PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA

UNIVERSITY EL-OUED

FACULTY OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL ENGINEERING

Master thesis

Presented to fulfill the requirements to obtain

ACADEMIC MASTER DEGREE

Domain: Sciences and Technology

Option: Telecommunication

Specialty: Systems of communications

THEME

TRANSFER LEARNING FOR KINSHIP VERIFICATION

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Was Debated in : 6June 2023 in front of The Examining Committee Composed from:

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Academic year: 2022/2023

Acknowledgeme

First and foremost,

we give thanks to God for giving us the power and patience to finish this work. Alhamdulillah, thank you very much.

We are very grateful to our supervisor, Dr. Tidjani Amina , for his outstanding support, guidance, and encouragement through all our senior periods of work.

We also thank the members of the jury who honored us by accepting the verdict on our work.

We would also like to thank everyone who helped us from close and far, and a special greeting to every professor in the Specialty of Communication and Domain Sciences and Technology.

Particularly, we would like to express our gratitude to our families for their support, encouragement, and great assistance to us during our academic.

Dedication

I dedicate my graduation :

To my dear parents for their support throughout my student life and without them I would not have been who I am now.

To those who shared my childhood with me and carried the burdens of life with me

to my sister and brothers

To my dear husband ... To my little sweetheart (Razane)

To my second family , may God protect her.

To my friends for anyone who has contributed to this work from near or far.

Ghrissi Aloui Majda

I dedicate this graduation :

To the one who gave me life, my father: my dear mother, my dear father, I ask God to prolong your life.

To my big family, my brothers and sisters.

To my beloved husband and my affectionate daughter Saja, I ask God for continued health and wellness for both of you.

To my mother-in-law who helped me take care of my daughter, I ask God for health and longevity.

To everyone who loves me and I love him.

Chelalga Ouafa

This thesis is dedicated

to Our spiritual guide: Dr. Tidjani Amina.

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

To my beloved husband: Chekar Anouar. To may boys (M. Ayssem and ouwais).

To my dear sisters: Bothayna and soso. To my beloved: Abd alhamid. protect them.

To all my friends To all those who are dear to me.

To all who love me. To everyone I love.

Labadi Khawla

Abstract

In this work, we focus on the use of computer vision techniques to automatically detect relationships between two people based on their faces. The research focuses on applying a deep learning-based kinship verification system that can accurately identify familial relationships based on facial features. Processing images and estimating features automatically for classification it using to one of the features characteristics of deep learning, Where we used transfer learning for feature extraction, we took a learning transfer model of convolutional neural networks (CNNs) and used them for extraction characteristics,and that to identify the most effective architecture for kinship verification.

Key words: kinship, verification, Deep Learning, Transfer laerning, Matlab.

Résumé

Dans ce travail, nous nous concentrons sur l'utilisation de techniques de vision par ordinateur pour détecter automatiquement les relations entre deux personnes en fonction de leurs visages. La recherche se concentre sur l'application d'un système de vérification de la parenté basé sur l'apprentissage en profondeur qui peut identifier avec précision les relations familiales en fonction des traits du visage. Traiter les images et estimer automatiquement les caractéristiques pour les classer en utilisant l'une des caractéristiques caractéristiques de l'apprentissage en profondeur, où nous avons utilisé l'apprentissage par transfert pour l'extraction des caractéristiques, nous avons pris un modèle de transfert d'apprentissage des réseaux de neurones convolutifs (CNN) et les avons utilisés pour les caractéristiques d'extraction, et cela pour identifier l'architecture la plus efficace pour la vérification de la parenté.

Mots clés: parenté, vérification, Deep Learning, Transfer learning , Matlab.

ملخص

في هذا العمل, نركز على استخدام تقنيات الرؤية الحاسوبية للكشف تلقائيا العلاقات بين شخصين من وجوههم . يركز البحث على نظام للتحقق من القرابة القائم على ميزات الوجه معالجة الصور وتقدير الميزات تلقائيًا لتصنيفها باستخدام إحدى السمات المميزة للتعلم العميق، حيث استخدمنا نقل التعلم لاستخراج الميزات ، أخذنا نموذج نقل التعلم للشبكات العصبية التلافيفية (CNNs) واستخدمناها لخصائص الاستخراج ، و هذا لتحديد الهيكل الأكثر فعالية للتحقق من القرابة.

الكلمات الأساسية : القرابة ، التحقق ، التعلم العميق، نقل التعلم ، ماتلاب.

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Abbreviations:

FKV: facial kinship verification.

DNA: Deoxyribose Nucleic Acid.

CNN : Convolution Neural Network.

DL: Deep learning.

TL: Trensfer learning.

KNN : K-Nearest-Neighbor.

SVM : Support vector machines.

VGG-16 : Visual Geometry Group 16.

VGG-19 : Visual Geometry Group 19.

ROC : Receiver Operating Characteristic.

General Introduction

The face is one of the most popular biometric modalities. is an important feature that individuals use to identify one another. Humans can rapidly and readily recognize one another by their faces, and as facial features are unaffected by lighting and stance, faces continue to be a dynamic method of human identification. Kinship recognition is the process of teaching a machine to recognize and verify the relationship between kin and non-kin faces based on facial similarity based on facial traits taken from photos.

Facial-based kinship verification, the primary focus is on analyzing the facial features and patterns shared among family members. Machine learning algorithms are trained on large datasets of labeled facial images, which include pairs of individuals with known kinship relationships. These algorithms learn to extract discriminative features that can differentiate between related and unrelated individuals.

Kinship verification aims to determine the familial relationship between two individuals based on their biometric information, such as facial images. However, collecting and annotating a large dataset for training a kinship verification model from scratch can be time-consuming and resource-intensive. Transfer learning overcomes this challenge by allowing us to take advantage of existing pre-trained models that have learned general visual representations from massive datasets..

The process of transfer learning for kinship verification typically involves two main steps. Firstly, a pre-trained convolutional neural network (CNN) model, such as VGGNet, ResNet, or Inception, is selected as the base network. This pre-trained model has already learned a rich set of features from a large dataset, typically ImageNet, which includes a wide range of general visual concepts. These features capture general visual patterns and can be applied to various visual recognition tasks.

In the second step, the pre-trained CNN model is fine-tuned or further trained on a smaller dataset specifically collected for kinship verification. This dataset consists of pairs of facial images with known kinship labels, such as parent-child pairs or sibling pairs.

Transfer learning for kinship verification offers a practical and efficient approach to building accurate models by leveraging pre-trained CNN models and adapting them to the specific task of determining familial relationships. It reduces the need for extensive data collection and training time while benefiting from the rich visual representations learned from large-scale datasets.

In the first chapter, By giving some concepts, definitions, and modalities required to understand this topic, we give an introduction of biometrics . Then, the subjects of kinship confirmation and facial recognition are explored. We've highlighted the idea's many interpretations as well as the difficulties inherent in automatic kinship recognition.

the second chapter**,**We offer an method that relies on features that are learned (rather than hand-crafted). a facial recognition technique. with approach Following the feature extraction step, a data preprocessing procedure called feature selection is used. The goal of the feature selection approach is to choose the most pertinent subset of the extracted features in order to produce a usable classification with the least amount of error. In the third chapter, View and debate the experimental findings from the facial kinship verification analysis. Using kinship verification relationships, there are four main types of kinship interactions considered in this study. CNN has been used (VGG 16, VGG 19, restNet101). CNN," the network gains knowledge of the filters that were manually constructed using traditional methods, several models. We used deep learning and transfer learning with CNNs, and we will end the manuscript with a general conclusion in which we will summarize the work done by reporting on the overall analysis of the results.

CHAPTER I :

INRODUCTION FOR BIOMETRICS

I.1. Introduction:

The methodologies from computer science, engineering, and statistics are applied in biometric face recognition and automatic face recognition. environments have achieved satisfactory performance even in systems large-scale biometrics. However, the performance of these systems remains low.in harsh and unconstrained environments, characterized by poor image quality.

Face recognition has recently gained significance in the culture of networked multimedia information access.

This chapter provides a general introduction to biometrics, verification of facial consanguinity, and affiliation to the same family. We also discuss systems, applications, challenges, databases, etc.

I.2. Biometrics :

While the word “biometrics” sounds very new and “high tech,” it stands for a very old and simple concept—human recognition. In technical terms, biometrics is the automated technique of measuring a physical characteristic or personal trait of an individual and comparing that characteristic or trait to a database for purposes of recognizing that individual. biometrics uses physical characteristics, defined as the things we are, and personal traits, defined as the things we do[1].

I.3. Biometric Applications :

Nowadays, biometric systems are increasingly used in civil applications civil. The applications of biometrics can be divided into three main groups[3] :

- **Commercial applications**:

Such as computer network opening, electronic data security, e-commerce, Internet access, credit cards, physical access control, cell phones, records management in medicine, distance learning, etc.

- **Governmental applications**:

Such as a national identity card, a driving license, social security, border control, passport control, etc. Legal applications include body recognition, criminal investigation, and terrorist identification, among others.

- **Legal applications**:

Include body recognition, criminal investigation, and terrorist identification, among others.

I.4. Biometric Modalities :

Emerging of this technology is motivated by traditional methods limitations in identity verification

[2]. Different types of biometric technologies focus on different physical characteristics. Within the biometric community , these different applications are referred to as “modalities”. The emerging biometric modalities include: Hand, Face, Fingerprint, Gait, Signature, Voice, Iris, Retina, Vein, DNA, Body Odor, Ear Pattern, Keystroke and Lip and other behavioral characteristics [4], some as follows:

- **Hand geometry:**

All biometric techniques differ according to security level, user acceptance, cost, performance, etc. One of the physiological characteristics for recognition is hand geometry, which is based on the fact that each human hand is unique. Finger length, width, thickness, curvatures and relative location of these features distinguish every human being from any other person. Hand geometry is considered to achieve [5]. medium security, but with several advantages compared to other techniques.

- **Speaker / Voice :**

Voice or speaker recognition uses vocal characteristics to identify individuals using a pass-phrase. A telephone or microphone can serve as a sensor, which makes it a relatively cheap and easily deployable technology. However, voice recognition can be affected by environmental factors such as background noise [6].

- **Gait :**

A unique advantage of gait as a biometric is that it offers potential for recognition at distance or at low resolution, when other biometrics might not be perceivable . Recognition can be based on the (static) human shape as well as on movement, suggesting a richer recognition cue. Further, gait can be used when other biometrics are obscured [4].

- **Face :**

Facial recognition records the spatial geometry of distinguishing features of the face [4]. Face recognition can be an import alternative for selecting and developing an optimal biometric system. Its advantage is that it does not require physical contact with an image capture device (camera). facial recognition should be considered as a serious alternative in the development of biometric [6].

Fingerprint, hand geometry, iris, retina, face, palm print, the geometry of the ear, the DNA, the voice, the gait, the signature or even the dynamics of keystrokes are all different biometric modalities are presented in the next picture [7]:

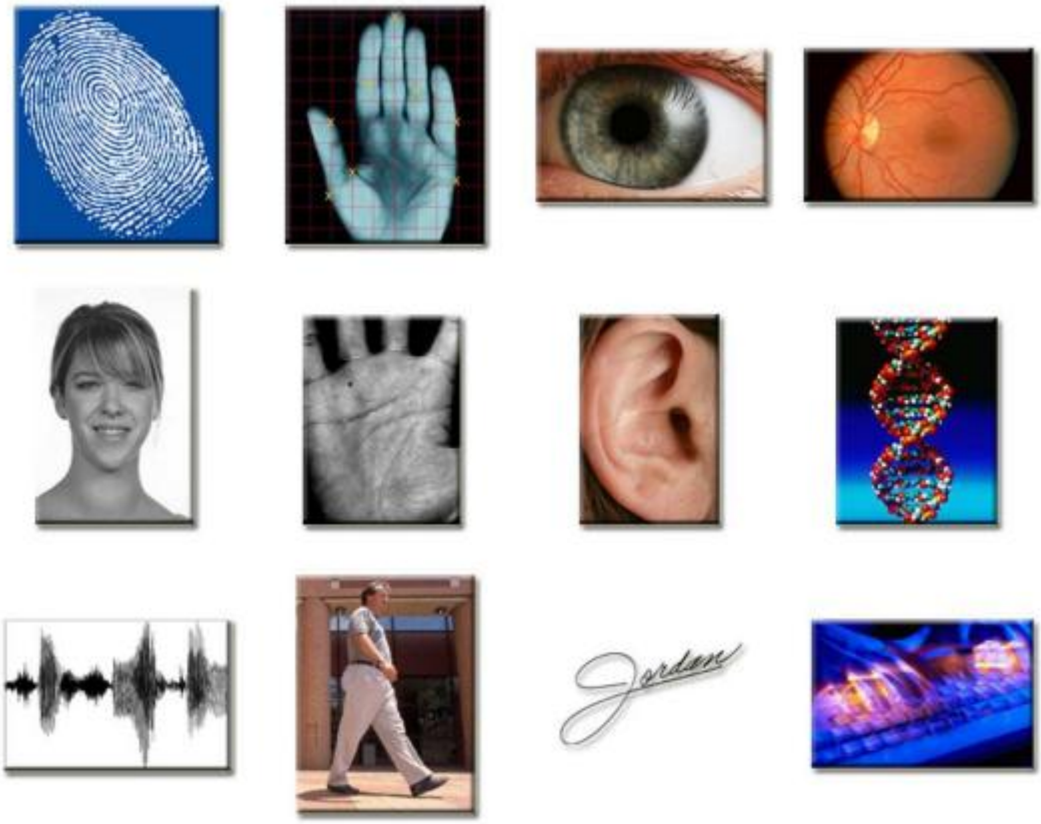


Figure I.1 : Different biometric modalities [8] .

I.5. Face recognition:

Face recognition primary objectives are to boost security and decrease compliance. to store keys and keep track of passwords. biometric system can have two operating modes: verification and identification. Once a user has his/her face sample presented to biometric system, the sample is compared with every biometric reference stored in database for the system yields the results.the procedures are shown in Figure I.2 [2].

- **Face acquisition:**

Is the point at which camera images of faces are obtained.

- **Face detection:**

Finds face and segments certain face parts in photos.

- **Preprocessing :**

Face images can be improved with preprocessing techniques such as histogram equalization, filtering, background removal, light normalization, and size normalization.

- **Facture extraction :**

Features are extracted from face images and presented to classification based on the concept.

- **Face identification:**

  Face identification system has identity of the input face image based on comparisons among all templates stored in database. It is an one to many (1: N) application.

- **Face verification:**

  Face verification system has to determine the identity of the input face image based on comparisons among all templates stored in database. It is a one to one (1: 1) concept which is commonly applied.

  .

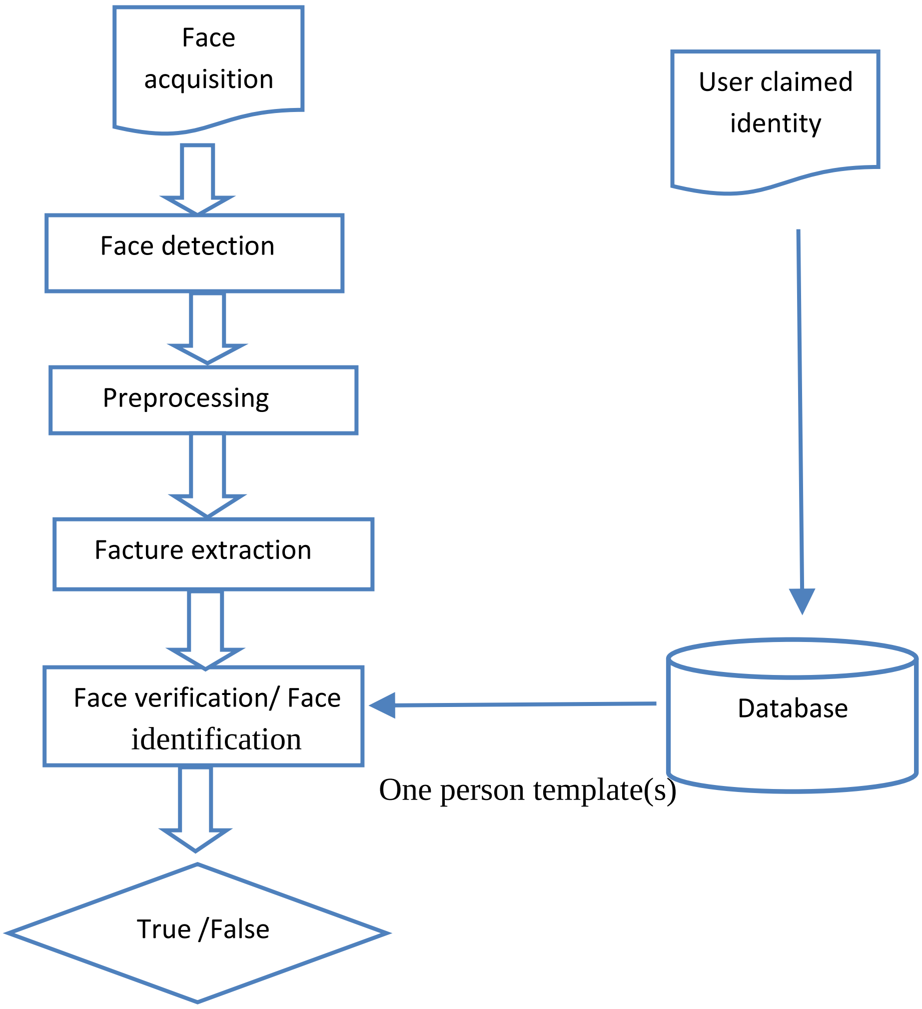


Figure I.2: Block diagram of Face identification and Face verification

I.6. kinship verification:

Kinship is the relationship between people who are biologically related with overlapping genes ,such as parent-children, sibling-sibling, and grandparent grandchildren. Image-based kinship identification is used in a variety of applications[9].

Kinship verification has also gained interest in the computer vision and machine learning communities. the authors roposed an algorithm for facial feature extraction and forward selection methodology[10].

The problem of kinship verification is particularly challenging because of the large intra-class variations among different kin pairs. At the same time, look-alikes decrease the inter-class variation among the facial images of kin. While existing algorithms have achieved reasonable accuracies[10].

I.7. Kinship terminology:

Before embarking on the nature of the problem and the solutions, we need to be familiar with different kinship terms, which will determine the course and ambit of this study[11].Despite the advances we see, most modern biological technologies do not apply. For example, the DNA test used to establish paternity is difficult and takes days to complete; However, people can use fast and affordable family relationship methods instead.

The study of kinship systems has been central in the development of anthropological theory. Kinship terminology is a system of classification. The principles by which it is organized frame experience. The kinship terminology plays a crucial role in understanding how a kinship system is organized[11].

Nevertheless, in other contexts, kinship may have different meanings. In biology, kinship typically refers to the degree of genetic relatedness or coefficient of relationship between individual members of the same species. Moreover, different societies classify kin relationships differently and therefore use different systems of kinship terminology [12].

I.8. kinship 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. 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) [12].

I.9. Face verification and kinship verification:

At first glance, the process of face verification and recognition may seem similar to that of kinship verification and recognition. In fact, face verification and recognition, and kinship verification and recognition are two different things. We might say that kinship verification and recognition is the highest level of face verification and recognition. At the same time, we cannot ignore the existence of common factors between them, such as the challenges or even the techniques used. The following describes remarkable differences between the facial recognition and kinship recognition based on seven criteria which are definition and target, mode, challenges, applications, features, processes, and accuracy.

Table I.1: Difference between kinship and face verification system [13].

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

I.10. Kinship System :

The use of models and algorithms to verify kinship relationships between people automatically. Kinship from facial images is a difficult problem that has recently attracted attention from the computer vision and pattern recognition research communities.

Usually, Four types of kinship relations are considered:mother-daughter (M-D), father-daughter (F-D), father-son (F-S), and mother-son (M-S). Since kinship also covers social connections, it has a wider role in society. Kinship verification has been studied in psychology and sociology [13] ,[14].

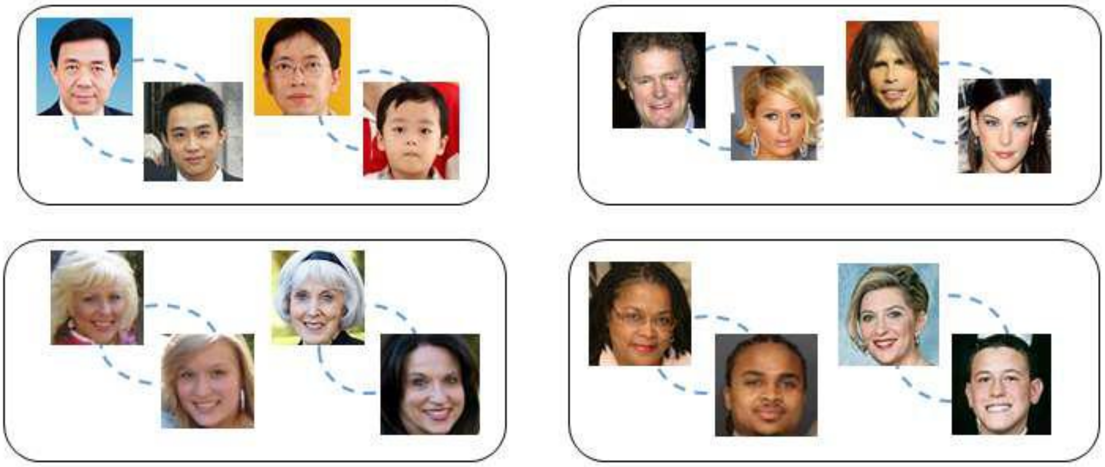


Figure I.3: Kin Face W-II database. Four types of relationships[13].

This figure presents a general schema of kinship verification based on facial images. This kinship system has the following essential components[13]:

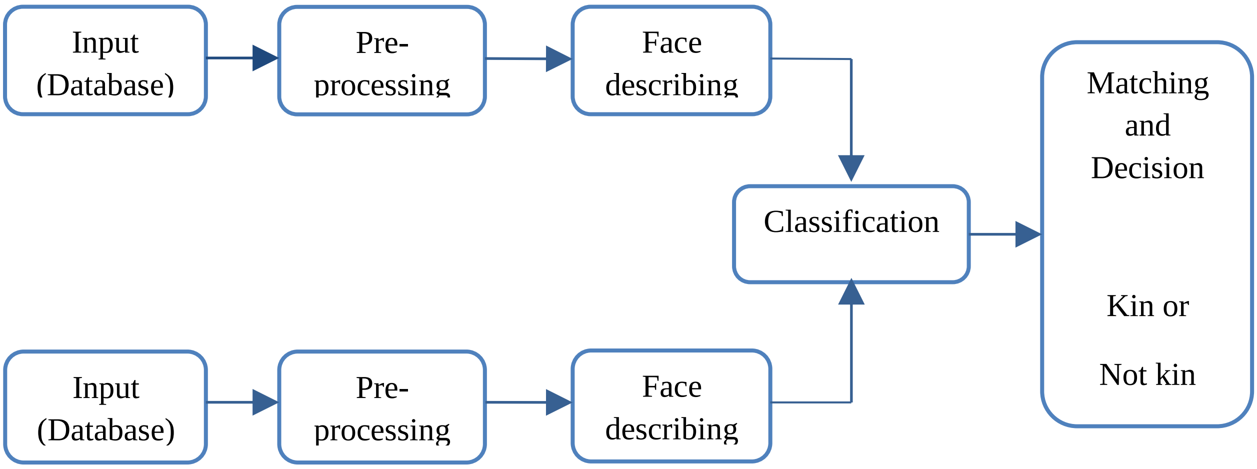


Figure I.4 : General schema of kinship verification system[13].

- **Input (database):**

Family members' public gure face photographs are included. As a result, the face images are collected in an unstructured environment with no constraints.

Pre-processing:

The pre-processing phase locates, detects, and segments the facial regions and separates them from the background. It ensures that the kinship verification system focuses on valuable regions to extract features. This phase also includes the normalization of head pose, illumination, and scale[17].

- **Face describing:**

The ideal strategy to study kinship analysis is to first learn how to distinguish different facial features in children and then relate them to their matching parents. Facial features must be described in such a way that they may be effectively characterized. The best way to learn kinship analysis is to first learn how to recognize different facial features in children and then match them with their matched parents. Facial features must be described in order to be effectively characterize.

- **Classification and Decision:**

The best way to learn about kinship analysis is to understand how to differentiate distinct facial features in children and then match them with their matched parents. Facial characteristics must be stated in order to be correctly classified. Kinship Verification is a bi-classification task that involves classifying a pair of input faces as positive or negative. (the true pairs of parents and children). (the false pairs of parents and children).

I.11. Kinship Application

The most common applications are surveillance, security, entertainment, access control, suspect tracking, and forensic . 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.

I.12. Kinship challenges

The obtain an effective solution to the kinship problem, we must initially determine the problems and challenges that hinder the achievement of the ultimate goal, Complications emerge because of variations in age, gender, illumination, pose, or minimal similarity between distant kin. Fundamentally, the problems are divided into the following two categories[12] :

(1) directly challenging (related to kinship itself) .

(2) indirectly challenging (related to the environment of the database).

I.13. Kinship Databases:

We used kinship databases to assess the performance of the proposed kinship verification technique: KinFaceW (I & II) ,UB Kin Face database, the TSKinFace database, and the Cornell Kinship database.These databases contain four different types of parent-child relationships.

Face images of people of various ages and ethnicities were captured in uncontrolled environments with no restrictions on pose. A brief description of the databases is provided below.

- **Kin FaceW I & II :**

This 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 & II is that face images with a kinship 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, 116 M–S, and 127 M–D pairs of kinship images. For the KinFaceW II dataset, each relation contains 250 pairs of kinship images[13] .

- **UB Kin Face :**

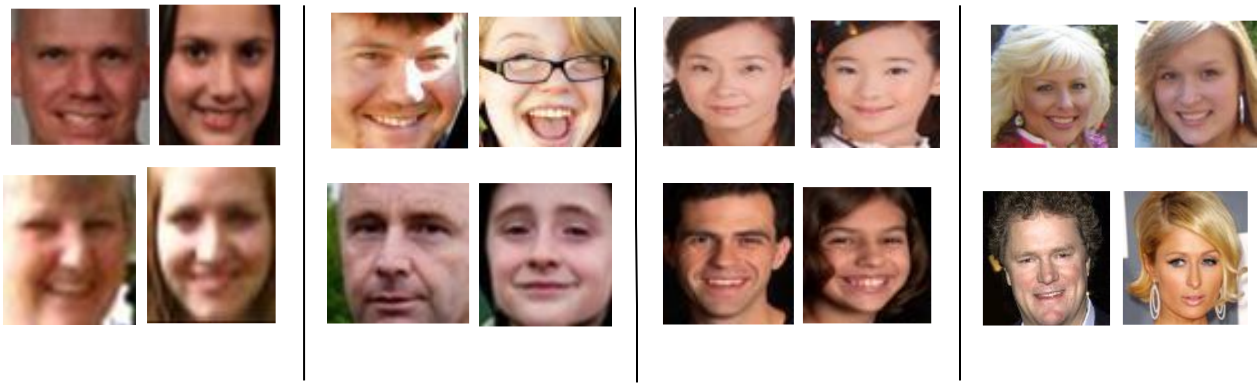
these unconstrained facial images show a large range of variations, including pose, lighting,expression, age, gender, background, race, color saturation, and image quality, etc. our database comprises 600 images of 400 people which can be separated into200 groups. Each group is composed of child, young–parent andold–parent images. The "UB KinFace Ver2.0" can be mainly divided into two parts in terms of race, each of which consists of 100 groups, 200 people and 300 images. Typically, there are four kin relations, i.e., "son–father,""son–mother," "daughter–father," and "daughter–mother," .not subject to any specific constraints, these images may reveal real-world conditions for practical evaluation. [16].

- **TSKinFace**:

Face database named TSKinFace (Tri-Subject Kinship FaceDatabase). All images in the database are harvested from the internet based on knowledge of public figures family and photo-sharing social network such as flickr.com. During images collecting, we impose no restrictions in terms of pose lighting, expression, background, race, image quality, etc Fig. 3 shows some image groups of child-parents pair from our TSKinFace database[18].

- **Cornell Kin Face:**

Contains 143 pairs of parents and children images collected from the Internet. In total, there are 286 cropped frontal face images of size 100×100 pixels. The majority of the images were taken from Google Images. To make sure that the facial extracted characteristics are of high quality, only frontal face images with a neutral facial expression are chosen. We note that, for privacy issue, 7 families are taken out of the original database that consists of 150 families[19].



KinFaceW-I **KinFaceW-II** **TSKinFace** **Cornell Kin Face**

Figure I.5 : Some examples of four widely used databases. Each row shows a paired sample, where the first image represents the parent and the second image belongs to the child[20].

I.14. Conclusion:

In this chapter, we have given an initial overview of biometric and automatic kinship verification by faces (photos). We have also introduced biometrics; once a user's face sample has been submitted to the biometric system, the sample is compared against each biometric reference stored in the database.

We also presented the process of using the kinship of the faces of two people to determine whether there is a family relationship between them. Our proposed method is divided into three stages: face pretreatment, feature extraction, and classification.

In the next chapter, we will focus on the technological study of kinship verification.

CHAPTER II :

THE TECHNIQUE USED TO CHECK KINSHIP

II.1. Introduction:

In this chapter, methods for feature extraction, performance evaluation, and classification are discussed. The face image contains many useful features. It is necessary to focus on this stage to extract the features as they are because they have a significant impact on the performance of the recognition system.

Kinship check is a binary classification problem in which a pair of input faces are classified as positive or negative. In this article, we provide an overview of the deep learning method, especially the cnn model that we will use in the extraction properties.

Finally, we talk about the feature selection and classification method used in our study.

II.2. Face Representation:

Face representation refers to the process of capturing and encoding facial characteristics in a numerical or computational form. It involves extracting meaningful features from a face, such as the shape, texture, and spatial arrangement of facial components, and transforming them into a format that can be analyzed and compared.There are different ways to represent a face, among them Convolutional Neural Networks (CNNs) based on deep learning.

II.2.1. Feature Extraction:

To establish an automatic facial kinship verification system , we first need to effectively represent the faces with features.
Recognize the different facial features of children and then learn how to relate them to their corresponding parents. For describing faces, we use deep learning features [14].
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[12].

II.2.1. Deep Learning :

Deep learning constitutes a recent, modern technique for image processing and data analysis, with promising results and large potential. As deep learning has been successfully applied in various domains deep learning provides high accuracy, outperforming existing commonly used image processing techniques [22].

Deep learning is a class of machine learning techniques, where many layers of information processing stages in hierarchical supervised architectures are exploited for unsupervised feature learning and pattern analysis/classification. The essence of deep learning is to compute hierarchical features or representations of the observational data, where the higher-level features or factors are defined from the lower-level ones[23].

II.2.2.Transfer learning (TL) :

Transfer learning is a machine learning technique whereby a model is trained and developed for one task and then re-used on a second related task. It refers to the situation whereby what has been learned in one setting is exploited to improve optimization in another setting. Transfer learning is usually applied when there is a new dataset smaller than the original dataset used to train the pre-trained model[24].

II.2.3.Convolution neural network (CNN):

Convolution neural network gained great attention for robust feature extraction and information mining. CNN had been used for variety of applications such as object recognition, image super-resolution, semantic segmentation etc. due to its robust feature extraction and learning mechanism. By keeping constant the baseline learning topology, various CNN architectures were proposed to improve the respective system performance. Among these, AlexNet, VGG16 and VGG19 are the famous CNN architecture introduced for object recognition task.[25].

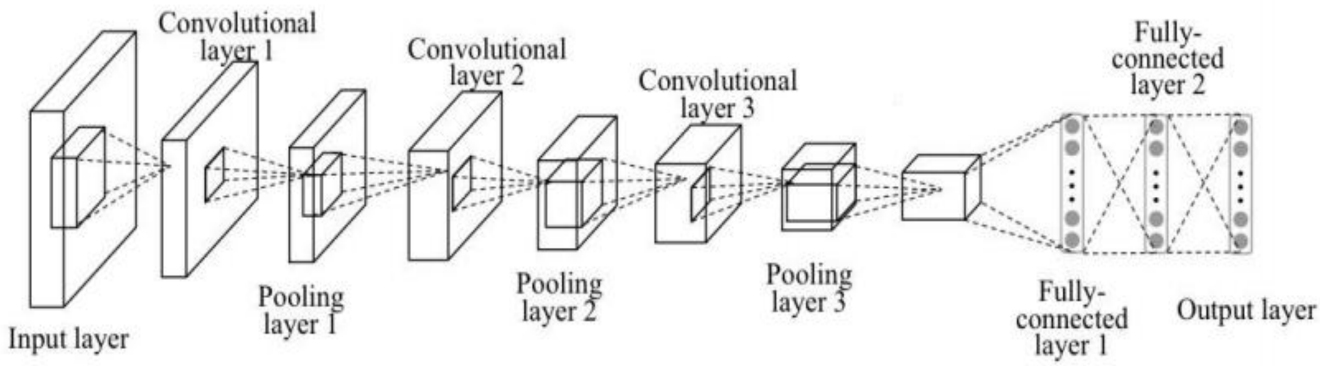


Figure II.1 : Example of a deep CNN architecture[25].

- **VGG16:**

The VGG16 model is a convolutional neural network (CNN) architecture that was introduced by the Visual Geometry Group (VGG) at the University of Oxford. It is widely used for image classification tasks. Here are the key components of the VGG16 model Input: The VGG16 model takes an input image of size 224x224 pixels, During training, the VGG16 model's weights are adjusted using backpropagation and gradient descent on a large labeled dataset, such as ImageNet. The model learns to recognize and classify objects in images by minimizing the difference between its predictions and the ground truth labels[28].

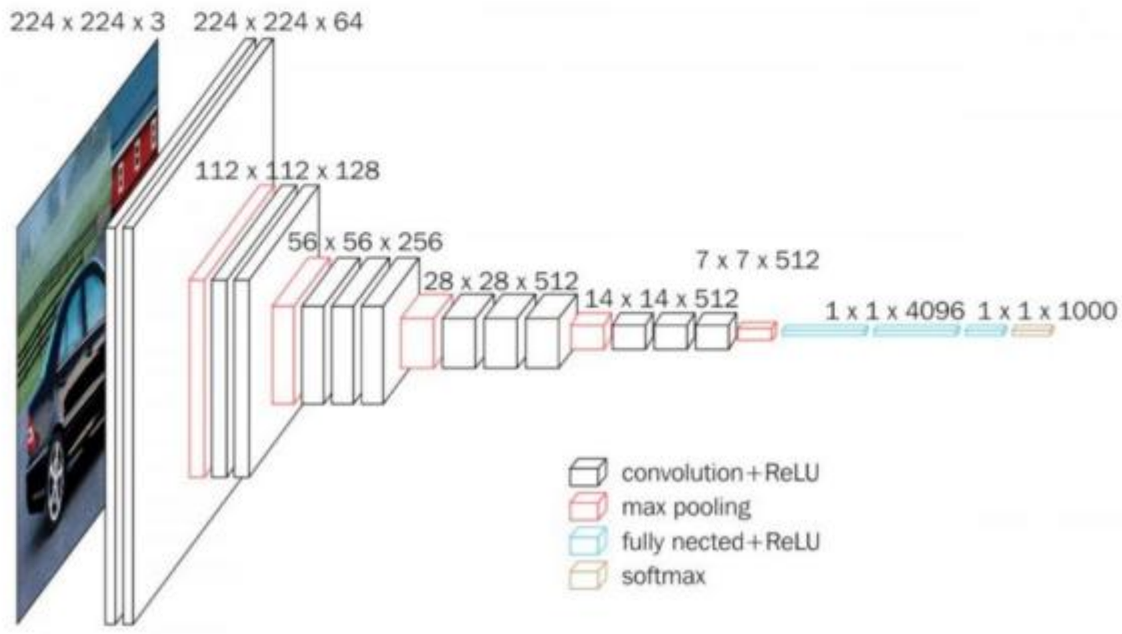


Figure II.2: VGG16 layered architecture[32].

- **VGG19:**

VGG-19 Network VGG CNN has six main structures, each of which is mainly composed of multiple connected convolutional layers and full-connected layers. The size of the convolutional kernel is 3*3, and the input size is 224*224*3. The number of layers is generally concentrated at 16~19 . The VGG-19 model structure is shown in VGG-19 CNN is used as a pre-trained model . Compared with traditional convolutional neural networks, it has been improved in network depth. It uses an alternating structure of

multiple convolutional layers and non-linear activation layers, which is better than a single convolution The layer structure can better extract image features [29].

- **ResNet-101:**

The design of ResNets was inspired by VGG-19 model. It is one of the deepest proposed architectures for ImageNet (Object detection and Image classification Challenge). Usually, in a CNN, several layers are connected to each other and are trained to perform various tasks. The network learns several levels of features at the end of its layers. The size of convolutional layers in this model have mostly 33 filters. ResNet-101 is 101-layer Residual Network and is a modified version of the 50-layer ResNet [30].

II.4. Classification :

After the features are extracted, the next step is image classification. In terms of biometric, classification means finding a proper identity for the query. Generally, image classification is performed by calculating the similarity between a target discriminating vector of feature and a query discriminating vector of feature. In addition, the similar facial components (features) are placed into one class and the others in different classes [12].

II.4.1. Support vector machines (SVM):

SVM is a powerful method for building a classifier. It aims to create a decision boundary between two classes that enables the prediction of labels from one or more feature vectors . This decision boundary, known as the hyperplane, is orientated in such a way that it is as far as possible from the closest data points from each of the classes. These closest points are called support vectors[26]. The operation of the SVM algorithm is based on nding the hyperplane that gives the largest minimum distance to the training examples. Twice, this distance receives the important name of margin within SVMs theory. Therefore, the optimal separating hyperplane maximizes the margin of the training data. Figure06 illustrate the SVM idea[13].

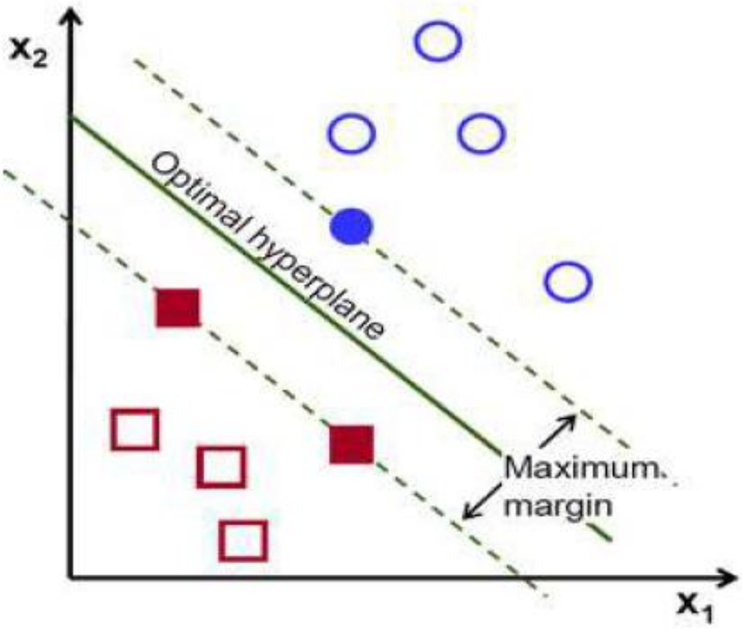


Figure II.3 : Linear SVM model. Two classes (red versus blue) were classified[26] .

II.4.2. The K-Nearest-Neighbours (KNN):

Is a non-parametric classification method. It is a widespread technique of classification in data mining scenarios. It is a distance-based classifier. It has been widely used in many fields because of the implementation ease. A class membership is the result of kNN classification. A majority vote of its neighbours categorises an object, with the item being assigned to the most common class among its k closest neighbours (k is a positive integer, typically small). However, in order to employ kNN, a suitable value for k must be chosen, and the classification success is strongly dependent on this number. The data determines the best value for k; in general, larger values of k reduces the effect of noise on classification while blurring class boundaries. If $k = 1$, the item is simply assigned to that single nearest neighbor's class. Euclidean or Manhattan distances can be used as a distance functions as seen [21].

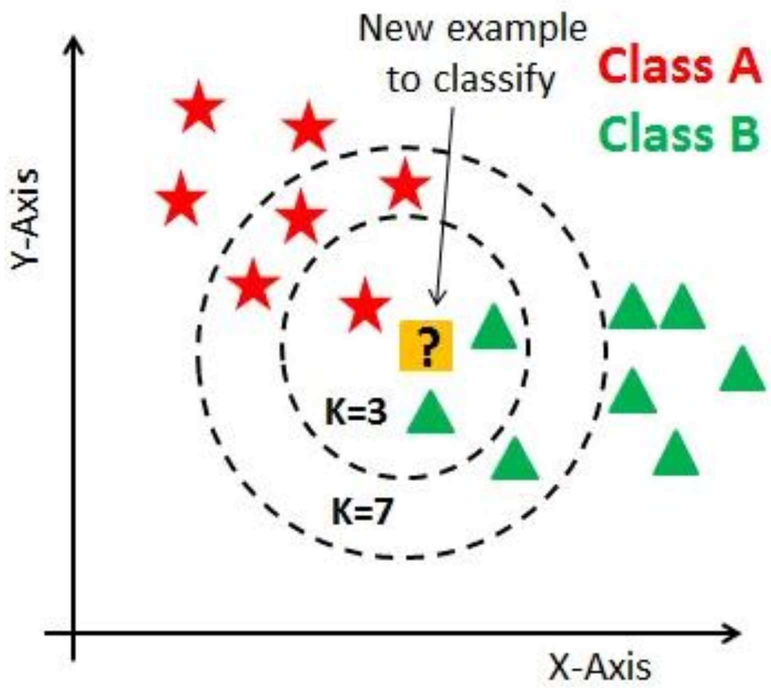


Figure II.4 : Linear KNN model. The support vectors are represented by the colors[21].

II.5. Performance Evaluation:

To evaluate the performance of the proposed kinship classification algorithm, we have collected a database of face images with kins and non-kins. The performance of the algorithm is also evaluated on the kinship database and compared with one existing kinship classification algorithm [27].

Each test pair's cosine similarity is computed. As a metric of system performance, we give the mean verification accuracy of the four kinship subsets. The Receiver Operating Characteristic (ROC) is used to evaluate system performance.

Classification Equations: [21].

$$Accuracy = (TP+TN)/(TP+FN+FP+TN) \quad (2.1)$$

$$Precision = TP/(TP+FP) \quad (2.2)$$

$$Recall = TP/(TP+FN) \quad (2.3)$$

$$F1 = 2*(Precision*Recall)/(Precision+Recall) \quad (2.4)$$

TP: is the number of images correctly classified as positive pairs.

TN: is the number of images correctly classified as negative pairings.

FP:is mis classified the input image pair as non-kin, even though they are related.

FN:is that the input image pairings are non-kin and that the system misclassified them as kin.

P: is the total number of positive pairs.

N: is the total number of negative pairs.

F1: score is calculated as the harmonic mean of precision and recall.

II.6. Fusion process:

Multi biometric systems overcome many practical problems that occur in single modality biometric systems, such as noisy sensor data, non-universality and/or lack of distinctiveness of a biometric trait, unacceptable error rates, and spoof attacks, by consolidating multiple biometric information pertains to the same identity . Biometric fusion can be implemented at various levels, such as raw data level, image level, feature level, rank level, score level, decision level, and colour may be seen as a fusion process too [14].

II.7. Conclusion:

In this chapter, we have introduced classification concepts as well as given an overview of extraction techniques and methods. where we introduced methods of deep learning and feature extraction by transfer learning using trained (CNN) convolutional neural network models. (VGG-16, VGG-19, and resNet101). where many layers of information are exploited.

In the chapter following, the implementation and the analysis of the results obtained by our method we used.

CHAPTER III

EXPERIMENTAL EVALUATION AND RESULTAT

III.1. Introduction:

In this chapter, we discuss the experimental results of tests performed on facial kinship verification. The tests involved the use of a deep learning algorithm known as a convolutional neural network (CNN). this Algorithm was trained using input images from the "KINFACEW-II" database, whitch was adopted for this study.

The purpose of the experiment was to determine whether two people were related to each other or not, based on facial features. The CNN algorithm uses different characteristics and characteristics of facial images to make this determination.

The experimental results obtained from these tests have been presented and analyzed in this chapter. We may discuss the accuracy of verification in correctly identifying kinship relationships between individuals based on the CNN trained model. The results of the experiment can include success rates, statistical metrics, and comparisons with other methods or methods in the field of facial kinship verification.

III.2. Kinship system:

Kinship verification is a system designed to automatically determine the degree of relatedness between individuals based on their facial appearance. It is a specific application of facial recognition technology that focuses on identifying familial relationships, such as parent-child, sibling, or grandparent-grandchild relationships.

system for using face photos to determine kinship. The following fundamental parts of this kinship system are depicted in **Figure III.1**. We did not use pre-processing techniques (graph equalization, filtering, background removal, light normalization, and volume normalization) because the database was pre-trained and processed during the previous training, so we took the model and applied it as is.

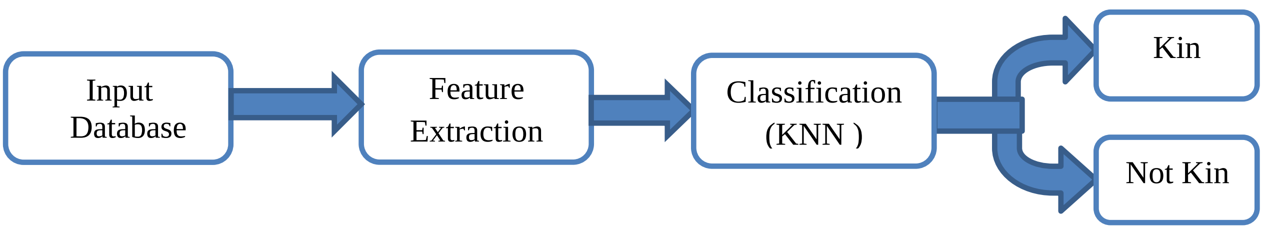


Figure III.1 : System for using face photos to determine kinship**.**

III.2.1. Database:

A previously trained KinFaceW-II dataset, was used for our examination. Where there are four kinship relationships: father-son (F-S), father-daughter (F-D), mother-son (MS), and mother-daughter (M-D). Each relationship contains 250 pairs and has been resized to 64 by 64 pixels.

Figure III.2 KinFaceW-II datasets, respectively. From top to bottom are the F-S, F-D, M-S, and M-D kinship relations[31].

III.2.2. Feature extraction:

CNN can be used as a feature extractor, which may be transferred to some distinct but related problems. Although the appearance of ultrasound images is quite different from natural images, the way of cognizing features is the same. ImageNet provides a large database for training deep models, thus in this work, we employ the VGG-16, VGG-19 and resnet101 model trained with ImageNet to extract features for our classification task.

Each of the mentioned models,consists of multiple layers that contribute to their architecture. These layers, with their specific configurations and connections, enable the models to learn and capture increasingly complex features and patterns in the input data, leading to improved performance in various computer vision tasks.

We use extracting features from specific layers of VGG16, VGG19, and ResNet101, we can obtain representations that capture different levels of abstraction. The early layers of these models tend to capture low-level features like edges and textures, while deeper layers capture more complex and high-level features. Extracting features from these layers allows us to leverage the learned representations for various downstream tasks such as classification, object detection, or kinship verification. These extracted features serve as powerful descriptors that can capture relevant information from the input data, enabling effective and efficient processing and analysis in subsequent stages of the pipeline.

III.2.3. Classification:

We have employed cosine similarity classification using K-nearest neighbors (KNN) to compute the similarity between each test pair. By calculating the cosine similarity, which measures the angle between vectors, we determine the similarity between the test pair and the training data. Using KNN, we identify the K nearest neighbors from the training data based on cosine similarity. Finally, we classify the test pair based on the majority voting of these K neighbors. It allows us to classify test pairs based on their similarity to the training data using the cosine similarity measure and the KNN algorithm.

The cosine similarity equation is defined as:

$$\text{cosine similarity} = (A * B) / (||A|| * ||B||) \quad (3.1)$$

where:

$A * B$ represents the dot product of vectors A and B.

$||A||$ represents the magnitude (or Euclidean norm) of vector A.

$||B||$ represents the magnitude (or Euclidean norm) of vector B.

III.3.Experimental Evaluation:

For the experiments, we use the trained kinwII database, take the same number of pairs by connecting the faces of the subjects. We apply a transfer learning technique for feature extraction. We do validation and cosine similarity is calculated for each test pair. We report the average validation accuracy of the four kinship groups as a measure of system performance.

III.4.Results and Analysis:

- The models CNN:

The basic idea of choosing kinship is to define a subset of properties, the distances between data points in the same categories (positive pairs) are as small as possible, while the distances between data points are as large as possible between data points in categories (negative pairs).

We experimented with vgg16, vgg19, and resnet101 modules to see the number of layers and the input size of each module.We note that each has its own number of layers and has the same input size.

The idea presented highlights a table that demonstrates the distinctions between the CNN models in two aspects: number of delays and input size. The table III.1 provides a comparison of these characteristics, indicating the variations among the CNN models in terms of the number of delays employed and the input size required by each model.

Table III.1: The difference between models CNN.

Models	Number dof layers	Input size
Vgg16	41	244*224*3
Vgg19	47	244*244*3
Resnet101	347	244*244*3

To better achieve the accuracy of results for kinship relations (FD-FS-MD-MS) by using different CNN models, specifically VGG16, VGG19 and ResNet101, we change the layer (pool5, fc8, relu7, drop6).

The results obtained have been summarized and presented in **Table III.2**, showing the performance of each model in the context of specific kinship relationships.

Table III.2: the accuracy of vgg16 using different layers.

Layer	Accuracy (%)
Pool5	**%73**
Fc8	**%70**
Relu7	**%68**
Drop6	**%69**

The VGG16 model is a common convolutional neural network architecture known for its deep layers and powerful performance in various computer vision tasks. Consists of 16 convolutional and fully connected layers In our case, after trying different layers of VGG16, we found that the best layer for classifying mother and daughter relatives is "pool5" with 73% accuracy.

The "pool5" layer refers to the fifth aggregation layer in the VGG16 architecture. Grouping layers are typically used to reduce feature maps and retain important information while reducing spatial dimensions. By defining the "pool5" layer, you have determined that the features extracted at this point in the network are the most distinct and informative to distinguish between mother-daughter husbands.

The idea described focuses on obtaining optimal results for a specific kinship relationship (FD-FS-MD-MS) by utilizing different CNN models, namely VGG16, VGG19, and ResNet101. The experimental outcomes of this approach are presented in **Table III.3**, showcasing the performance metrics and comparisons among the various CNN models in relation to the given kinship relationship.

Table III.3 : Kinship verification accuracy in % of KinFace W-II databases.

KinFaceW- II	FD	FS	MD	MS	Mean
Vgg16	73.60	81.40	80.40	78.60	**78.50**
Vgg19	72.20	73.60	77.60	78.60	**75.50**
Resnet101	75.80	81.80	82.60	82.20	**80.60**

After evaluating different CNN models, including VGG16, VGG19, and ResNet101, for relationship classification (FD-FS-MD-MS), the best-performing model was found to be ResNet101. Among the relationships, the MD relationship achieved the highest accuracy of 82.60% using ResNet101. ResNet101 outperformed both VGG16 and VGG19 in capturing the relevant features for this specific relationship classification task. The accuracy of 82.60% indicates the percentage of correctly classified instances for the MD relationship. This demonstrates that ResNet101 has a strong capability to distinguish between mother-daughter pairs and generalize well to this specific relationship classification task

These are the curves obtained from Matlab after a change to KinFace W-II (FD-FS MD MS) databases. Within the resnet101 layer shows the accuracy of the % kinship check:

$$\text{Accuracy} = TP+TN /P+N \qquad (3.2)$$

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 allpositive pairs, and N is the number of all negative pairs .

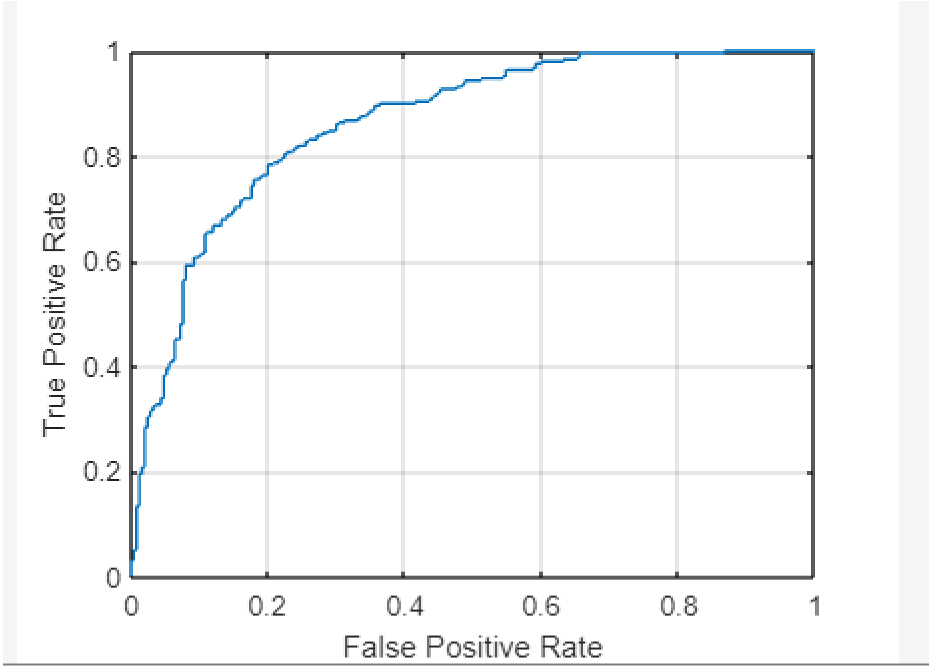


Figure III.3: Graphical approach showing the accuracy of FS on KinFaceW-II in databases.

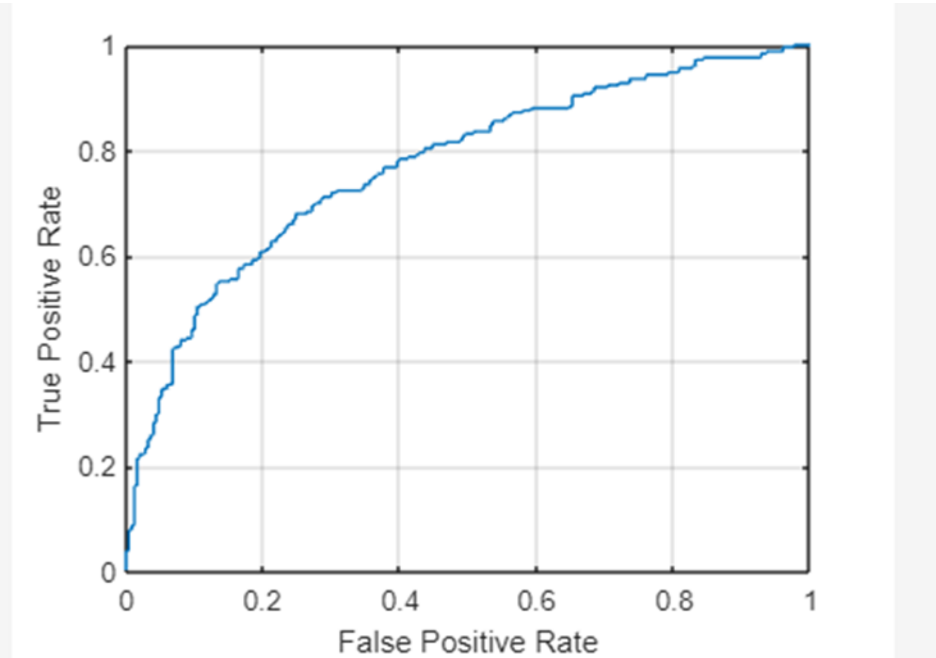


Figure III.4: Graphical approach showing the accuracy of FD on KinFaceW-II in databases.

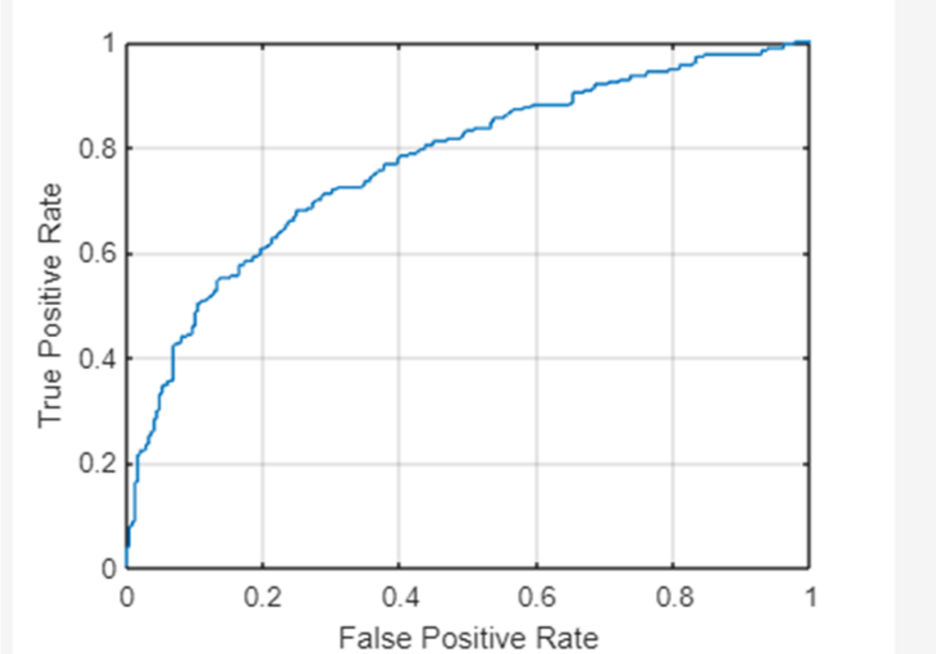


Figure III.5: Graphical approach showing the accuracy of MS on KinFaceW-II in databases.

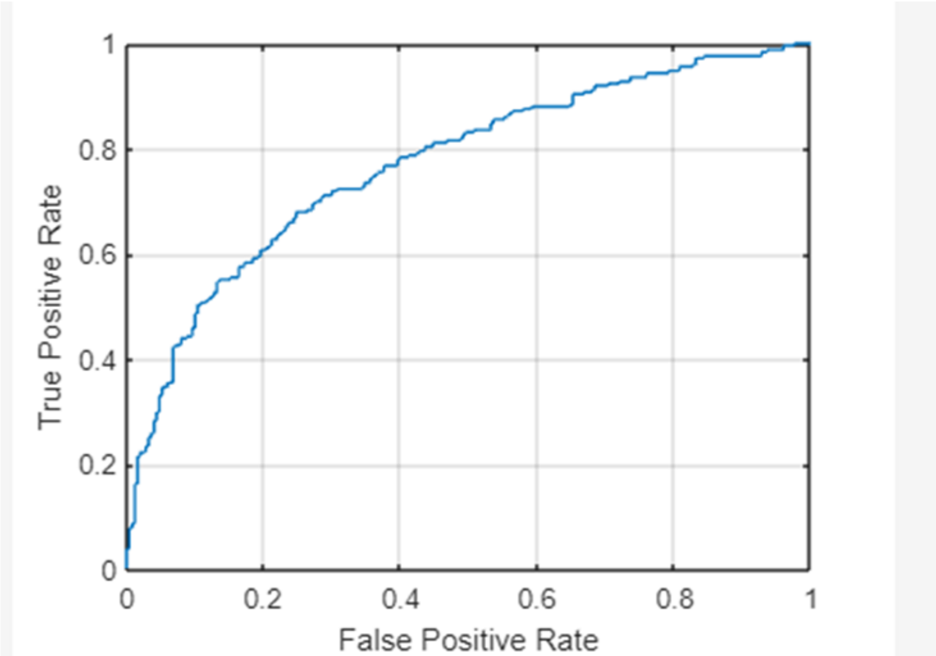


Figure III.6: : Graphical approach showing the accuracy of MD on KinFaceW-II in databases.

After changing the relations (FD-FS-MD-MS) in the model (resnet101) and getting the curves we came to the conclusion: the best relationship (FD-FS-MD-MS) in resnet101 is the MD relationship with 87.60% accuracy.

Transfer learning is a highly effective and efficient approach for learning about kinship in a relatively straightforward manner. By leveraging pre-trained deep learning models trained on large-scale datasets, transfer learning allows us to apply the knowledge and representations learned from related tasks to the kinship verification task. This method is particularly advantageous when labeled kinship data is limited, as it enables the model to benefit from the pre-existing understanding of facial features and relationships. By adapting and fine-tuning the pre-trained model specifically for kinship verification, we can effectively capture the subtle cues and patterns indicative of kinship relationships. Overall, transfer learning offers a practical and successful pathway for exploring and understanding kinship through the lens of deep learning.

III.6. Conclusion:

In this study, the focus was on automatic kinship verification using facial images from four types of family relationships: father-son (F-S), father-daughter (F-D), mother-son (M-S), and mother-daughter (M-D). The objective was to employ a system that can accurately determine whether two individuals share a familial bond.

To achieve this, two different approaches were employed: K-Nearest Neighbors (KNN) and Convolutional Neural Networks (CNN). The KNN algorithm was utilized as a baseline for comparison, while three CNN models, namely VGG19, VGG16, and Resnet101, were used to extract features from the facial images.

In this study we addressed automatic kinship verification from facial images of four linkages: F-S, F-D, M-S and M-D. Using KNN and CNN (VGG19, VGG16,Resnet101), It selects the strong features and neglects the weak ones to improve the performance of family validation.

General Conclusion

The purpose of the work was to the kinship verification from face images. We used a comprehensive discussion of the important concepts needed to understand kinship recognition through facial images. Features are based on the learning of the surface properties and appearance of an object given by the shape, size, arrangement, density, and proportion of its elementary parts. The performance of a recognition system largely relies on representations of features. For this, we are taking advantage of the deep learning (DL) technique in order to address this problem. Because deep learning recognition methods automatically learn and understand features from massive amounts of data like text and images,.Transfer learning makes it possible to adapt pre-trained convolutional neural network (CNN) models to the specific job of kinship verification. These models have been trained on large-scale datasets for general image identification tasks. This shows how automatically generated features from learning algorithms can deliver incredibly insightful representations for a classification problem, improving accuracy.

These techniques have been put into practice in Matlab and validated using Kin Face in the Wild-II (KinFaceW-II) data.

A practical and efficient method for kinship verification, transfer learning makes use of pre-trained CNN models, lowers the need for lengthy data collection, and takes advantage of the generalization properties of the pre-trained models. Transfer learning techniques are anticipated to significantly improve kinship verification systems, enabling more precise and effective assessment of familial ties based on biometric data, as research and breakthroughs in the fields of deep learning and computer vision continue.

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.

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