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Feature fusion for automatic kinship verification

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Abstract

Feature fusion for automatic kinship verification refers to the process of combining multiple types of features or information to improve the accuracy and reliability of automatic kinship verification systems. Kinship verification involves determining the familial relationship between two individuals based on their facial images.

To address this limitation, feature fusion techniques can be employed. Feature fusion involves integrating different types of features or information to create a more comprehensive representation of the data. This can be done at various levels, such as early fusion (combining features at the input level), mid-level fusion (combining features at a higher-level representation), or late fusion (combining features at the decision level).

So that we obtained that the integration between the CNN with the HOG is good at a rate of 85.80% on Father Son relationship

It is important to note that the observed degradation in accuracy when using fusion of CNN, HOG, and LBP features with cosine similarity, can be attributed to various factors: redundancy or noise, feature fit, and feature weight.

Overall, feature fusion for automatic kinship verification aims to leverage multiple modalities or sources of information to improve the performance of kinship verification systems, enabling more accurate identification of familial relationships based on facial images.

Keys Words: Kinship, Verification, Fusion, facial.

الملخص:

يشير اندماج الميزات للتحقق التلقائي من القرابة إلى عملية الجمع بين أنواع متعددة من الميزات أو المعلومات لتحسين دقة وموثوقية أنظمة التحقق التلقائي من القرابة. يتضمن التحقق من القرابة تحديد العلاقة الأسرية بين شخصين بناءً على صور وجههما.

لمعالجة هذا القيد، يمكن استخدام تقنيات دمج الميزات. يتضمن دمج الميزات دمج أنواع مختلفة من الميزات أو المعلومات لإنشاء تمثيل أكثر شمولاً للبيانات. يمكن القيام بذلك على مستويات مختلفة، مثل الاندماج المبكر (دمج الميزات على مستوى الإدخال) ، أو الانصهار متوسط المستوى (دمج الميزات في تمثيل أعلى مستوى) ، أو الاندماج المتأخر (دمج الميزات على مستوى القرار).

بحيث حصلنا على أن التكامل بين CNN مع HOG جيد بنسبة 85.80٪ على علاقة الأب والابن

من المهم ملاحظة أن التدهور الملحوظ في الدقة عند استخدام اندماج ميزات CNN و HOG و LBP مع تشابه جيب التمام ، يمكن أن يُعزى إلى عوامل مختلفة: التكرار أو الضوضاء ، وتناسب الميزة ،

ووزن الميزة.

بشكل عام ، يهدف دمج الميزات للتحقق التلقائي من القرابة إلى الاستفادة من أساليب أو مصادر متعددة للمعلومات لتحسين أداء أنظمة التحقق من القرابة ، مما يتيح تحديد العلاقات الأسرية بشكل أكثر دقة بناءً على صور الوجه.

الكلمات المفتاحية: –التحقق، الاندماج، القرابة، الوجه.

Résumé:

La fusion de caractéristiques pour la vérification automatique de la parenté fait référence au processus de combinaison de plusieurs types de caractéristiques ou d'informations pour améliorer la précision et la fiabilité des systèmes de vérification automatique de la parenté. La vérification de la parenté consiste à déterminer la relation familiale entre deux individus en fonction de leurs images faciales.

Pour remédier à cette limitation, des techniques de fusion de caractéristiques peuvent être utilisées. La fusion d'entités implique l'intégration de différents types d'entités ou d'informations pour créer une représentation plus complète des données. Cela peut être fait à différents niveaux, tels que la fusion précoce (combinant des fonctionnalités au niveau de l'entrée), la fusion de niveau intermédiaire (combinant des fonctionnalités à un niveau de représentation supérieur) ou la fusion tardive (combinant des fonctionnalités au niveau de la décision).

Si bien que nous avons obtenu que l'intégration entre le CNN avec le HOG est bonne à un taux de 85.80% sur la relation Père Fils

Il est important de noter que la dégradation observée de la précision lors de l'utilisation de la fusion des caractéristiques CNN, HOG et LBP avec une similitude cosinus peut être attribuée à divers facteurs : redondance ou bruit, ajustement des caractéristiques et poids des caractéristiques.

Dans l'ensemble, la fusion de fonctionnalités pour la vérification automatique de la parenté vise à tirer parti de plusieurs modalités ou sources d'informations pour améliorer les performances des systèmes de vérification de la parenté, permettant une identification plus précise des relations familiales sur la base d'images faciales.

Mots clés : Vérification, intégration, parenté, visage.

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Fatma&Nadjah

Dedication

To my mother the light of my eyes.

And for the soul of my father, may God have mercy on him.

For my husband, my companion, ***Ossama Maameri****. my brothers.*

Above all I thank ALLAH Then My parents who gave me life, tenderness, who sacrificed themselves for the symbol of happiness and success, who gave meaning to my life, and who was the shadow during all the years of study.

My Brothers: ***Brahim, Tarzi, Chamsou, Ishak, Yakoub , Djamel***

My dear children: ***Nidhal, Ikbal, Nour*** *To everyone who contributed to the journey*

Fatma

Dedication

To my mother.

And for the soul of my father, may God have mercy on him.

For my husband, my companion ***Salah edine kabli****. my brothers and my sisters.*

Above all I thank ALLAH Then 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.

My Brothers: ***Mechri, Ossama, Mouhamed****.*

My sisters: ***Abir, Wissal, Safa, Torki, Safa, Hadil****.*

My sweetheart: ***Louai, Tasnim, El hadi, Mouhamed****.*

To everyone who contributed to the journey.

Nadjah

Table of contents:

Abstract....i
Acknowledgments....iii
Dedication....iv
Dedication....v
Table of contents:....vi
List of figures....viii
List of table:....ix
General introduction....1

CHAPTER 01: Kinship verification

I.1 Introduction :....3
I.2 Definition:....3
I.3 Biometrics:....4
1.3.1 Types of biometrics:....4
1.3.2Advantages and disadvantages of biometrics:....5
I.4 Meaning of kinship:....6
1.4.1 Kinship Verification:....6
I.5 Face Verification and kinship verification:....7
I.6 System design:....7
I.7 Application of kinship verification:....10
1.7.1 Social media and family album organization....10
1.7.2 Finding missing children 10
1.7.3 Entertainment....10
I.8 Principals challenges of kinship verification systems:....10
1.8.1 Age gape....10
1.8.2 Gender Differences....11
1.8.3 Poses, illumination and expression variation....12
Conclusion:....13

CHAPTER 02: Kin ship verification method

II.1 Introduction:....15
II.2 Datasets:....15
Datasets The effectiveness of the kinship verification algorithm used in the following publicly available databases is evaluated....15

II.3 Feature extraction: 16
II.3.1 LBP (local binary pattern): 16
II.3.2 HOG (Histogram of Oriented Gradients): 17
II.3.3 CNN (Convolution Neural Network): 19
II.4 Features fusion: 20
II.5 Classification : 21
II.6 k-Nearest Neighbor for Classification: 22
II.7 conclusion: 22

CHAPTER 03: Results and Discussions

III.1 Introduction: 24
III.2 Experimental Setup: 24
III.2.1 datasets KinFaceW-II: 24
III.2.2 KinFaceW-II: 24
III.3. Feature extraction: 25
III.4. features fusion: 25
III.5 Classification: 27
III.5.1 Classification NN (Nearest Neighbor): 27
III.5.2 Classification SVM 27
III.6 Result and discussion: 27
III.7. Conclusion: 31
General Conclusion 33
Bibliography 35

List of figures

CHAPTER 01: Kinship verification

Fig.I.1.type of biometric. 5
Fig.I.2: KinFaceW-II database. Four type relationships: (F-S), (F-D), (M-D), and (M-S). 8
Fig.I.3: General schema of kinship verification system. 9
Fig.I.4 Changes in facial features over time. 11
Fig.I.5 Gender different Daughter-Father (b)Son-Mother 11
Fig.I.6 Same gender (c)Father-Sun (d) Mother-Daughter 12
Fig.I.7 Changing of poses. 12
Fig.I.8 Variation of illumination. 12
Fig.I.**9** Example of the Variation facial expressions. 13

CHAPTER 02: Kin ship verification method

Fig II.1: Kinship verification databases. 15
Fig II.**2**: Face description with local binary patterns..[6] 17
Fig.II.3: Histogram of oriented gradients..[10] 19
Fig II.4: Convolution Neural Network .[9] 20
Fig. II.5. The procedure of the multi-feature fusion strategy. 21
Fig. II.**6**. identifying decision boundaries 22

CHAPTER 03: results and Discussions

Fig.III 01: KinfaceW-II. 25
Fig.III.02: The proposed kinship verification system. 26
Fig. III.03: Kinship verification flowchart based on SVM classifiier 27
Fig-III.**04**: Kinship verification accuracy in % using different features on KinFaceW-II. 28
Fig-III.**05**: Verification Accuracy in % for features fusion (CNN+LBP) on KinFaceW-II 29
Fig-III.**06**: Verification Accuracy in % for features fusion (CNN+HOG) on KinFaceW-II 30
Fig-III.**07**: Verification Accuracy in % for features fusion (CNN+HOG+LBP) on KinFaceW-II. 30

List of table:

CHAPTER I: Kinship verification

Table I.1: Difference between kinship and face verification system. 7

CHAPTER 02: Kin ship verification method

Table II.1: Kinship verification databases. 15

General introduction

Automatic kinship verification in biometrics is a challenging problem with significant real-world applications. Feature fusion techniques play a crucial role in improving the accuracy and reliability of kinship verification systems. By effectively combining multiple biometric features, these techniques enhance the discriminative power and robustness of the system, enabling accurate determination of kinship relationships based on biometric traits. Further research and advancements in feature fusion methods hold great promise for the development of more accurate and efficient kinship verification systems in the future.

In first Chapter We offer some ideas, definitions, and an overview of automated kinship verification from faces.

And jargon need to comprehend this subject. The system design for facial kinship verification is then described. The chapter also discusses potential applications for facial kinship verification and its difficulties. Finally, we review a few current databases.

In second Chapter Kinship verification method:

We defined the extraction of features in its various fields such as machine learning, computer vision, natural language processing and signal processing.

We have used some features:

LBP (local binary style), what it is, how it is used, how it works, and its areas of work

HOG (Historam of Oriented Gradients), definition and methods of use.

CNN (Convolution Neural Network) We included the axis with its structure and definition mentioned the advantages, types, what it is and how it is used

We also showed

So that we have how we used classification and its algorithms, Nearest Neighbor and SVM

In third Chapter Results and Discussions:

We explained that the data set used to verify kinship consists of pairs of facial images, where each pair contains a pair of individuals classified as either relatives or non-relatives. The dataset is divided into training and testing kits, using appropriate mutual verification techniques to ensure reliable evaluation. The feature extraction phase involves extracting facial features from images using LBP, HOG and CNN. Late merger is applied to combine the extracted features. Performance is evaluated using KNN and SVM.

CHAPTER 01: Kinship verification

I.1 Introduction :

The goal of Facial Kinship Verification (FKV) is to automatically determine whether two individuals have a kin relationship or not from their given facial images or videos. It is an emerging and challenging problem that has attracted increasing attention due to its practical applications. Over the past decade, significant progress has been achieved in this new field. Handcrafted features and deep learning techniques have been widely studied in FKV. The goal of this paper is to conduct a comprehensive review of the problem of FKV. We cover different aspects of the research, including problem definition, challenges, applications, benchmark datasets, a taxonomy of existing methods, and state-of-the-art performance. In retrospect of what has been achieved so far, we identify gaps in current research and discuss potential future research directions.[1]

I.2 Definition:

Kinship verification refers to the process of determining the biological relationship or degree of relatedness between individuals. It is commonly used in various fields such as forensics, immigration, and genealogy. The goal of kinship verification is to establish whether individuals share a parent-child relationship, sibling relationship, or other familial connections.

There are several methods used for kinship verification, including:

➢ DNA Testing: DNA analysis is the most accurate method for kinship verification. It compares specific genetic markers or DNA sequences between individuals to determine the probability of their relationship. DNA testing can be done through various techniques, such as PCR-based DNA amplification, short tandem repeat (STR) analysis, or whole-genome sequencing.[2]

➢ Blood Typing: Blood typing can provide some information about the likelihood of kinship. The compatibility of blood types, such as the ABO and Rh systems, can suggest certain relationships, such as parent-child or sibling relationships. However, blood typing alone is not as conclusive as DNA tasting.

➢ Facial Recognition: Facial recognition technology has been explored as a potential tool for kinship verification. It analyzes facial features and structures to identify similarities between individuals. While facial recognition can provide some insights, it is not as accurate as DNA testing and can be influenced by environmental factors and aging.

- Anthropological Analysis: Anthropologists and forensic experts can examine skeletal remains and physical characteristics to determine the likelihood of kinship. They analyze bone structure, dental records, and other physical traits to assess the biological relationship between individuals. This method is often used in forensic investigations or when DNA testing is not feasible.

It's important to note that the accuracy of kinship verification methods can vary. DNA testing, particularly using advanced techniques like STR analysis or whole-genome sequencing, is considered the gold standard for precise and reliable results. Other methods may provide indications or support but are generally not as conclusive.

I.3 Biometrics:

Biometrics is a study that assesses a person's personality based on physical, physiological, and anatomical features. It includes the ability to automatically identify people's identities based on their physical, physiological, and anatomical features. This proof surpasses fingerprints as well as the comfort of the palms and feet. Each person's uniqueness refers to their individuality, and computers can match them in seconds using distinctive signs and points, as well as identification through the voice, pupil of the eye, or facial features, because these members are distinguished by their uniqueness in each person, such as fingerprints and the palm of the hand and feet. As a result, we'll look at the face recognition system, which is a technology that can automatically identify or verify a person in a digital image or a video frame obtained from a video clip. Facial recognition systems function in a variety of ways, but they all operate. In general, it matches the specified facial traits in a snapshot to the faces contained in the database.[3]

1.3.1 Types of biometrics:

The two main types of biometric identifiers are either physiological characteristics or behavioral characteristics. Physiological identifiers relate to the composition of the user being authenticated and include the following:

- facial recognition
- fingerprints
- finger geometry (the size and position of fingers)
- iris recognition

- vein recognition
- retina scanning
- voice recognition
- DNA (deoxyribonucleic acid) matching
- digital signatures

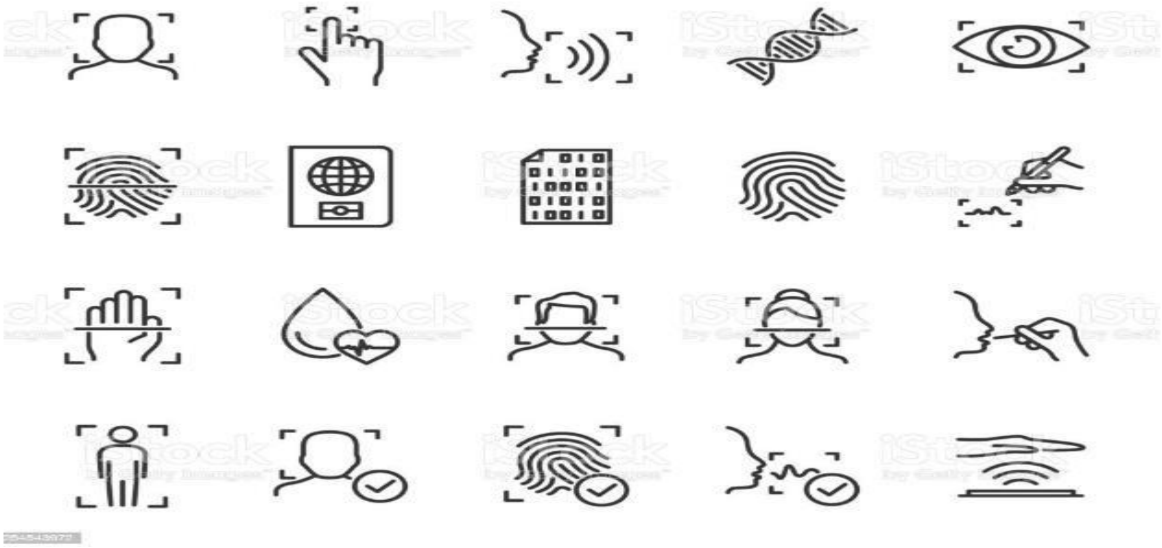


Fig.I.1.type of biometric. .[3]

-Behavioral identifiers include the unique ways in which individuals act, including recognition of typing patterns, mouse and finger movements, website and social media engagement patterns, walking gait and other gestures. Some of these behavioral identifiers can be used to provide continuous authentication instead of a single one-off authentication check. While it remains a newer method with lower reliability ratings, it has the potential to grow alongside other improvements in biometric technology.

Biometric data can be used to access information on a device like a smartphone, but there are also other ways biometrics can be used. For example, biometric information can be held on a smart card, where a recognition system will read an individual's biometric information, while comparing that against the biometric information on the smart card.[3]

1.3.2Advantages and disadvantages of biometrics:

The use of biometrics has plenty of advantages and disadvantages regarding its use, security and other related functions.

Biometrics are beneficial for the following reasons

- Hard to fake or steal, unlike passwords.

- Easy and convenient to use.
- Generally, the same over the course of a user's life.
- Nontransferable.
- Efficient because templates take up less storage.

-Disadvantages, however, include the following:

- It is costly to get a biometric system up and running.
- If the system fails to capture all of the biometric data, it can lead to failure in identifying a user.
- Databases holding biometric data can still be hacked.
- Errors such as false rejects and false accepts can still happen.
- If a user gets injured, then a biometric authentication system may not work -- for example, if a user burns their hand, then a fingerprint scanner may not be able to identify them.

I.4 Meaning of kinship:

We need to be familiar with the various kinship terminologies before we start studying. In the study of social networks, kinship is crucial.as a particular kind of social connection. The word "kinship" has multiple meanings.

It is a word used to describe the degree of genetic link between two members of the family and is generally used to describe likeness and intimacy. In psychology, kinship is the relationship that arises from birth, shared ancestry, adoption, or marriage in an anthropological setting. To evaluate children's relationships with parents based on the similarity of their signs and to determine the child's kinship network, which is a network of social links between people that plays a significant and significant role in the lives of most cultures.

1.4.1 Kinship Verification:

has recently gained interest as a task in machine learning and computer vision community. The task refers to bi-subject verification; that is, classifying a pair of input images as kin or non-kin. A smaller number of methods have explored tri-subject kinship verification, which compares a couple (Mother and Father) against a child, or whole family classification , as well as kinship recognition. The seminal work on kinship verification is by Fang et al. The first kinship annotated dataset is introduced and facial parts (FP), such as mouth hair and nose, are extracted using a pictorial structure model.

That is, the facial structures are represented as parts in a deformable configuration. The representation also included color information, facial distances (FD) and gradient histograms (GH). The difference between the feature vectors of the query couple are classified using methods like k-NN and SVM. The experiments performed in the paper indicate that the most discriminant feature was the color of the eyes. Moreover, the highest accuracy was achieved for Father-Son image-pairs, while the algorithm outperformed the human workers. Such results suggest that kinship verification of other people is a difficult task for humans. Similar to the above, this section is organized based on the facial representation used for the task

I.5 Face Verification and kinship verification:

The job of comparing a candidate's face with another face and determining whether they are identical or not is known as face verification. It is the process of matching a group of faces or two sides together with the aim of certifying the proper individual. Extensive research called "verification of kinship" aims to confirm people's kinship and their connection to one another. There are other approaches, including the face-verification method. The verification of kinship and the verification of the face are two separate issues,. although they both have some fundamental evidence in common

The basic structure is the common factor between kinship verification and face verification system and the differences between the facial and kinship verification is shown in Table I.1

Table I.1: Difference between kinship and face verification system. .[7]

Facial Verification	Kinshipverification
Extract features from same person	Extract features from different person
Verify or identity	Verify the relationships
Same trait of query image1 and query image2	Different trait of query image1 andquery image 2
Heightlevel system	Highestlevel system
The most common application is the security, monitoring and extensively by government a agencies	Studying the biological relationshipand utilizes by people and lessby government agencies
In decision stage Matched or not matched	In decision stage Kin or not kin
Performance of the machine is very roughly as accurate as human.	Accuracyis not satisfactory

I.6 System design:

Kinship verification is the determination of whether or not persons in the picture have the same kinship. This is done between people who have a common group in heredity and also tend to be family members of another person in the picture. With the development of technology in social media, facial recognition is used to organize billions of photos automatically using a system, when relationships between people are recognized and then verifies kinship using technique face recognition, it is possible to create a family tree automatically from this network community. Despite, many convincing experimental results that have already been published in the past years; verification of kinship remains a prominent problem of exploration. Human facial expressions and degrees of illumination, as well as the situation (eye, nose and mouth), reinforce the complexity of the problem of checking for kinship because each of the aforementioned elements [4]

Leads to the development of a facial image that in turn produces many features. Most methods of kinship verification focus on the mother's daughter (MD), the daughter of the father (FD), the mother son (MS) along with the father and son associations (FS). This process is categorized based on two unique categories, meaning "same closest" or "different relatives"[5].

Fig.I.2: KinFaceW-II database. Four type relationships: (F-S), (F-D), (M-D), and (M-S) [5].

Human faces have abundant features that explicitly or implicitly indicate the family linkage, giving rich information about genealogical relations. We address the novel challenge by posing the problem as a binary classification task, and extracting discriminative facial features for this problem. Our method works according to the following steps :[3]

Step 1: Parent-child database collection:

The facial image database of parentchild pairs is collected through a controlled on-line search for images of public figures and celebrities and their parents or children. We collected 150 pairs using this method, with variations in age, gender, race, career, etc., to cover the wide distribution of facial overview of the facial image database collected .

Step 2: Inherited facial feature extraction:

We start with a list of features that may be discriminative for kinship classification (such as distance from nose to mouth or hair color). We first identify the main facial features in an image using a simplified pictorial structures model, then compute these important features and combine them into a feature vector.

Step 3: Classifier training and testing:

Using the extracted feature vectors, we calculate the differences between feature vectors of the corresponding parents and children, and apply K-Nearest-Neighbors and Support Vector Machine methods to train the classifier on these difference vectors, as well as a set of negative examples (i.e., image pairs of two unrelated people) The final outputs provide two different types of information: the most discriminative facial features for kinship recognition and trained classifier to differentiate between true and false image pairs of parents and children.

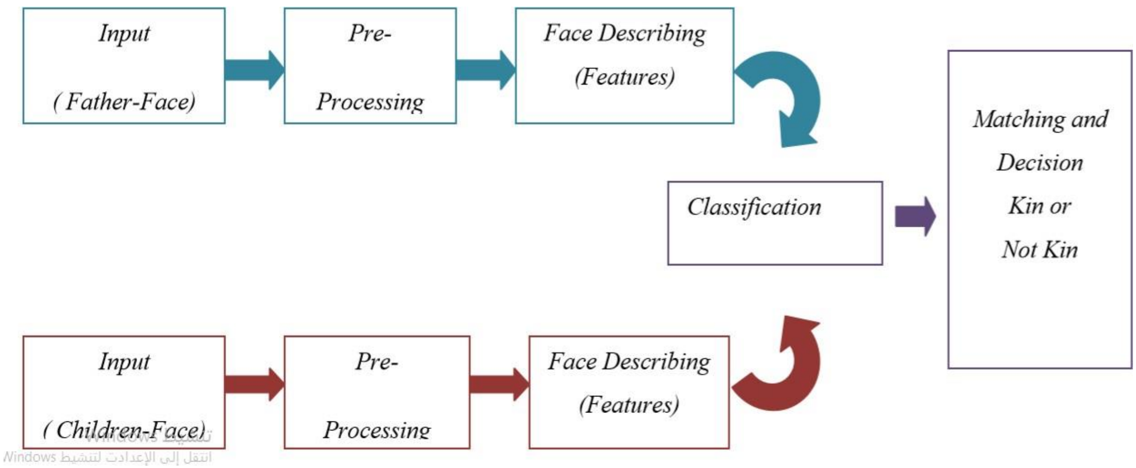


Fig.I.3: General schema of kinship verification system. .[7]

- **Input (face datasets)**: includes public figure face images of family members collected from the Internet. Therefore, the face images are captured under uncontrolled environments with no constraints.
- **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.
- **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.

- **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.) [7]

I.7 Application of kinship verification:

1.7.1 Social media and family album organization .

With the development of technology in social media such as smartphones, Google and Facebook, it can be used in the facial recognition system to automatically organize many photos and then verify the kinship, so identifying the relationships between people, enables us to automatically create a family tree from this network community .

1.7.2 Finding missing children .

Find missing children is an important kinship check app. We know very well that a Deoxyribonucleic Acid (DNA) is the most accurate test to verify family kinship, but it is restricted in some applications, unlike facial verification which is convenient and very low cost. For example, if we want to find a child missing from thousands of children, it is difficult for us to use a DNA test. Facial photos we can quickly identify and verify some potential candidates their relationship. After that, a DNA test is applied to get the accurate search result.

1.7.3 Entertainment

Make-up artists who specialize in transforming the face add effects to the face of the actors who require similarities between them. This enables them to benefit from building specific models of people, age and relatives. These effects are not limited to movies but have been applied on a large scale [3]

I.8 Principals challenges of kinship verification systems:

To verify kinship, we confront four major challenges: age gap, gender disparities, postures, lighting and expression variances, and hierarchy in kinship verification, which will be discussed more below

1.8.1 Age gape

As we check the members of a generation, we discover that there is a significant age difference between the spouses of relatives. The substantial age difference between parents and children, especially owing to aging and the emergence of indications of aging, results in large disparities that have a detrimental impact on the composition between the two faces, and then postpone the Kinship computation process.

The image of senior parents when they were young was exploited and paired with images of their children in order to decrease the vast age difference between older parents and their young offspring.

Humans can quickly recognize a person despite all of the continual changes that occur to the individual over time, such as the intricacies of facial characteristics and the like

Fig.I.4 Changes in facial features over time. .[1]

1.8.2 Gender Differences

Gender is a significant variable in determining kinship, and it is a major source of contention between kin pairs, particularly between mother and son and father and daughter, where we find it difficult to prove kinship, as seen in the image below.

Fig.I.5 Gender different Daughter-Father (b)Son-Mother [4]

Nevertheless, one thing to keep in mind is that the accuracy rate is high for the same gender, such as a father and his son or a mother and daughter; this result drives us to discover the qualities that separate the differences, as seen in the picture below more.

Fig.I.6 Same gender (c)Father-Sun (d) Mother-Daughter [4].

1.8.3 Poses, illumination and expression variation

Poses, illumination and expression variation are among the main problems hindering face analysis and making the face recognition system weak, we explain them as follows

- ***Poses***

Fig.I.7 Changing of poses.[1]

- ***Illumination***

Fig.I.8 Variation of illumination.[1]

- ***Expression variation***

Fig.I.9 Example of the Variation facial expressions.[1]

There are other types of difficulties that must be taken into account and not ignored in the face recognition system; among these problems we find for example occlusions, obstacles, beards, mustaches, identical twins, surgeries, scarves and glasses.[4]

Conclusion:

Kinship verification systems are used to determine the biological relationship between individuals. The primary method employed is DNA testing, which involves analyzing genetic markers such as STRs and SNPs to compare DNA profiles and calculate the probability of a biological relationship. Different types of DNA testing, such as maternal lineage testing and paternal lineage testing, focus on specific aspects of kinship. Autosomal DNA testing and genetic genealogy techniques are used to assess overall genetic relatedness and construct family trees. Forensic DNA analysis plays a role in legal and criminal investigations related to kinship verification. It is crucial to consult experts and accredited laboratories to ensure accurate and reliable results in kinship verification processes.

CHAPTER 02: Kin ship verification method

II.1 Introduction:

Kinship verification methods involve various techniques and approaches to establish the biological relationship or kinship between individuals. These methods aim to provide reliable and accurate evidence of relatedness using scientific and technological advancements

II.2 Datasets:

Datasets The effectiveness of the kinship verification algorithm used in the following publicly available databases is evaluated.

- KinFace-I
- KinFace-II

Table II.1: Kinship verification databases.

Input	Database	Number of Pair image	Type of relation	kinship Pairs	Controlled condition	Pairs from same photo	Publicly available
Image	KinFaceW-I	533	F-S	156	No	Partially	Yes
			F-D	134			
			M-S	116			
			M-D	127			
	KinFaceW-II	1000	F-S	250	No	Yes	Yes
			F-D	250			
			M-S	250			
			M-D	250			
	UBKinFace	400	Old P-C	200	No	No	Yes
			Yong P-C	200			
	TSKinFace	1015	F-M-S	285	No	Yes	Yes
			F-M-D	274			
			F-M-S-D	228			
	Family 101	206	FamilY	206	No	No	Yes
	IIITD Kin	272	S-S	52	No	No	No
			F-D	33			
			F-S	52			
			M-D	26			
			M-S	15			
			B-S	49			
			B-B	42			
	Cornell Kin	143	P-C	143	No	Partially	Yes

KinFaceW-II :

Includes public figure face images of family members collected from the Internet. Therefore, the face images are captured under uncontrolled environments with no constraints. The difference between KinFaceW-I & KinFaceW-II is that face images with a kin relation were acquired from different photos in KinFaceW-I while, in most cases, faces are cropped from the same photo in KinFaceW-II. KinFaceW-I dataset contains 156 F-S, 134 F-D.[2]

II.3 Feature extraction:

Feature extraction and representation is a crucial step for multimedia processing. How to extract ideal features that can reflect the intrinsic content of the images as complete as possible is still a challenging problem in computer vision.

Can a computer program discover semantic concepts from images?

The short answer is yes. The first step for a computer program in semantic understanding, however, is to extract efficient and effective visual features and build models from them rather than human background knowledge. So, we can see that how to extract features and what kind of features will be extracted play a crucial role in various tasks of image processing [3].

That is why we employ a number of features:

II.3.1 LBP (local binary pattern):

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

- **Face description using LBP:**

In the LBP approach for texture classification, the occurrences of the LBP codes in an image are collected into a histogram. The classification is then performed by computing simple histogram similarities. However, considering a similar approach for facial image representation results in a loss of spatial information and therefore one should codify the texture information while retaining also their locations. One way to achieve this goal is to use the LBP texture descriptors to build several local descriptions of the face and combine them into a global description. Such local descriptions have been gaining interest lately which is understandable given the limitations of the holistic representations. These local feature-based methods are more robust against variations in pose or illumination than holistic methods.

The basic methodology for LBP based face description proposed by Shonen et al. (2006) is as follows: The facial image is divided into local regions and LBP texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the face, as shown in Figure II.2.

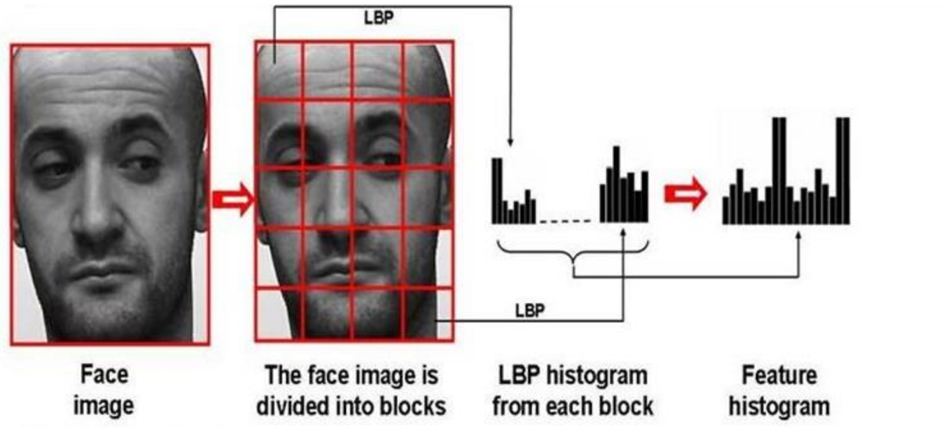


Fig II.2: Face description with local binary patterns..[6]

This histogram effectively has a description of the face on three different levels of locality: the LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face.[6]

It should be noted that when using the histogram-based methods the regions do not need to be rectangular. Neither do they need to be of the same size or shape, and they do not necessarily have to cover the whole image. It is also possible to have partially overlapping regions.

II.3.2 HOG (Histogram of Oriented Gradients):

Histogram of Oriented Gradients (HOG) is a feature extraction technique commonly used in computer vision and image processing tasks, particularly in object detection and recognition. It aims to capture the local structure and shape information of an image by analyzing the distribution of gradient orientations.

The HOG algorithm involves the following steps:[10]

1. **Preprocessing:** The input image is typically to improve its quality and remove noise. This may include operations like grayscale conversion, contrast normalization, and gamma correction.

2. **Gradient Computation:** The gradients of the image are computed to capture the

intensity variations. This is usually done by applying derivative filters (such as Sobel or Scherr filters) in both the horizontal and vertical directions to estimate the image gradient magnitude and orientation at each pixel.

3. **Cell Formation:** The image is divided into small cells, typically square regions. The size of the cells is an important parameter that affects the level of detail captured. The gradient magnitudes and orientations within each cell are used to compute histograms.

4. **Histogram Calculation:** For each cell, a histogram of gradient orientations is constructed. The orientations are binned into a fixed number of orientation bins (e.g., 9 bins covering 0 to 180 degrees). The contribution of each gradient to the histogram is determined by its magnitude. Typically, gradient magnitudes are weighted by a function that decreases with distance from the center of the cell, giving more weight to gradients closer to the center.

5. **Block Normalization:** To make the descriptor more robust to illumination variations, neighboring cells are grouped together to form blocks. The histogram values within each block are normalized by various methods like L1-norm, L2-norm, or power normalization. This normalization reduces the influence of overall contrast changes.

6. **Descriptor Formation**: The normalized histograms from all the cells in the image are concatenated to form a feature vector, known as the HOG descriptor. This vector represents the local structure and shape information of the image.

The resulting HOG descriptor can be used for various tasks such as object detection, pedestrian detection, and image classification. It can be fed into machine learning algorithms such as support vector machines (SVM) or neural networks to train models for specific recognition tasks.

HOG has proven to be effective in capturing local shape information and has been widely used in many computer vision applications. However, it has certain limitations, such as being sensitive to deformations and not encoding color information. To overcome some of these limitations, extensions to HOG, such as Histogram of Oriented Gradients for Dense Descriptor (HOG-DD), have been proposed

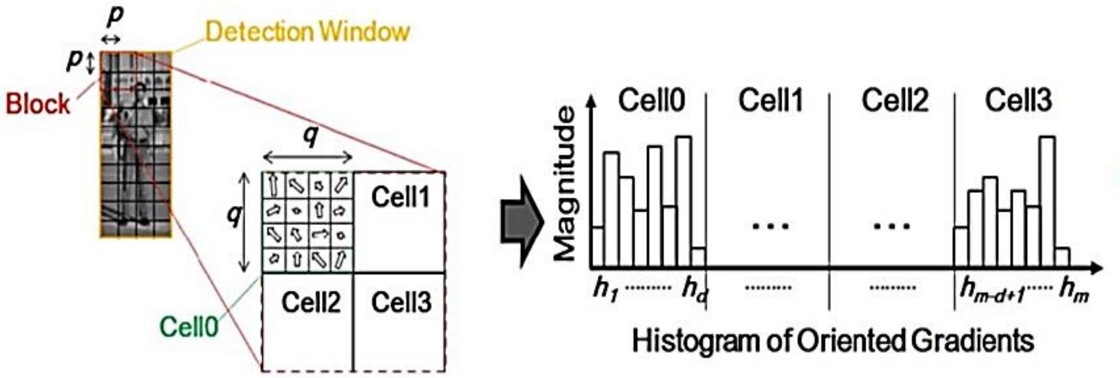


Fig.II.3: Histogram of oriented gradients..[10]

II.3.3 CNN (Convolution Neural Network):

A Convolutional Neural Network (CNN) is a deep learning algorithm that is primarily used for analyzing visual data, such as images and videos. It is a specialized type of neural network architecture that is designed to automatically and adaptively learn hierarchical representations of data.[9]

The key idea behind CNNs is to exploit the spatial structure of data by using convolutional layers. These layers apply a set of learnable filters (also known as kernels) to the input data, which slide across the input in a sliding window manner, performing element-wise multiplications and aggregations. This operation allows the network to learn local patterns and features from the input data.

Typically, a CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers perform the convolution operation to extract local features from the input data. The pooling layers down sample the spatial dimensions, reducing the amount of parameters and computation in the network. Finally, the fully connected layers combine the features learned by the previous layers to make predictions or classifications.

CNNs have achieved remarkable success in various computer vision tasks, such as image classification, object detection, and image segmentation. They are known for their ability to automatically learn hierarchical representations of data, allowing them to capture both low- level features (e.g., edges, corners) and high-level semantic information (e.g., object shapes, textures).

By using large amounts of labeled training data, CNNs can be trained in a supervised manner to learn complex patterns and make accurate predictions on unseen data. The training process involves forward propagation, where the input data passes through the layers of the network, and backpropagation, where the gradients of the network parameters are computed to update the weights and biases through optimization algorithms like stochastic gradient descent (SGD).

Overall, CNNs have revolutionized the field of computer vision and have become the state- of-the-art approach for many visual recognition tasks. They have also been adapted and applied to other domains, such as natural language processing, where they have shown promising results in tasks like text classification and sentiment analysis.

- **Architecture of CNNs**

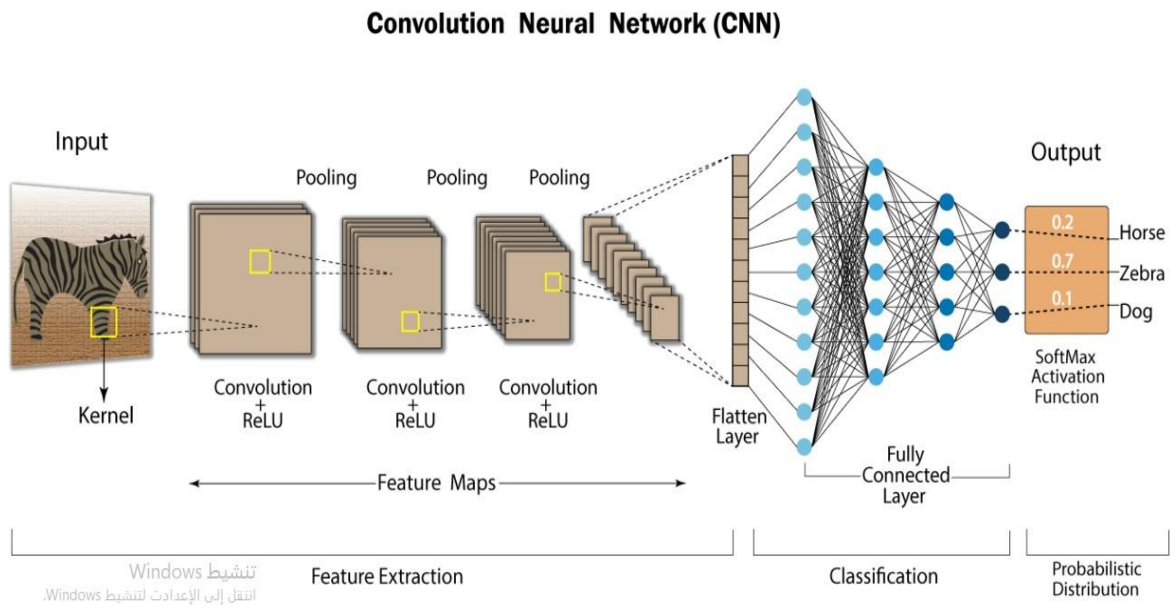


Fig II.4: Convolution Neural Network .[9]

II.4 Features fusion:

Feature fusion refers to the process of combining or integrating multiple features or representations extracted from different sources or modalities to obtain a more comprehensive or informative representation. This concept is commonly used in various fields such as computer vision, natural language processing, and signal processing.

In computer vision, feature fusion aims to leverage the strengths of different feature extraction techniques or models to improve the overall performance of a task, such as object recognition, image segmentation, or action recognition.

There are different strategies for feature fusion, including early fusion, late fusion, and hybrid fusion. In early fusion, the features from different sources are combined at the beginning of the processing pipeline, typically before any further analysis or modeling. Late fusion, on the other hand, combines the outputs of multiple models or classifiers trained on different features or modalities at the end of the pipeline. Hybrid fusion techniques combine both early and late fusion strategies to leverage the benefits of both.

Overall, feature fusion plays a crucial role in integrating diverse information sources and can lead to improved performance and richer representations in various fields of study.

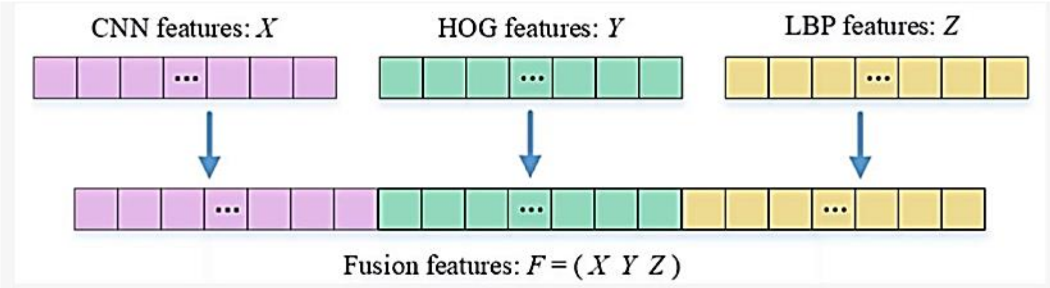


Fig. II.5. The procedure of the multi-feature fusion strategy.

II.5 Classification :

The problem of classification consists of the learning of a function of the form $y = (x)$, where x is a feature vector and y is a vector corresponding to the classes associated with observations. Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN) are both widely used machine learning algorithms for classification tasks

➢ ***Support vector machines* for Classification**

SVM performs classification by finding the optimal separating hyperplane which maximizes the margin (the distance of closest data, regardless its class, to the hyperplane) of the high dimensional training data. The training feature vectors along with their labels are input to SVM, which outputs a model able to predict the labels of new unseen data.

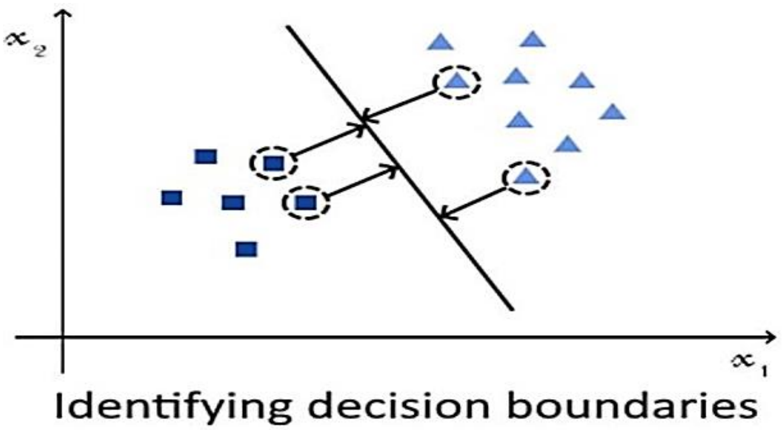


Fig. II.6. identifying decision boundaries

II.6 k-Nearest Neighbor for Classification:

The complete training dataset is kept in memory as part of the NN algorithm's operation. The method determines the distances between each new data point and all training examples using a distance metric, such as the Euclidean distance, when a new data point has to be classed or predicted. Based on the estimated distances, the algorithm then determines the k closest neighbors to the new data point.

When classifying data, the method gives the new data point the class label that has the highest percentage among its k nearest neighbors. This procedure is referred to as k-Nearest Neighbor (k-NN) classification, where k is a user-defined parameter that indicates how many neighbors should be taken into account.

II.7 conclusion:

In conclusion, feature fusion and classification using K-nearest neighbors (KNN) and support vector machines (SVM) are both effective approaches in machine learning.

Feature fusion involves combining multiple sources of information or feature sets to improve the performance of a classifier. By integrating different features, such as text, image, or numerical data.

CHAPTER 03: Results and Discussions

III.1 Introduction:

This chapter presents the results and discussions of the feature fusion approach applied to kinship verification. Kinship verification is a challenging task in the field of computer vision and pattern recognition, aiming to determine the relatedness between two individuals based on their facial features. Feature fusion techniques have been widely explored to improve the performance of kinship verification systems by combining multiple sources of information. This chapter focuses on evaluating the effectiveness of feature fusion methods and discussing the obtained results.

III.2 Experimental Setup:

The dataset used for kinship verification consists of pairs of facial images, where each pair contains a pair of individuals labeled as either kin or non-kin. The dataset is divided into training and testing sets, with appropriate cross-validation techniques employed to ensure reliable evaluation. The feature extraction stage involves extracting facial features from the images using LBP, HOG and CNN. Late fusion is applied to combine the extracted features. The performance evaluation is carried out using KNN and SVM.

III.2.1 datasets KinFaceW-II:

KinFaceW-II datasets are commonly used in the field of face recognition and kinship verification. These datasets contain pairs of facial images along with their corresponding kinship labels.

III.2.2 KinFaceW-II:

KinfaceW-II: database has a large scale, the thing what makes it the most popular one among to all the other databases. That database has divided into two Chapter 2 kinship verification systems, algorithms and methods 25 subsets are: KinFaceW-II ,contains 533 pair image and 1000 pair image in order .all images in the two subsets collected from the Net and captured in uncontrolled conditions no facial expression , no restriction of illumination, pose, age and race .every single image is aligned and cropped into 64 64 pixel, at beginning those subsets look like are same but we find the difference that in the kinfaceW-I images are captured from different images while in the other one are from the same picture. KinfaceW consist four kinds of relationship are: Father-Son, Mother-Son, Father-Daughter and Mother- Daughter (F-S, M-S, F-D and M-D) [1].

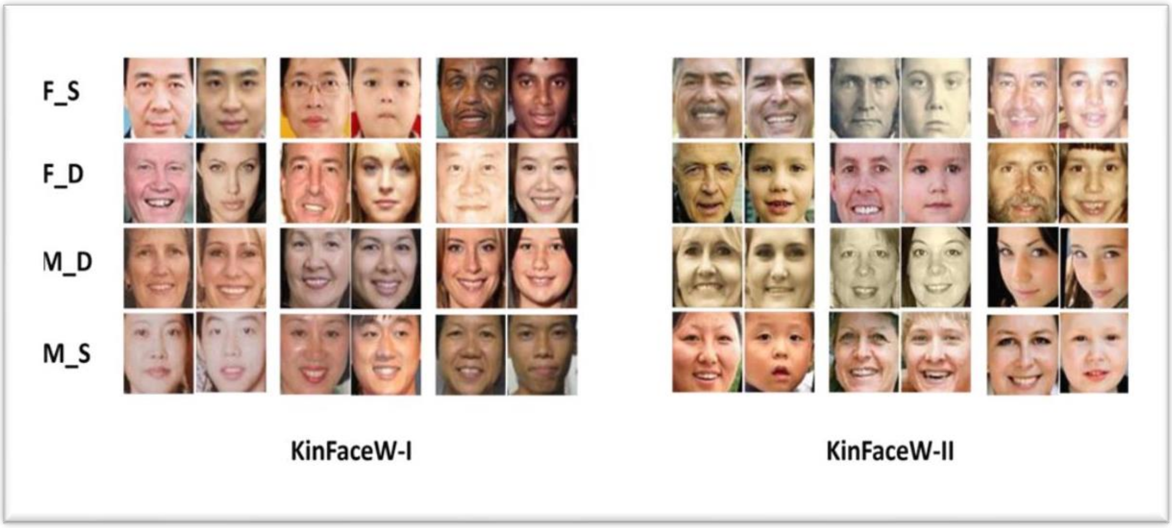


Fig.III 01: KinfaceW-II [1].

III.3. Feature extraction:

In our study, we focused on utilizing two hand-crafted descriptors and deep descriptor for extracting facial features.

In practice, the Local Binary Patterns (LBP) and the Histogram of Oriented Gradients (HOG) are traditional feature extraction methods that are computationally efficient but may lack the ability to capture complex and high-level features. On the other hand, Convolutional Neural Network (CNNs) excel at learning intricate features but are more computationally demanding. Depending on the task and available resources, you can choose the appropriate method or even combine them to extract complementary features and improve performance.

With regards to descriptor sizes, the LBP has 243, HOG has 468, and the deep features 4,096.

III.4. features fusion:

In the feature fusion approach used, a three-stage fusion process is used. Each stage combines different feature offerings to capture complementary information and enhance the discriminatory power of the kinship verification system.

The three stages of feature fusion are as follows:

1. ***Stage 1***: (LBP) descriptor and the (CNN) embeddings are combined.

- LBP captures texture information, while the CNN embeddings capture high- level abstract representations.
- This fused representation combines the texture details captured by LBP with the semantic features learned by the CNN.

2. ***Stage 2:*** (HOG) descriptor and the CNN embeddings are combined.

- HOG captures shape and edge information, while the CNN embeddings capture higher-level features.
- This fused representation combines the shape and edge information captured by HOG with the rich semantic features learned by the CNN.

3. ***Stage 3:*** the final stage, the features obtained from Stage 1 and Stage 2 are combined with the original CNN features.

- This fused representation combines the rich semantic information from the CNN with the texture, shape, and edge details captured by HOG and LBP.
- The final fused feature representation is used for subsequent kinship verification tasks, such as classification and similarity measurement.

The three-stage feature fusion approach aims to leverage the complementary information captured by different feature representations, including texture, shape, edges, and high- level semantics. By combining these features in a staged manner, the proposed approach seeks to improve the discriminative power and robustness of the kinship verification system. The effectiveness of this approach will be evaluated and discussed in the results and discussion section [2].

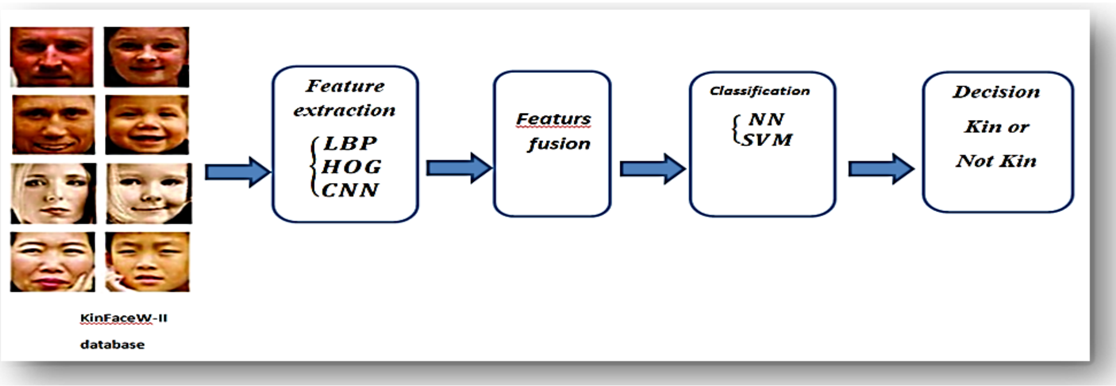


Fig.III.02: Kinship verification system used.

III.5 Classification:

The K-Nearest-Neighbor (KNN) and Support Vector Machine (SVM) are used to classify the pairs of images as having kin relation or not.

III.5.1 Classification NN (Nearest Neighbor):

The cosine similarity of each test pair is computed. the mean accuracy of the five folds. To evaluate the performance of system, the Receiver Operating Characteristic (ROC) is used.

Cosine distance(cos):Cosine similarity is a measure of similarity between tow vectors and con be computed as :

$$d_{cos} = \sum_{i} \frac{x_{i.}y_{i}}{\sqrt{\sum_{i} x_{i}^{2} . \sqrt{\sum_{i} y_{i}^{2}}}}$$

III.5.2 Classification SVM

Before training the SVM machine, we convert a pair of features into a single feature vector as required by the classifier. concatenation techniques of combining a pair of features is used.

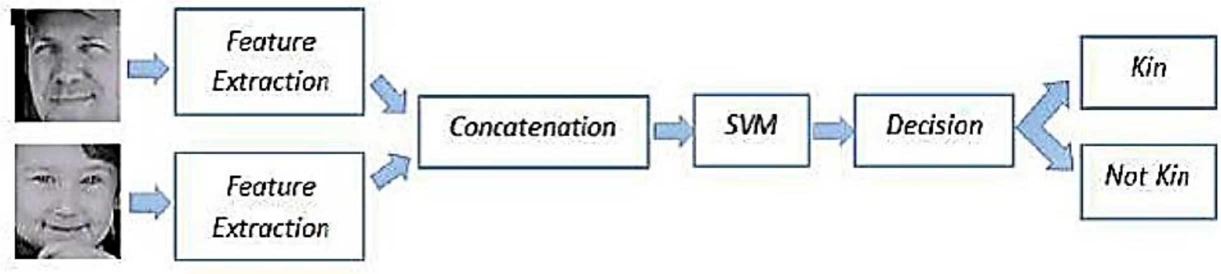
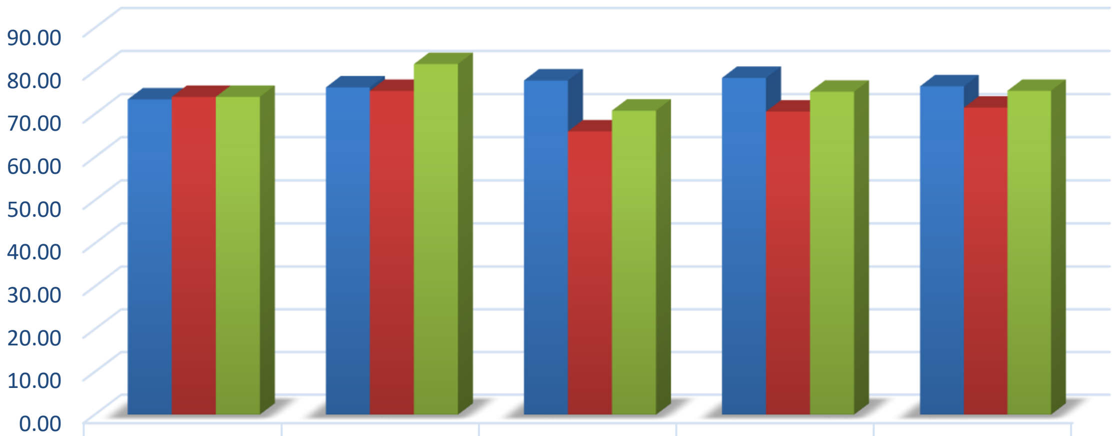


Fig. III.03: Kinship verification flowchart based on SVM classifier [1].

III.6 Result and discussion:

We discuss the obtained results from feature extraction using LBP, HOG, and CNN techniques for kinship verification. We analyze the performance of each technique individually and in combination through feature fusion

❖ The results of using cosine similarity as a classifier with different features different are reported in figure III.04.



	Fd	Fs	Md	Ms	Mean
CNN	73.40	76.20	77.80	78.40	76.45
LBP	74.00	75.40	66.00	70.60	71.50
HOG	74.00	81.60	70.80	75.20	75.40

Fig-III.04: Kinship verification accuracy in % using different features on KinFaceW-II.

When comparing the performance of feature extraction techniques for kinship verification, it is indeed often observed that Convolutional Neural Networks (CNN) achieve superior results compared to Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG).

❖ In this part, we compared the performance of combined feature, using the Support Vector Machines (SVM) and Nearest Neighbor (NN). In the following, we present the reported results.

❖ The results are shown in figure III.06, We observed that the fusion descriptor, obtained by combining CNN and HOG features, achieves a higher accuracy of 82.45% using cosine similarity. This performance improvement compared to using a single descriptor suggests that the fusion of CNN and HOG captures complementary information that enhances the kinship verification accuracy.

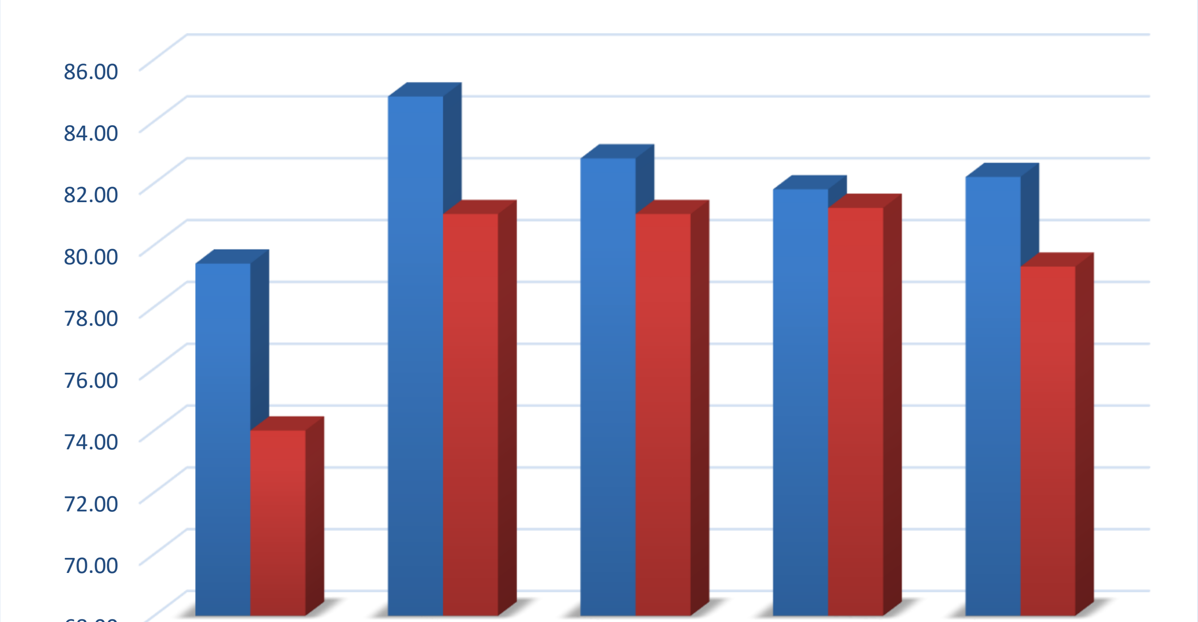
❖ (CNN +LBP) reported the best performance on all kinship relations and the higher accuracy of human performance on the task of kinship verification is 85.80% on Father-Son relationship.

❖ We observed that cosine similarity outperformed SVM in terms of classification accuracy for kinship verification. This indicates that the cosine similarity metric is more effective in capturing the similarity between feature vectors.

- It is important to note that the unsatisfactory results in accuracy ratios when using the amalgamation of CNN, HOG and LBP features with cosine similarity, can be attributed to various factors:
- Redundancy or noise: The fusion of multiple feature extraction techniques may

introduce redundant or noisy information, leading to a decrease in accuracy. The combined feature vector may contain conflicting or irrelevant information, affecting the kinship verification performance.

- Feature compatibility: Not all feature extraction techniques may be compatible with each other in the context of kinship verification. Some features may be more informative for this task, while others may introduce noise or inconsistencies when combined. The compatibility between the feature extraction techniques needs to be carefully considered.
- Feature weighting: The weights assigned to the individual feature vectors during fusion can significantly impact the overall performance. If the weights are not properly tuned or adjusted, it can lead to a suboptimal fusion and a decrease in accuracy.



	fd	fs	Md	Ms	Mean
NN	79.40	84.80	82.80	81.80	82.20
SVM	74.00	81.00	81.00	81.20	79.30

Fig-III.05: Verification Accuracy in % for features fusion (CNN+LBP) on KinFaceW-II

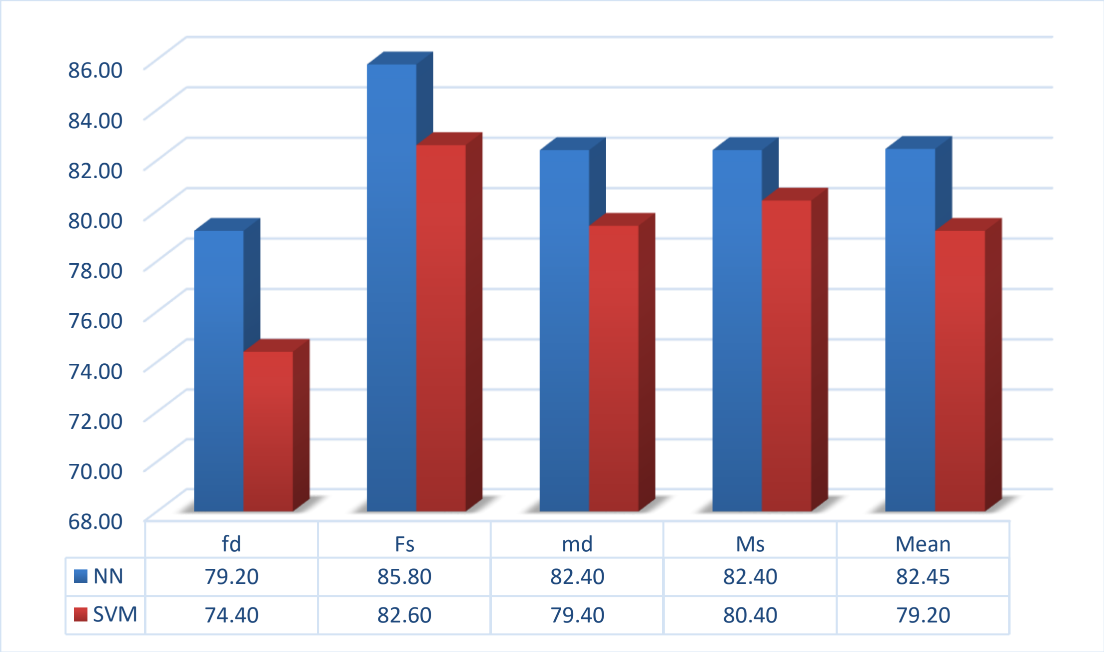


Fig-III.06: Verification Accuracy in % for features fusion (CNN+HOG) on KinFaceW-II

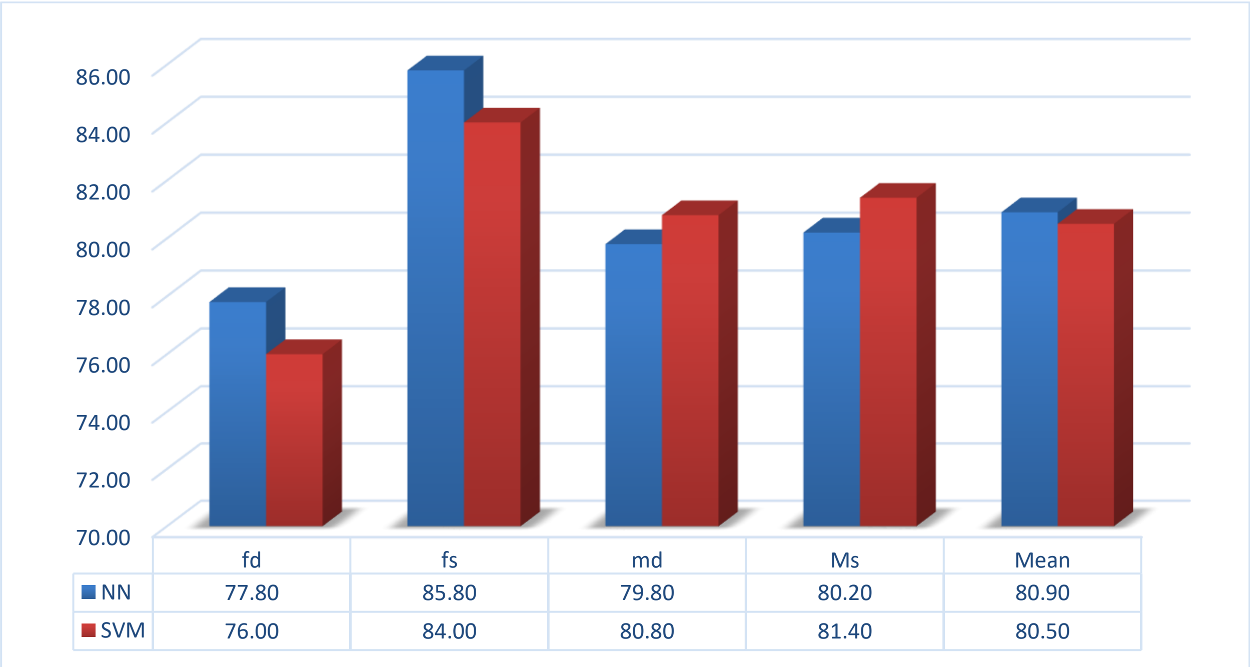


Fig-III.07: Verification Accuracy in % for features fusion (CNN+HOG+LBP) on KinFaceW-II.

III.7. Conclusion:

In the end, we summarize that the three-stage feature integration approach has been achieved to take advantage of supplementary information captured through various feature representations and by combining these features in stages, we have investigated that the proposed approach sought to improve the discriminatory power and strength of the kinship verification system.

General Conclusion

General Conclusion

Feature fusion plays a crucial role in automatic kinship verification systems. By combining multiple modalities, such as facial images, textual descriptions, and genetic information, feature fusion enables more accurate and reliable kinship verification.

The fusion of different modalities helps to capture complementary information and overcome the limitations of each individual modality. For example, while facial images can provide visual similarities between family members, textual descriptions can offer additional contextual information about the relationship. By fusing these modalities, the system can make more informed and accurate decisions.

Feature fusion algorithms vary depending on the specific application and available data. Some common approaches include early fusion, late fusion, and hybrid fusion techniques. Early fusion combines features at the input level, while late fusion combines features at a higher level, and hybrid fusion combines both strategies. The choice of fusion technique depends on the characteristics of the data and the specific requirements of the kinship verification task.

The effectiveness of feature fusion for automatic kinship verification has been demonstrated in various research studies. These studies have reported significant improvements in verification accuracy compared to using individual modalities alone. Feature fusion has also shown robustness against variations in imaging conditions, such as lighting, pose, and facial expressions.

However, there are still challenges and limitations in feature fusion for automatic kinship verification. One major challenge is the availability and quality of multi-modal data. Collecting and annotating large-scale datasets that include diverse kinship relationships across different modalities can be time-consuming and expensive. Additionally, designing fusion algorithms that effectively integrate information from multiple modalities is an ongoing research area.

In conclusion, feature fusion is a promising approach for automatic kinship verification. It enables the integration of multiple modalities to improve accuracy and robustness. While there are challenges and areas for further research, feature fusion holds great potential for advancing the field of kinship verification and contributing to various applications such as forensic investigations, genealogy research, and social network analysis.

Bibliography

Bibliography-CHAPTER-I:

[1]- Automatic Kinship V omatic Kinship Verification in Unconstr erification in Unconstrained F ained Faces using Deep aces using Deep Learning Naman Kohli West Virginia University, nakohli@mix.wvu.edu

[2]- Tidjani, A., "Automatic Kinship Verification ," in Electronic and Telecommunication 2018- 2019, Kasdi Merbah ouargla: Ouargla. p. 103.

[3]- AdemAsma Sahraoui Sara Proposed and Supervised: Dr. CHOUCHANE Ammar Automatic Kinship Verification under Unconstrained environment Based Deep Learning and Local features:

Class 2019/2020

[4]- P. Sinha, B. Balas, Y. Ostrovsky, and R. Russell, “Face recognition by humans: Nineteen results all computer vision researchers should know about,” Proceed ings of the IEEE, vol. 94, no. 11, pp. 1948–1962, 2006.

[5]- M.Mahdi Dehshibi, J.S., "Cubic norm and kernel-based bi-directional PCA : toward age aware facial kinship verification,". 2017: p. 18

[6]- Chandra, H.Y.P.a.A., "Deep Learning based Kinship Verification on KinFaceW-I Dataset,". IEEE Region 10 Conference (TENCON), 2019: p. 2529-2532.

[7]Amina Tidjani, Automatic Kinship Verification, DEMOCRATIC AND POPULAR REPUBLIC OF ALGERIA MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH UNIVERSITY OF KASDI MERBAH OUARGLA

Bibliography-CHAPTER-II:

[1]-Lu, X.Z., Y.-P. Tan, Y. Shang, and J. Zhou, "Neighborhood repulsed metric learning for kinship verification,". IEEE transactions on pattern analysis and machine intelligence, 214. 36

p. 331–345.

[2]- Ahonen, T., Hadid, A. and Pietikäinen, M. (2006), Face Description with Local Binary Patterns: Application to Face Recognition. IEEE Trans. Pattern Analysis and Machine Intelligence 28(12):2037-2041.

[3]- Hadid, A. and Pietikäinen, M. (2009), Combining Appearance and Motion for Face and Gender Recognition from Videos. Pattern Recognition 42(11):2818-2827.

[4]- Heikkilä, M. and Pietikäinen, M. (2006), A Texture-Based Method for Modeling the Background and Detecting Moving Objects. IEEE Trans. Pattern Analysis and Machine

Intelligence 28(4):657-662.

[5]- Heikkilä, M., Pietikäinen, M. and Schmid, C. (2009), Description of Interest Regions with Local Binary Patterns. Pattern Recognition 42(3):425-436.

[6]- Heusch G., Rodriguez Y. and Marcel S. (2006), Local Binary Patterns as an Image Processing for Face Authentication, Proceedings of the IEEE International Conference on Automatic Face and Gesture Recognition.

[7]- Kellokumpu, V., Zhao, G. and Pietikäinen, M. (2011), Recognition of Human Actions Using Texture Descriptors. Machine Vision and Applications 22(5):767-780.

[8]- Li, S.Z., Chu, R.F., Liao, S.C. and Zhang, L.(2007), Illumination Invariant Face Recognition Using Near-Infrared Images. IEEE Trans. Pattern Analysis and Machine Intelligence 29(4):627-639.

[9]- Liao, S., Law M.W.K. and Chung A.C.S. (2009), Dominant Local Binary Patterns for Texture Classification. IEEE Trans. Image Processing 18(5):1107-1118.

[10]- Liu, L., Lao, S., Fieguth, P., Guo, Y., Wang, X. and Pietikäinen, M. (2016a), Median Robust Extended Local Binary Pattern for Texture Classification. IEEE Trans. Image Processing 25(3):1368-1381.

[11]- SVM Vs Neural Network, Last updated: November 15, 2022 Written by: Gabriele De Luca

Bibliography-CHAPTER-III:

[1]-J. Lu, X.Z., Y.-P. Tan, Y. Shang, and J. Zhou, "Neighborhood repulsed metric learning for kinship verification,". IEEE transactions on pattern analysis and machine intelligence, 214. 36 p. 331–345.

[2]- ADEM, Asma; SAHRAOUI, Sara; CHOUCHANE, Ammar. Automatic Kinship Verification under Unconstrained environment Based Deep Learning and Local features. 2020.