram, a bin with zero occurrences is not a sample. In the ranking method, it should be overlooked.

(b) Calculate v_b^d where $v_b^d = \sqrt{\overline{H_b^d}}$.

Normalize v_b^d with L_2 norm to obtain v_b^d c

(c) The final TR normalized histogram feature vector is obtained by Concatenate all $\hat{v}_b^d$. Where $v = [\hat{v}_1^1, \hat{v}_2^1, \dots, \hat{v}_B^1, \hat{v}_1^2, \dots, \hat{v}_B^D] \in R^{(2^P L)BD}$.

We use a deep learning machine, which has several levels of information processing steps. The input of the network is a gryscale picture to extract the discriminating characteristics for kinship verification.

The picture is then subjected to a 2D DCT filter bank to remove the most important inherited characteristics. As seen in **Figure. 8**, some areas of the face have a higher frequency, such as the eye and nose, while some others, such as the frontal face, have a lower frequency.

These filters produce only the most popular facial features. The visualization's light blue and yellow regions illustrate the inheritable genetic trait regions in the kinship images. The base collection is a critical problem to solve when incorporating 2D DCT basis into the network as a filter bank.

The prior knowledge of human face characteristic is taken into account. Since human face distinct features are composed of more high frequency horizontal components (eyes, eyebrows, and lips) than low-frequency vertical component, it is natural to rank the 2D DCT basis by horizontal-frequency major order. The DCTNet keeps the importance of horizontal frequency direction at each turn to extract inherited feature passed from parents to his children that are a result of genetic inheritance.

On the other hand, block-wise histogramming, which is capable of implicitly encoding spatial information of image regions, is useful for the classification task. We propose an efficient method normalisation (TR normalisation) to regulate the histogram of DCTNet for robustness. We adopt the ranking idea by quantifying the correlation between variables.

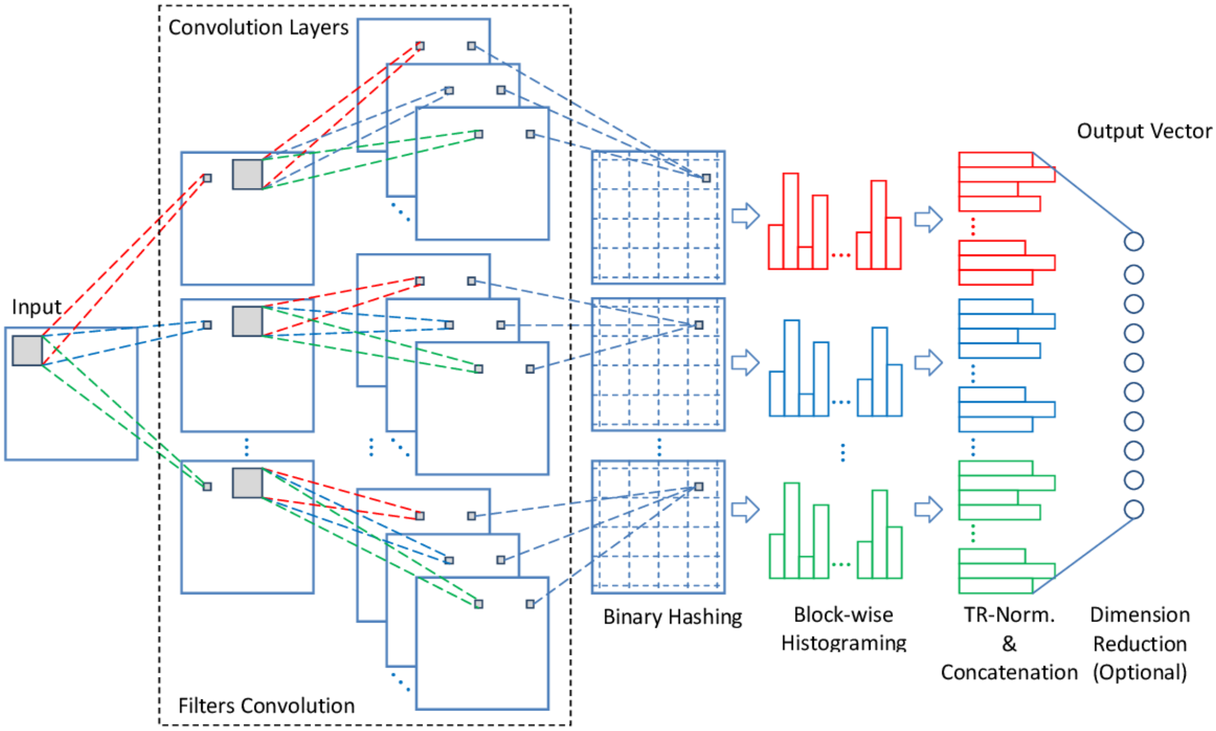


Figure 8: *The block diagram of DCTNet*

III.3 Classification:

Kinship verification is a bi-classification problem in which a pair of input faces is labeled as either positive (true pairs of parents and children) or negative (false pairs of parents and children) (the false pairs of parents and children). The task was completed using nearest neighbor classifiers in this analysis.

To create training and testing results, we create positive and negative examples. Children with randomly selected parents who are not their true parents are positive examples, whereas children with randomly selected parents who are not their true parents are negative examples. We conduct fivefold cross-validation on each example and calculate the mean accuracy of the five folds. As a measure of system success, we report the mean verification accuracy of the four kinship subsets.

III.3.1 Metric Study:

Metric learning has been given a lot of focus in last years in computer vision and machine learning. The literature proposes numerous metric learning algorithms, which aim to learn distance. In many facial image analyzing applications metric learning techniques pursue a suitable distance measurement for classification tasks and achieved a reasonable level of success.

We present in these works a simple approach, which does not include training data, calculate the gap between pairs of features with various features and use the result to decide whether or not they are a child. In our case, one distances below are used:

Cosine distance (*cos*): Cosine similarity is a measure of similarity between two vectors and can be computed as:

$$d_{\cos} = \sum_i \frac{x_i y_i}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}} \qquad (3.6)$$

Where x and y are the two feature vectors of the pair of images being compared. Figure 10 depicts the basic schema for facial kinship verification based on Metric Learning classifier.

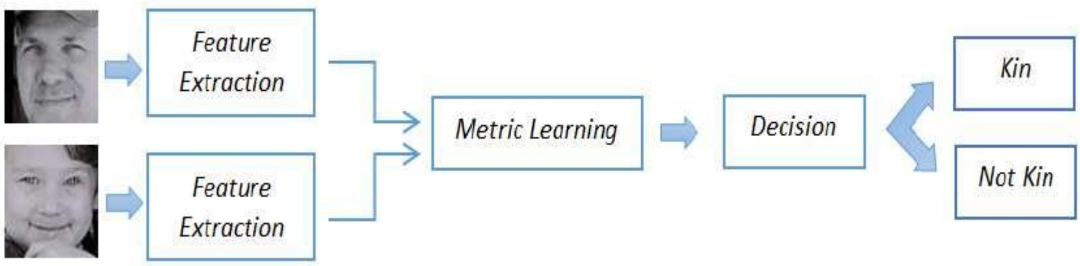


Figure 9: *Kinship verification flowchart based on Metric classifier*

III.4 Feature Selection:

In machine learning, Feature Selection (FS) is a data preprocessing step that is applied after feature extraction step. Feature selection method aims to select the most relevant subset of extracted features to provide a useful classification with the smallest error and to discard non-relevant features. In this dissertation, we used Fisher/Correlation feature selection using Wrapper for Spider toolbox [71], [72] and [73].

Spider Wrapper is a library of objects in Matlab. It is meant to handle large unsupervised, supervised or semi-supervised machine learning problems.

The fundamental idea of choosing Fisher/Correlation (F/C) [74] score for kinship verification is to find a subset of characteristics, the distances between data points in same classes (positive pairs) are as small as possible, while the distances are as large as possible between data points in different classes (negative pairs).

Let I = (xi; yi)ji = 1:::N be the training data of pairs of parent and child images, where xi is the vector of the ith parent and yi of the ith child, and L the class of this data.

Each xi and yi are ranked with Fisher/Correlation algorithm, next the size of the optimal (F/C) set is heuristically found.

The feature selection method is presented in Algorithm 2.

Data: Input images, labels and the number of features to be selected. Result: The selected features. 1 Trasformation the pair features into a single feature vector using U.; 2 Calculate S.; 3 Output the features selected.;

Algorithm 2: Feature Selection Algorithm.

In order to give a complete description of Feature Selection methodology, we detail each step of the previous algorithm: The input of the algorithm are: data I = (xi; yi)ji = 1:::N, labels of data and the number of features to be selected.

- **First step**. It based on normalized absolute difference U to transform the pair features into a single feature vector.

$$U = \sum_i \frac{|x_i - y_i|}{\sum_i (x_i + y_i)} \qquad (3.7)$$

Where *x* are the parents images and *y* are the children images.

- **Second step**. Select the most relevant descriptors of the input features based on Fisher score *S*.

$$S_i = \frac{\sum_{k=1}^{K} n_j(\mu_{ij} - \mu_i^2)}{\sum_{k=1}^{K} n_j \eta_j \rho_{ij}^2} \qquad (3.8)$$

Where μj is the mean, σj denote the standard deviation of the whole data set and K= number of selected features.

Fisher score is one of the most widely used supervised feature selection methods. However, it selects each feature independently according to their scores under the Fisher criterion, which leads to a suboptimal subset of features.

We calculates the Fisher score for each feature by returning the fisher object initialized with parameter (K: numSelect; the number of descriptors that are selected for each feature). In our experiments we change the K in order to identify the best performance for the algorithm.

Result. The output of the algorithm is features selected.

III.5 Cross Validation:

("Cross-validation") is a method of estimating the reliability of a model based on a sampling technique. In fact, there are at least three cross-validation techniques: "test set validation" or "holdout method", "k-fold cross-validation" and "leave one-out cross-validation" (LOOCV).

- The first method is very simple, it suffices to divide the sample of size n into two sub-samples, the first of learning (commonly greater than 60% of the sample) and the second of testing. The model is built on the training sample and validated on the test sample. The error is estimated by calculating a test, measure, or model performance score on the test sample, for example the root mean square error.

- In the second, we divide the original sample into k samples, then we select one of the k samples as the validation set and the (k-1) other samples will constitute the training set. As in the first method, we calculate the Performance score. Then the operation is repeated by selecting another validation sample from among the (k-1) samples, which have not yet been used for the validation of the model. The operation is thus repeated k times so that in the end each sub-sample has been used exactly once as a validation set. Finally, the mean of the k mean squared errors is calculated to estimate the prediction error.

- The third method is a special case of the second method where k = n, that is to say that we learn on (n-1) observations then we validate the model on the nth observation and we repeat this operation n times.

III.5.1 K-fold Cross Validation:

The data is first partitioned into k equally (or approximately equally) sized segments or folds in k-fold cross-validation. Following that, k iterations of training and validation are done, with each iteration holding out a separate fold of the data for validation while the remaining k-1 folds are used for instruction. Prior to splitting data into k folds, it is standard practice to stratify it. Stratification is the method of rearranging data so that each fold is an accurate representation of the whole.

To put it another way, the K-fold Cross-validation is a computer-intensive methodology that employs all available examples as both teaching and evaluation examples.

Figure depicted a 5-cross validation example.

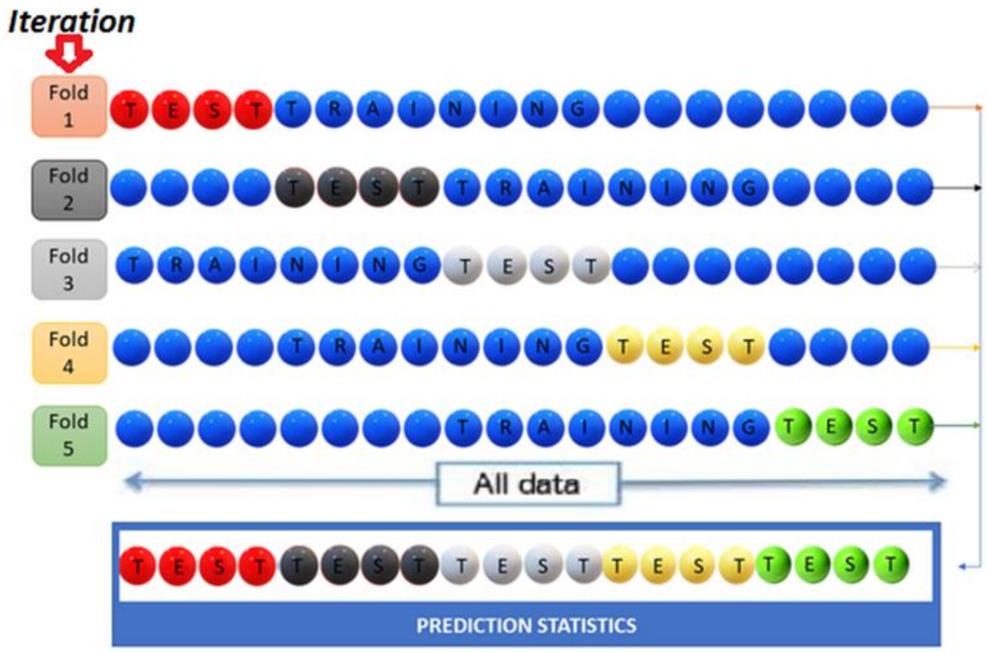


Figure 10: *Example of 5-cross validation.*

Mathematically, the k-fold cross-validation operator is defined as following:

• Divide the data into K roughly equal parts.

• for each k=1,2,...K, fit the model with parameter λ to the other K-1 parts, giving β-$k(\lambda)$ and compute its error in predicting the *kth* part:

$$E_k(\lambda) = \sum_{i \in \text{kth part}} \left(y_i - x_i \hat{\beta}^{-k}(\lambda)\right)^2 \qquad (3.9)$$

• This gives cross validation error

$$CV(\lambda) = \frac{1}{K} \sum_{k=1}^{K} E_k(\lambda) \qquad (3.10)$$

• Do this for many values of λ and chose the value of λ that makes $CV(\lambda)$ smallest.

III.6 Performance evaluation:

Receiver Operating Characteristic (ROC) is an acceptable and commonly used approach in machine learning research to demonstrate the efficiency of recognition systems.

ROC curve, which may be established in accordance with the decision threshold, creates the rate of real positive (i.e. image properly categorized as positive or negative pairings) versus the rate of false positive (i.e. improperly categorized) at different threshold settings.

ROC curve point indicates a positive/negative pair which matches a certain threshold of judgment. Consequently, ROC curve and accuracy are the basis for our evaluation performance. In particular,

$$\text{Accuracy} = \frac{TP+TN}{P+N} \qquad (3.11)$$

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

III.7 Conclusion:

We covered the basics of automated kinship authentication from faces in this chapter. We discussed several concepts and meanings. The facial kinship verification scheme is defined in detail.

We spoke about some interesting applications for ongoing research in this area. We've also mentioned a few realistic roadblocks to solving facial kinship authentication issues, as well as summarized the current databases. We have included an outline of automated kinship authentication methods as well as the current state of the art. We went through several commonly used approaches, which were split into two categories: Hand-Crafted Feature-based methods and Deep Learning Feature-based methods.

We addressed the issue of automated kinship authentication from facial images in this article, taking into account four relationships: F–S, F–D, M–S, and M–D. We suggested a novel approach based on a DCTNet and a bank of 2D-DCT filters. Discriminative biological knowledge is used to enhance kinship authentication accuracy. On the used KinFaceW-II, and UBKinFace, our method demonstrated a high efficiency of deep features in representing faces for inferring kinship relations. Furthermore, as compared to previous works, our method shows substantial increases in verification accuracy.

Chapter IV

Result and Discussion

IV.1 Introduction:

We construct many research in this chapter to use the theories provided throughout this dissertation on facial kinship verification. We report the experimental findings of facial kinship verification tests that we conducted. Using learning approaches, we explore the feature characteristic. DCTNet is one of the learning strategies. We run extensive experiments on one of the available kinship datasets, KinFace-II. The data are evaluated, and some intriguing conclusions are drawn.

The user databases is ***Kin FaceW II*** **[**http://www.kinfacew.com/]: This includes public Figure face images of family members collected from the internet. For the ***KinFaceW II*** dataset, each relation contains 250 pairs of kinship images.

There are four kin relations in two datasets: Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S), and Mother-Daughter (M-D). For ease of use, we manually labeled the coordinates of the eyes position of each face image, and aligned and cropped facial region into 64x64 to remove background. The following Figures show some cropped face images from KinFaceW-II datasets.

Figure11. *Aligned and cropped examples of KinFaceW-II datasets*

IV.2 The Experiment:

Due to the widespread variations in the face of the parent and offspring, the verification of kinship is particularly difficult. A proper facial depiction is often necessary to address this difficulty. Different global and local representations have been introduced in this experiment. The global approaches based on appearance strive to discover the entire picture. Some area features are represented by the local texture descriptors. Various forms of visual elements resulting from these actions have been overviewed. In addition, some of the approaches proposed to solve the problem have been summarized.

In addition, we suggested a new kinship verification learning approach, which has four basic phases:

1) A DCTNet implemented in every face to extract, using convolutionary layers based on a 2D DCT filter bank, the most significant heritable characteristic of the face.

2) The last layer's answer is binarised and divided into block-wise histograms that are not overlapping.

3) The normalization of Tied Rank (TR) is utilized to remove discrepancy in DCTNet histogram vectors.

4) Distinguishing the distinct pairings is the last step.

The distances between data points in same classes (positive pairs) are as small as possible, while the distances are as large as possible between data points in different classes (negative pairs).

IV.2.1 The Experiment Setting:

For our method, first, we tested the mean area under ROC with the restricted setting on F–S relationship in KinFace -II database with varying the number of different parameters, and then the number who has performed the best performance for all relationships including F–D, M–D, and M–S.

IV.2.2 Feature Extraction:

- **DCTNet:** The network is composed of 2 convolution layers, to achieve the best performance, we tested different values of filters number, and filters size, and block wise histogram size. The results are shown in Table 3

To evaluate the performance of kinship verification, three step is performed: feature selection, dimensionality reduction and classification. Firstly, we used the Fisher/Correlation algorithm to select the most informative features from the obtained histograms. Next, the obtained features were projected into a 399-dimensional using PCA. Finally, the cosine similarity of each test pair is computed. For each of the four kinships, we performed 5-fold cross-validation and computed the mean accuracy of the five folds. To evaluate the performance of system, the Receiver Operating Characteristic (ROC) is used.

Number of Filters	The filter Size	The block-Wise Histogram Size	Accuracy FS
[2 2]	[4 4]	[2 2]	**88.4%**
[2 2]	[2 2]	[2 2]	**84.0%**
[4 4]	[4 4]	[2 2]	**87.4%**
[5 5]	[5 5]	[12 12]	**88.4%**
[5 5]	[5 5]	[6 6]	**92.8%**
[5 5]	[5 5]	[8 8]	**91.9%**
[5 5]	[6 6]	[8 8]	**91.6%**
[6 6]	**[6 6]**	**[8 8]**	**93.8%**
[6 6]	[6 6]	[6 6]	**92.8%**
[5 5]	[8 8]	[6 6]	**90.2%**
[6 6]	[5 5]	[8 8]	**92.8%**
[6 5]	[6 6]	[8 8]	**92.9%**

Table 3 *Average area under ROC of KinfaceW-II versus varying the parameters.*

The selected filters are six in the first and six in the second layer, and when the filter size was 8 to 8, the ideal result was produced. Real values are given via the convolution layer outputs. The last layer output is converted into binary. We then split binary pictures into 6 blocks that did not overlap. All histograms of each block are combined to provide the qualities of these photos.

We next use TR normalization to remove the histogram vector discrepancy. After that we apply the number who has performed the best performance for all relationships including F–D, M–D, and M–S. Showing in Table 4 below, We employ a deep learning engine that uses many layers of information processing stages. A gray-scale picture is used as the network's input to extract discriminant characteristics for kinship verification. After that, the picture is passed through a 2D DCT filter bank to extract the most important inherited characteristics. As described in Figure 12, some regions of the face have a greater frequency, such as the eye and nose, while others, such as the frontal face, have a lower frequency. Only the most important face characteristics are shown as a result of these filters. The inheritable genetic feature areas in the kinship photos are highlighted in light blue and yellow in the visualization. The basis selection is an important consideration when using 2D DCT as a filter bank in a network.

Prior knowledge of human facial characteristics is considered. Because high-frequency horizontal components (eyes, brows, and lips) make up more of a human face's distinguishing characteristics than low-frequency vertical components, it's only reasonable to organize the 2D DCT bases by horizontal-frequency major order.

The DCTNet maintains the relevance of horizontal frequency direction at each turn to extract acquired features that are a product of genetic inheritance handed down from parents to children.

Block-wise histogramming, on the other hand, is effective for classification since it is capable of implicitly storing spatial information of picture sections.

To control the DCTNet histogram for robustness, we suggest an effective approach normalizing (TR Normalization). By measuring the correlation between variables, we apply the ranking concept.

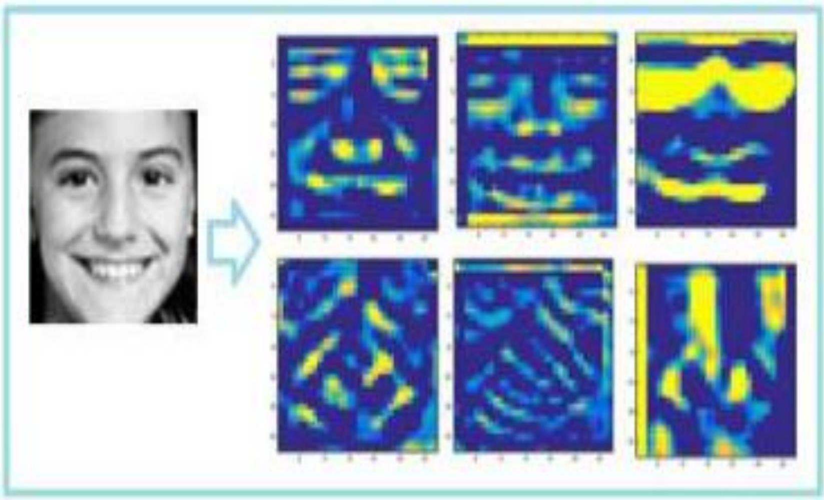
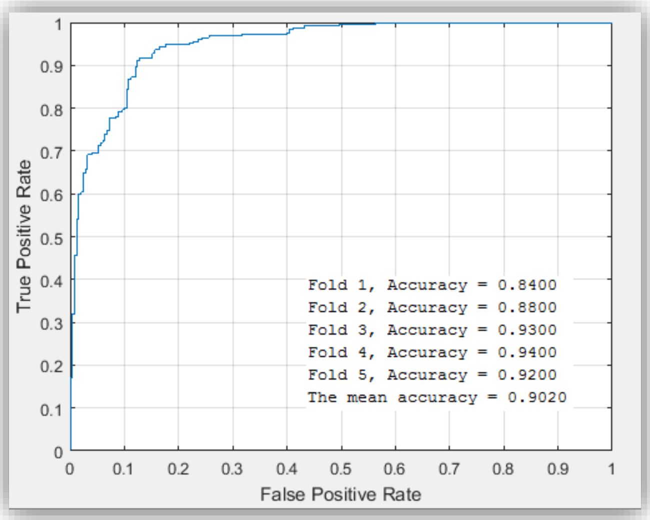


Figure 12: *Example of the DCTNet filter bank on gray-scale image.*

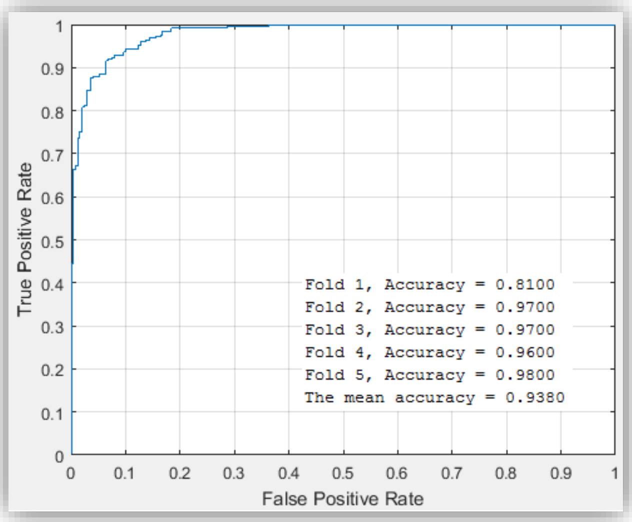
Number of Filters	The filter Size	The block-Wise Histogram Size	**Accuracy FS**	**Accuracy FD**	**Accuracy MD**	**Accuracy MS**
[6 6]	[6 6]	[8 8]	**93.8%**	**90.2%**	**91%**	**88.8%**

Table 4 *Kinship verification accuracy in percentage on KinFaceW-II database*

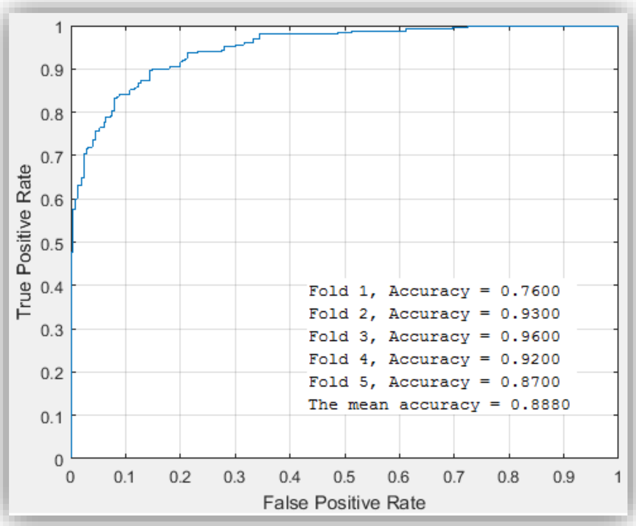
These are the curves obtained from **Matlab** after changing the values on all KinFace - II database F-S,F–D, M–D, and M–S:



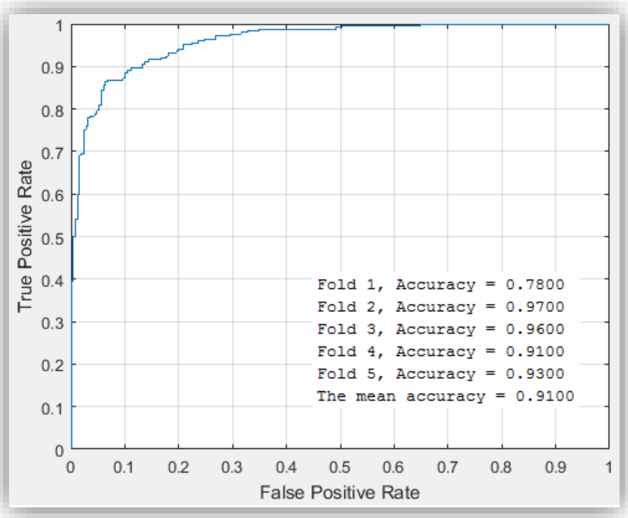
F-D



F-S



M-S



M-D

IV.2.3 Results and analysis:

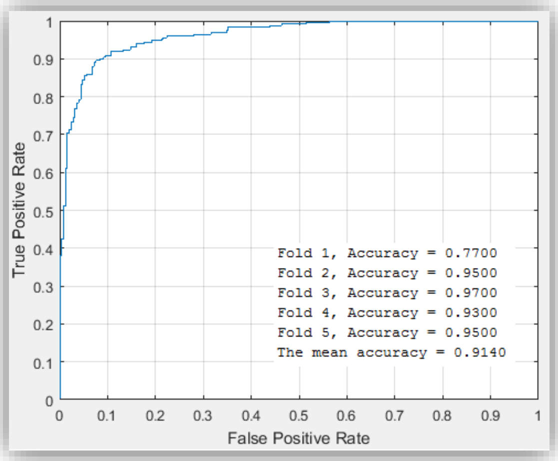
Without TR normalization we have evaluated our suggested DCTNet approach with TR Normalization against DCTNet. Table 5 shows the results.

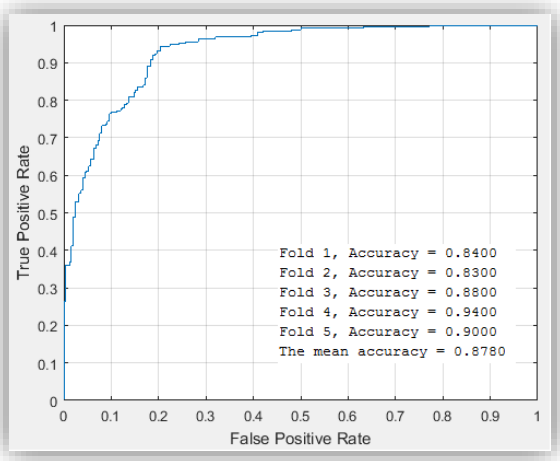
DCTNet's performance with Normalization technology shows the best results in all four relationships. TR normalization overall increased verification accuracy by an important margin, F–S (**2.4**% improved), F–D (**3.2**% improved), M–D (**4.0**% better), and M – S (**4.8%** improved)

TR normalization	FS	FD	MD	MS
Yes	**93.8%**	**91%**	**91%**	**88.8%**
No	**91.4%**	**87.8%**	**87%**	**84%**

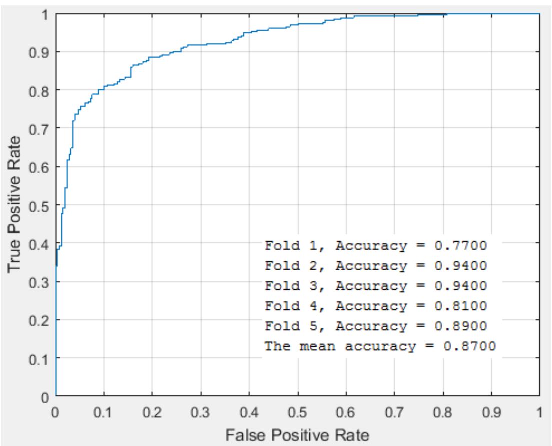
Table 5 *Kinship verification accuracy in percentage on KinFaceW-II using DCTNet*

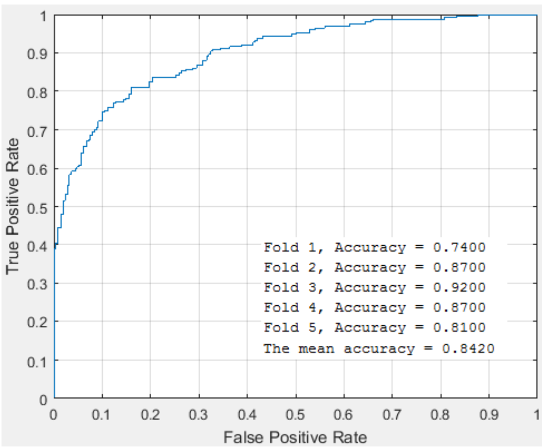
These are the curves obtained from **Matlab** without TR Normalization:





F-S **F-D**





M-D **M-S**

Comparisons with other methods

We compared our suggested DCTNet approach to other state-of-the-art profound learning, which is based on different ways of metrics. Table 6 shows comparative findings.

Method	FD	FS	MD	MS	Mean
MNRML	74.3	76.9	77.6	77.4	76.6
DDMML	76.5	78.5	79.5	78.5	78.2
CNN-Basic	79.6	84.9	88.5	88.3	85.3
DSMM [1]	82.8	89.4	88.0	87.8	87.0
Our Method	**93.8%**	**91%**	**91%**	**88.8%**	**91.15**

Table 6: Comparison of DCTNet against state of the art on KinFaceW-II

IV.3 Conclusion:

In this study we addressed the automatic kinship verification from facial images of four links: F-S, F-D, M-S and M-D. Using a 2D-DCT filters bank, we suggested an innovative solution. Discriminatory biological information is utilized to improve the performance of family verification. Our approach has demonstrated a high deep efficiency

Description faces on the, KinFaceW-II for inference relations. A comparison of our methodology to other works further shows considerable changes in the accuracy of verification

General Conclusion

General Conclusion

The objective of the work presented in this dissertation was to automatically verify whether two people come from the same family or not. Several analytical approaches are proposed in the literature. In our work, we have focused on automatic parentage verification. We focused on the global, local and geometry approach. The first approach based on appearance makes it possible to find a representation of the whole image. While the texture-based approach extracts attributes from pixels. The third approach based on geometric methods allows the localization of facial characteristic regions.

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

The system based on a simple deep learning method called Discrete Cosine Transform Network (DCTNet), where 2D-DCT is adopting as a filter bank to extract the most significant inherited facial features.

Deep learning recognition methods automatically learn high-level features from multilayer and parameters, rather than designed features manually and a spatial relation between blocks are encoded. To the best of our knowledge, the DCTNet is being used for the first time in our work for the kinship verification. Moreover, we introduced the multimodal system based on some discriminative biological information. Our results highlight the high ability of DCTNet in learning kinship verification.

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