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Title

A transfer Learning features for fingers recognition

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Dedication Abimouloud Mouhamed laid

Praise to God who has enabled us for this which we would not have reached it if were not for the grace of God to us.

I dedicated this modest work to those who are dearest to me, I remember:

First all: **my dears mother** , No words can express their true value of gratitude and love who are the two dearest people in the world, may God protect and take care of them for me.

My fathers: my dears fathers, **Abdel Fatah**. Who encouraged me in my academic path , May God bless you and grant you health, happiness, and a long life.

To my brother: **Taha El Amine**,

To my sisters: **Fatiha**, **Hammida Hadil**,

To my Gra-mother:**Ben mouaiza-Fatma**,

To my Gra-Father: **Laid**"May God have mercy on him and make heaven his abode", **Habiche Lazhari**, **Ghalem Ammar**

To My Uncles: **Bachir , khaled ,Nordine , Ahmed**.

To My aunts: **Fathia ,Oum-el-khir , Khadija** .

To my Colleague: **Lakhdari Abdesslam**Thank you for your patience and your love, I wish you a life full of success, happiness.

To my dear friends:**Merad amine**, **Hassan Bougaffa**, **Boumedien Houed Maissa**, **Aness Medjouel**, **Djazzar Nordine**, **Nadir Ben Arbi**, **Adel Madadi**, I can't find the sincere words to express my feelings and thoughts, you are my brothers.

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My supervisor: **Dr Khaled Ben sid**. May Allah grant your health and happiness and long life .

Dedication Lakhdari Abdessalam

This thesis is dedicated to:
The sake of Allah, my Creator.
And my Master,My great teacher and messenger, Mohammed (May Allah bless and grant him), who taught us the purpose of life.
It is with genuine gratitude and warm regard that
I dedicate my dissertation work to my family and many friends. A special feeling of gratitude to my loving **parents** , whose words of encouragement and push for tenacity ring in my ears. My **grandparents**, who helped me in all things great and small and have never left my side. they are very special.
I also dedicate this work to my Colleague **Abimouloud Mohamed Laid**, who helped me a lot in this work. and give special thanks to all my friends specially **Benlarbi Nadir** . I also want to remember my friend **Ahmed Chaib Saila** whose life was cut short and left a void never to be filled in our lives, May Allah (SWT) grant you Jannah.
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Abstract

Person identification security is one of the most pressing challenges in current times. There is a high need for a trustworthy and secure identity verification solution. A biometric identification system can be a safe and secure way to identify someone. Because it has the ability to identify individuals,in other way we find the finger knuckle print (FKP) and finger vein (FV) is considered two of the developing hand biometrics. In our experience, we used convolutional neural networks as one of the basic structures for deep learning because they are the best in image analysis. With Using transfer learning (Pre-trained CNN models) we will test a biometric system based on fingers knuckle and finger vein.with two datasets of finger-knuckle-print and finger-vein, containing 11736 images of finger knuckle and finger vein (7920 knuckle, 3816 vein). In addition, we will apply a multimodal system, by using the fusion of the unimodal scores in order to improve the performance and get better results. The experimental results were very encouraging and showed the potential for biometric applications utilizing the finger knuckle print and finger vein. The thesis also performs a comparison of the identification performance of the system with different CNN models to choose the best result for the knuckle and vein recognition task,we detail all the results of our tests in this thesis.

Keywords

Biometrics, Figure knuckle print ,Finger Vein, artificial intelligence, machine learning, deep learning, image processing, convolutional neural network.

Résumé

La sécurité de l'identification des personnes est l'un des défis les plus urgents à l'heure actuelle.donc Il existe un besoin important pour une solution de vérification d'identité fiable et sécurisée. Un système d'identification biométrique peut être un moyen sûr et sécurisé d'identifier quelqu'un. Parce qu'il a la capacité d'identifier les individus, d'une autre manière, nous constatons que l'empreinte digitale (FKP) et la veine du doigt (FV) sont considérées comme deux des biométries de la main en développement. D'après notre expérience, nous avons utilisé les réseaux de neurones convolutifs comme l'une des structures de base de l'apprentissage en profondeur, car ils sont les meilleurs en analyse d'images. Avec l'utilisation de l'apprentissage par transfert (modèles CNN pré-formés), nous testerons un système biométrique basé sur l'articulation des doigts et la veine du doigt, avec deux base des donnés d'empreinte de l'articulation du doigt et de la veine du doigt, contenant 11736 images de l'articulation du doigt et de la veine du doigt (7920 articulation, 3816 veine). De plus, nous appliquerons un système multimodal, en utilisant la fusion des scores unimodaux afin d'améliorer les performances et d'obtenir de meilleurs résultats. Les résultats expérimentaux ont été très encourageants et ont montré le potentiel d'applications biométriques utilisant l'empreinte digitale et la veine du doigt. La thèse effectue également une comparaison des performances d'identification du système avec différents modèles CNN pour choisir le meilleur résultat pour la tâche de reconnaissance des articulations et des veines, nous détaillons tous les résultats de nous tests dans cette thèse.

Mote Clé

Biométrie, FKP/FV, intelligence artificielle, machine learning, deep learning, traitement d'image, réseau de neurones convolutifs.

الملخص: يعد تأمين الهوية الشخصية أحد أكثر تحديات اليوم إلحاحًا .لأن هناك حاجة ماسة إلى حل موثوق وآمن للتحقق من الهوية. يمكن أن يكون نظام تحديد الهوية البيومترية طريقة آمنة ومضمونة للتعرف على شخص ما. نظرًا لأن لديها القدرة على تحديد الأفراد ، بطريقة أخرى ، نجد أن بصمة الإصبع ووريد الإصبع تعتبر من القياسات الحيوية لليد النامية. من تجربتنا ، استخدمنا الشبكات العصبية التلافيفية كأحد الهياكل الأساسية للتعلم العميق لأنها الأفضل في تحليل الصور. من خلال استخدام التعلم عن طريق النقل (نماذج الشبكات العصبية التلافيفية المدربة مسبقًا) ، سنختبر نظامًا بيولوجيًا يعتمد على مفصل الإصبع ووريد الأصابع ، مع قاعدتي بيانات مشتركين لبصمات الأصابع ووريد الأصابع ، تحتوي على ١١٧٣٦ صورة لمفصل الإصبع ووريد الأصابع (٧٩٢٠ مفصل ، ٣٨١٦ الوريد). علاوة على ذلك ، سوف نطبق نظامًا متعدد الوسائط ، باستخدام دمج الدرجات أحادية الوسائط لتحسين الأداء والحصول على نتائج أفضل. كانت النتائج التجريبية مشجعة للغاية وأظهرت إمكانات تطبيقات القياسات الحيوية باستخدام بصمات الأصابع وريد الأصابع. تقوم الأطروحة أيضًا بمقارنة أداء التعرف على النظام مع نماذج الشبكات العصبية التلافيفية المختلفة لاختيار أفضل نتيجة لمهمة التعرف على المفاصل والوريد ، ونفصل جميع نتائج اختباراتنا في هذه الأطروحة.

الكلمات الدلالية: القياسات الحيوية ، بصمة مفصل الاصبع ،وريد الاصبع ، الذكاء الاصطناعي ، التعلم الآلي ، التعلم العميق ، معالجة الصور ، الشبكة العصبية التلافيفية.

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Acronyms

ANN Artificial Neural Network

AI Artificial Intelligence

CMC Cumulative Match Characteris

CNN Convolutional Neural Network

DL Deep learning

DNA Deoxyribonucleic Acid

EER Equal Error Rate

FAR False Reject Rate

FC Fully Connected

FKP Fingure Knuckle Print

FRR False Reject Rate

FV Fingure Vein

GAR Genuine Acceptance Rate

ID Identity Doucument

MAX Maximum rule

ML Machine Learning

MIN Minimum rule

PROD Product rule

PIN Personal Identification Number

ReLU Rectified Linear Unit

RGB Red Green Bleu

ROC Receiver Operating Characteristi

RPR Rank of Perfect Recongtion

SUM Simple Sum Rule

T_o Treshold

TL Transfer Learning

VGG Visual geometry group

General Introduction

Since the beginning of the 21st century, humans have always been searching for ways to improve their lifestyle in many domains, especially their own security, and here we see their huge step in technological evolution towards improving their safety in several sectors through several methods and ways.
The science of measuring and evaluating the particular physical or behavioral attributes that are used to identify a person is known as biometrics [1] . The term ”biometric” is derived from the Greek words ”metric” or ”metrikos” (measure), which means ”life measurement” in English. Physical traits are connected to the form or measures of the human body and include the face, fingerprint, Deoxyribonucleic Acid (DNA), ear, iris, retina, and hand geometry. Signature, voice, and gait are examples of behavioral traits that are connected to a person's behavior or dynamic measures [2].
Biometrics is the most appropriate technology for identity verification and/or identification of people using their physiological characteristics, including biological, morphological, and behavioral characteristics.
This technology makes identity data theft more difficult and thus increases user confidence, as physical presence is required during identification [3]. In this reason , we will focus on the Fingure Knuckle Print (FKP) and Fingure Vein (FV) . This trait has been selected according to many great advantages: it is accepted by people; it is easy to use; simple; permanent; stable; lifelong; and unique to each individual.
Unimodal biometric systems frequently have a number of restrictions, including public unacceptability, inaccuracies, the potential for infiltration, and other issues. This led to the development of multimodal biometrics, which combines data from a variety of biometric sources.

These sources can include many iterations of the same modality, various biometric techniques, numerous prototypes of a modality deriving from various sensors, or various data from various algorithms for extracting a single modality's properties [4] .

According to research, these multimodal biometric systems can thus perform better than unimodal systems. Multimodal biometric systems are therefore appropriate for a wide range of applications [5] .

The aim of this work is to achieve unimodal and multimodal biometric identification systems based on a deep CNN technique using multi-sample FKP and FV images to create a strong and precise recognition system. Our experience is based on the pretrained models of convolutional neural network method. the use of transfer learning Convolutional Neural Network (CNN) has shown outstanding success in the recognition field [1] .

Finally, this thesis is organized into three chapters:

In the first chapter, we present general information about biometric identification systems.

In the second chapter, we delve into the world of deep learning and the feature extraction method and classification based on CNN.

The last chapter, covers the analysis and comparison of the proposed methods that apply to the pre-trained models and presents the results obtained on a database of FKP/FV.

1

Biometrics Systems

1.1 Introduction

People have begun to expect strong security in order to keep their information and things safe in this modern day. The majority of storage locations today include some kind of protection, such as a password, pin number, or biometric identification system [6].

This chapter will introduce biometrics and its different modalities, beginning with the definition and application of biometrics. Following that, we go through the various biometric modalities and we give the biometric system assessment metrics, as well as the meanings and everything else relevant to biometric systems. [7].

1.2 Biometric Definition

Biometrics is automated methods of recognizing a person based on a physiological or behavioral characteristic. Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. Examples of physiological characteristics include hand or finger images, facial characteristics, and iris recognition. Utilizing biometrics for personal verification is becoming convenient and considerably more accurate than current methods (such as the utilization of passwords or Personal Identification Number (PIN) or Identity Doucument (ID)). This is because biometrics links the event to a particular individual (a password or token may be used by someone other than the authorized user); is convenient (nothing to carry or remember); accurate (it provides for positive verification); can provide an audit trail; and is becoming socially acceptable and Inexpensive [8].

1.3 Biometric Modalities

Human biometrics can be classified into two groups, physiological and behavioral. The first group is based on stable physical characteristics, while the second group uses learned, alterable behavioral characteristics [9].

To be useful, biometric data should be:

- as unique as possible (uniqueness).

- should occur in as many people as possible (universality).
- should stay relatively constant over time (permanence).
- and should be able to be measured easily (measurability).
- and without causing undue inconvenience or distress to a user (acceptability).

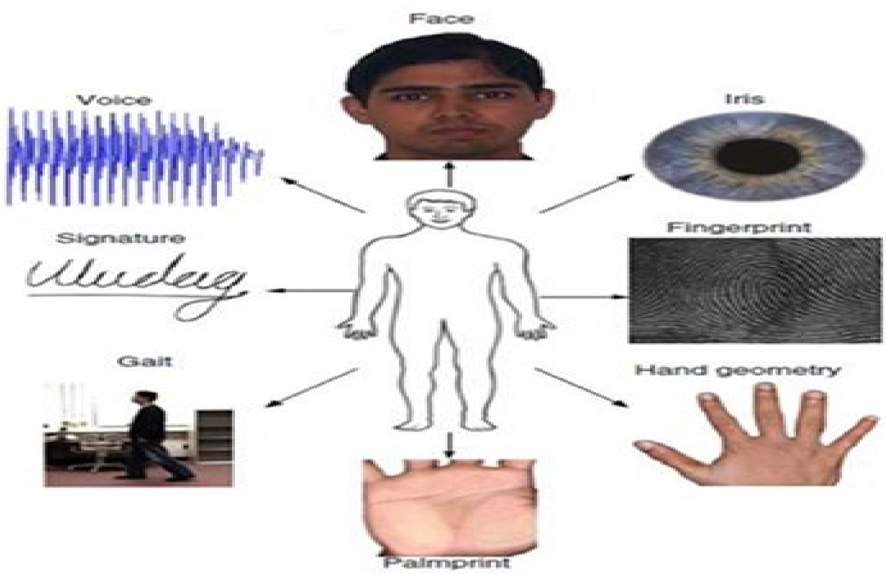


Figure 1.1: Examples of Biometric Modalities

1.3.1 Biological modality

The biological modality is based on the examination of a person's biological traits. Smell, DNA, and physiological impulses are all part of it.

- **DNA**

All the genetic information required for the growth and operation of living organisms is contained in DNA. Except for identical twins, who have the same DNA sequence, DNA is a one-dimensional unique code for one's identity [10] Figure1.2.

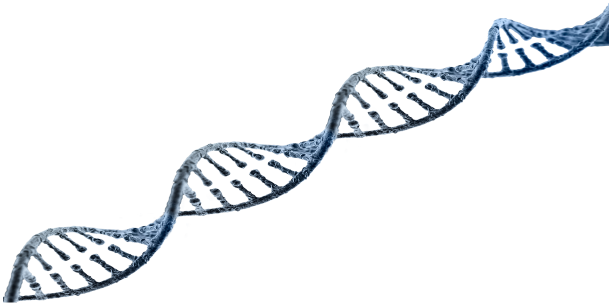


Figure 1.2: Examples of DNA Structure

1.3.2 Behavioral modality

To prove identification, employ a number of behavioral traits such as a voice pattern, signature, etc.

- **Signature**

Is a behavioral biometric that the manner in which a person writes their name is recognized to be a feature of that individual. A behavioral biometric is one that varies over time and is impacted by the physical and emotional situations of the signatories. Although signatures need contact with the writing instrument and effort on the part of the user, they have been recognized as a technique of authentication in government, legal, and economic transactions [10] Figure1.3.

Figure 1.3: Examples of Signature

- **Voice**

Is a biometric composite of physical and behavioral factors. The form and size of the appendages involved in sound synthesis (e.g., vocal tract, mouth, nasal cavities, and lips) determine the physical characteristics of an individual's voice. Individually, these physical features of human speech are unchangeable [10] Figure1.4.

Figure 1.4: Examples of Voice Recongtion

1.3.3 Physical modality

This classification is based on an examination of each person's unique and permanent physical traits. The fingerprint, the face, the geometry of the hand, the drawing of the veins of the hand, the iris, the retina, and are all examples of these unique physical characteristics. These variables have the benefit of remaining constant throughout an individual's life and are unaffected by physiological circumstances like stress or exhaustion, which are detrimental to the behavioral modality [10] .

In this study case we have selected two physical modalities:

A) FKP (finger knuckle print)

By observing that the texture pattern produced by bending the finger knuckle is highly distinctive, with a high confidence we could recognize a person's identity based on his FKP [6] Figure1.5 .

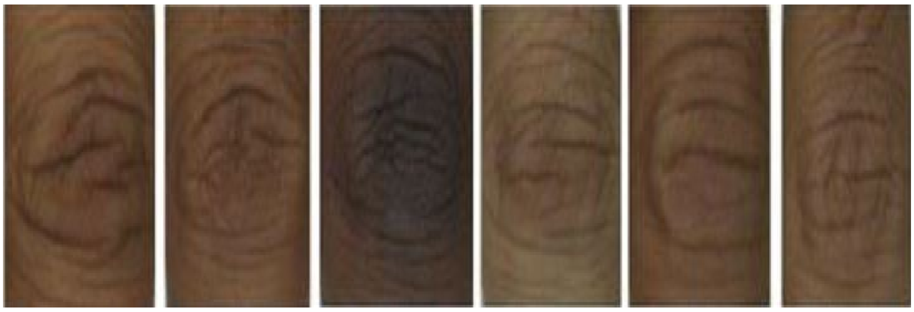


Figure 1.5: finger knuckle print photo

B) FV (finger vein)

Finger-vein biometric system used a specifically designed device to capture image of the vein patterns. The vein is inside of the human's finger. [6] Finger-vein features exhibit several Figure1.6 .

Figure 1.6: Finger vein

1.4 Choice of biometric trait

The choice of a biometric feature for a certain application is based on a number of factors. To establish the acceptability of a physical or behavioral attribute for use in a biometric application, seven elements must be examined be used in a biometric application [10] .

- Universality:

This is a quality that should be possessed by everyone who uses the program. The biometric system's failure to enroll (FTE) rate is determined by this factor [10].

- Uniqueness:

The supplied attribute should be sufficiently diverse among the user population's individuals [10] .

- Permanence:

In terms of the matching method, an individual's biometric feature should be sufficiently invariant through time. A biometric that changes greatly over time isn't very useful [10].

- Measurability:

The biometric attribute should be able to be acquired and digitized using appropriate methods that do not cause the user excessive hardship. Furthermore, the obtained raw data should be process able so that discriminative feature sets may be extracted [10].

- Performance:

The computing resources necessary to attain that accuracy, as well as the biometric system's throughput (number of transactions handled per unit time), must fulfill the application's requirements [10].

- Acceptability:

Individuals in the target audience who will use the app must be willing to give the system their biometric characteristic [10].

- Circumvention:

In the case of physical characteristics, this refers to the simplicity with which an individual's attributes may be mimicked using artifacts (e.g., false fingers) and imitation in the case of behavioral features. It also refers to the obfuscation process, in which a user modifies a biometric feature to avoid recognition [10].

1.5 Biometric System

Generally, a biometric system is a computer system implemented by exploiting corresponding biometric identification methods, techniques, and technologies. Biometric systems can be regarded as pattern recognition systems, where a feature set is first extracted from the acquired data, and then compared with the stored template set to make a decision on the identity of an individual. A biometric system can be applied to two fields, verification and identification. In verification mode, the decision is whether a person is "who he claims to be?" In identification mode, the decision is "whose biometric data is this?" A biometric system is thus formalized into a two-class or multi-class pattern recognition system [11].

1.5.1 Biometric System Functionalities:

A) Enrollment:

During the enrollment phase, the biometric data is acquired from the individual and stored in a database along with the person's identity. Typically, the acquired biometric data is processed to extract salient and distinctive features. In many cases, only the extracted feature set gets stored, while the raw biometric data is discarded [10] .

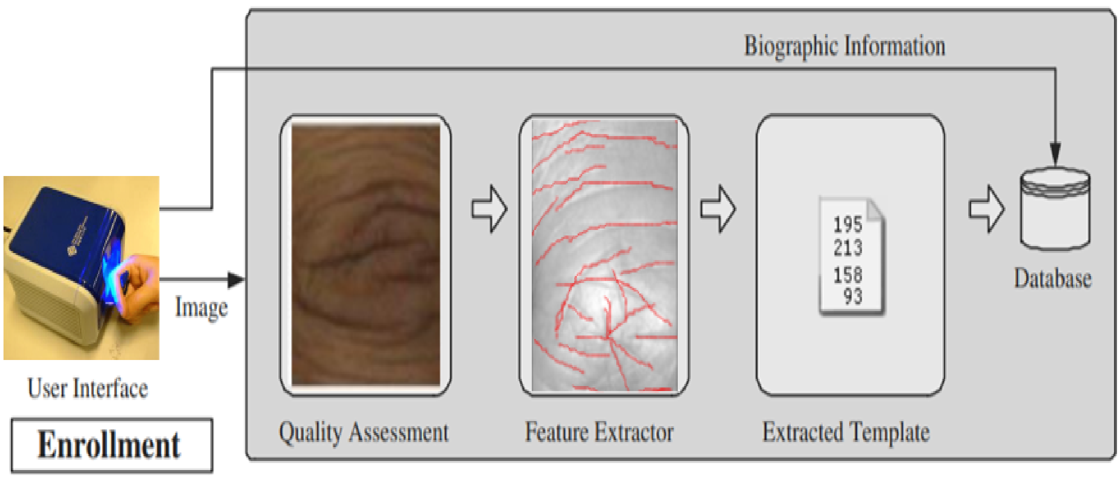


Figure 1.7: Enrollment Phase

B) Verification:

In this scenario, the query is compared only to the template corresponding to the claimed identity (a one-to-one match). The identity claim is usually made through the use of PIN, a user name, or a token (e.g., smart card). If the user's input and the template of the claimed identity have a high degree of similarity, then the claim is accepted as "genuine". Otherwise, the claim is rejected and the user is considered an "impostor". The dotted line in the verification module Fig1.8 is an optional operation to update a specific user's template [10] .

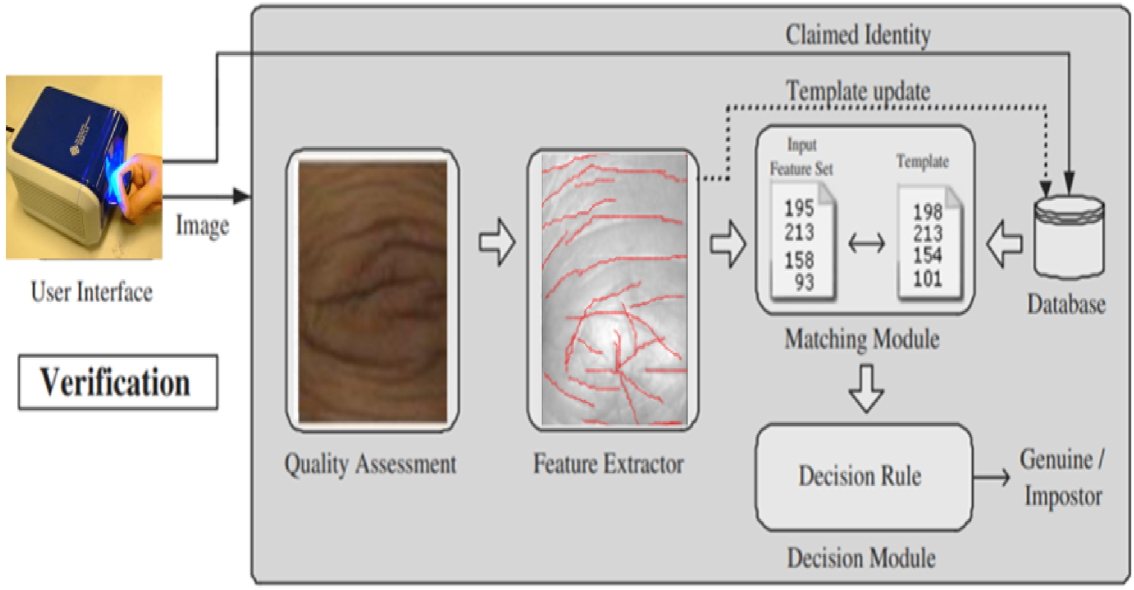


Figure 1.8: Verification module

C) Identification:

Identification functionality can be further classified into positive and negative identification. In positive identification, the user attempts to positively identify himself to the system without explicitly claiming an identity. A positive identification system answers the question "Are you someone who is known to the system?" by determining the identity of the user from a known set of identities. In contrast, the user in a negative identification application is considered to be concealing his true identity (either explicitly or implicitly) from the system. Negative identification is also known as screening and the objective of such systems is to find out "Are you who you say you are not?" [10] .

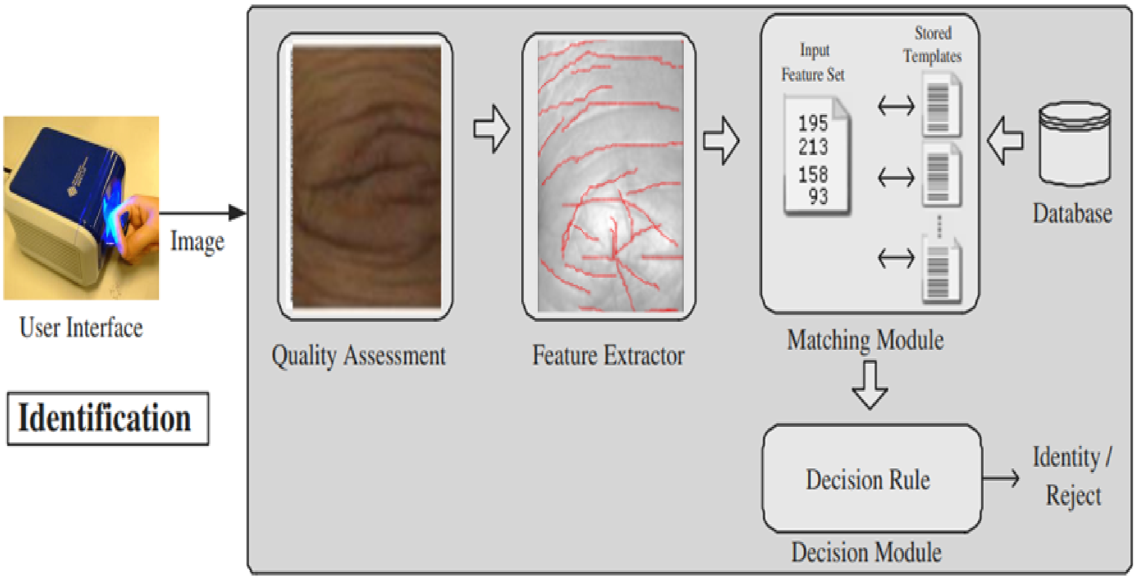


Figure 1.9: Identification module

1.6 Components of biometric system

Biometric System is multiple individual components (such as sensor, matching algorithm, and result display) that combine to make a fully operational system. A biometric system is an automated system capable of :

- capturing a biometric sample from an end user.
- extracting and processing the biometric data from that sample.
- storing the extracted information in a database.
- comparing the biometric data with data contained in one or more references.
- deciding how well they match and indicating whether or not an identification or verification of identity has been achieved.

1.7 Operation of a biometric system

A biometric system is essentially a pattern recognition system consisting of four basic building blocks, namely, (a) sensor, (b) feature extractor, (c) database, and (d) matcher as shown these four modules will now be discussed in turn.

- Sensor module

A suitable biometric reader or scanner is required to acquire the raw biometric data of an individual. for example, an optical fingerprint sensor may be used to image the friction ridge structure of the fingertip. The sensor module defines the human machine interface and is, therefore, pivotal to the performance of the biometric system. A poorly designed interface can result in a high failure to-acquire rate and, consequently, low user acceptability. The quality of the raw data is also impacted by the characteristics of the camera technology that is used [12] .

- Quality assessment and feature extraction module

The quality of the biometric data acquired by the sensor is first assessed in order to determine its suitability for further processing. Typically, the acquired data is subjected to a signal enhancement algorithm in order to improve its quality. However, in some cases, the quality of the data may be so poor that the user is asked to present the biometric data again. The biometric data is then processed and a set of salient discriminatory features extracted to represent the underlying trait. For example, the position and orientation of minutia points (local ridge and valley anomalies) in a fingerprint image are extracted by the feature extraction module in a fingerprint-based biometric system. During enrollment, this feature set is stored in the database and is commonly referred to as a template [12] .

- Matching and decision-making module

The purpose of a biometric matcher is to compare the query features against the stored templates to generate match scores. The match score is a measure of the similarity between the template and the query. Hence, a larger match score indicates greater similarity between the template and the query. If a matcher measures the dissimilarity (instead of the similarity) between the two feature sets, the score is referred to as a distance score. A smaller distance score indicates greater similarity [10] .

- System database module

The biometric system database acts as the repository of biometric information. During the enrollment process, the feature set extracted from the raw biometric sample (i.e., the template) is stored in the database along with some personal identity information (such as name, PIN, address, etc.) characterizing the user. One of the key decisions in the design of a biometric system is whether to use a centralized database or a decentralized one [10] .

1.8 Multimodal biometric

Unimodal biometrics has several problems cause this system less accurate and secure, multimodal is used to overcome these problems and to increase level of security. limitations imposed by unimodal biometrics can be overcome by including multiple sources of information for establishing identity of person. Multimodal biometrics refers to the use of a combination of two or more biometric modalities in a Verification or Identification system. They address the problem of non- universality, since multiple traits ensure sufficient population coverage [13] Multimodal biometrics also address the problem of spoofing as it concerns with multiple traits or modalities, it would be very difficult for an imposter to spoof or attack multiple traits of genuine user simultaneously [13] .

1.8.1 Types Of Multimodal Biometrics

A multibiometric system relies on the evidence presented by multiple sources of biometric information. Based on the nature of these sources, a multibiometric system can be classified into one of the following fivecategories: multi-sensor, multi-algorithm, multi-instance, multi-sample, multimodal [14] .see figure 1.10 .

A) Multi-sensor systems

Multi-sensor systems employ multiple sensors to capture a single biometric trait of an individual. For example,an infrared sensor may be used in conjunction with a visible-light sensor to acquire the subsurface information of a person's face. The use of multiple sensors, in some instances, can result in the acquisition of complementary information that can enhance the recognition ability of the system [15] .

B) Multi-algorithm Systems

multi-algorithm systems combine the output of multiple methods such as feature extraction or/and classification algorithms for the same biometrics data. In other words, the supplementary information by more than one algorithm helps to improve the performance. So, utilization of new sensor is not required thus it is cost effective. However, this system has a drawback due to many features extraction and matching modules can cause complexity of system computation [15] .

C) Multi-instance Systems

These systems use multiple instances of the same body trait and have also been referred to as multi-unit systems in the literature. For example, the left and right index fingers, or the left and right FKP of an individual, may be used to verify an individual's identity [14] .

D) Multi-sample Systems

A single sensor may be used to acquire multiple samples of the same biometric trait in order to account for the variations that can occur in the trait, or to obtain a more complete representation of the underlying trait.A face system, for example, may capture (and store) the frontal profile of a person's face along with the left and right profiles in order to account for variations in the facial pose [14] .

E) Multimodal Systems

multi-modal systems use the evidence of multiple biometric traits to extract the biometric information of an individual. These different biometric traits can come from a variety of modalities. The multi-modal system is reliable due to the presence of multiple independent biometrics. However, the drawback of this system is due to the substantial cost because of the requirement of many sensors , For example, using a combination of FKP and FV [15] .

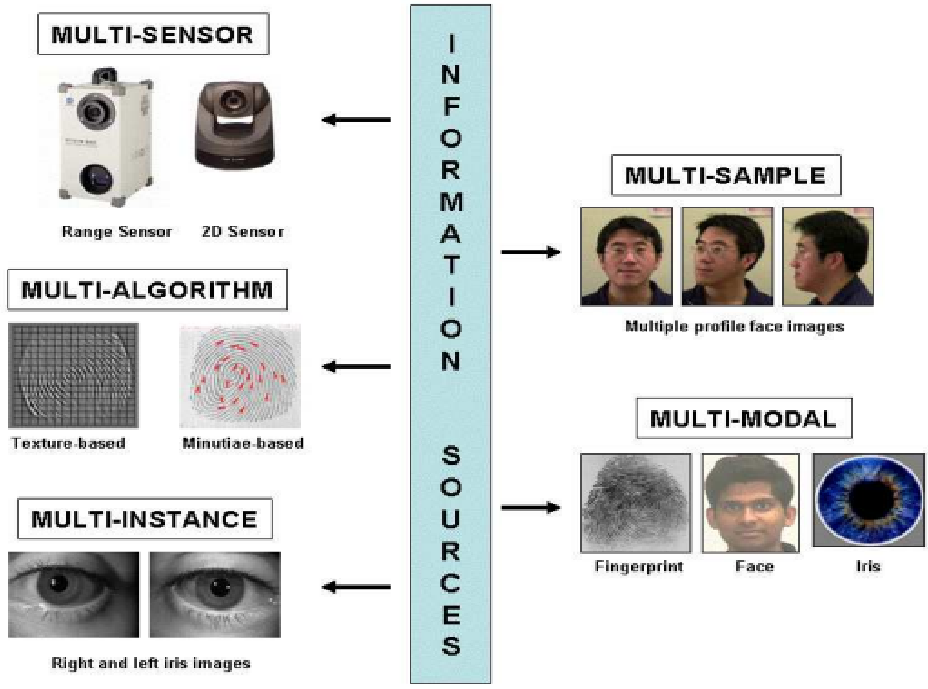


Figure 1.10: Sources of information for biometric fusion

1.8.2 Modules Of Multimodal Biometrics

Multimodal biometric system has four modules - sensor module, feature extraction module, matching module and decision-making module respectively. Multimodal biometric system can operate in serial mode or parallel mode. In serial mode of operation, the output of one modality is used to narrow down the number of possible identities before the next modality is used. This can reduce the overall recognition time. In parallel mode of operation, information from different modalities is used simultaneously. In case of multimodal biometric system decision can be made at various levels of fusion like Feature level fusion, Matching score level fusion and Decision level fusion [13] The block diagram for general multimodal biometric system is as shown in figure1.11 .

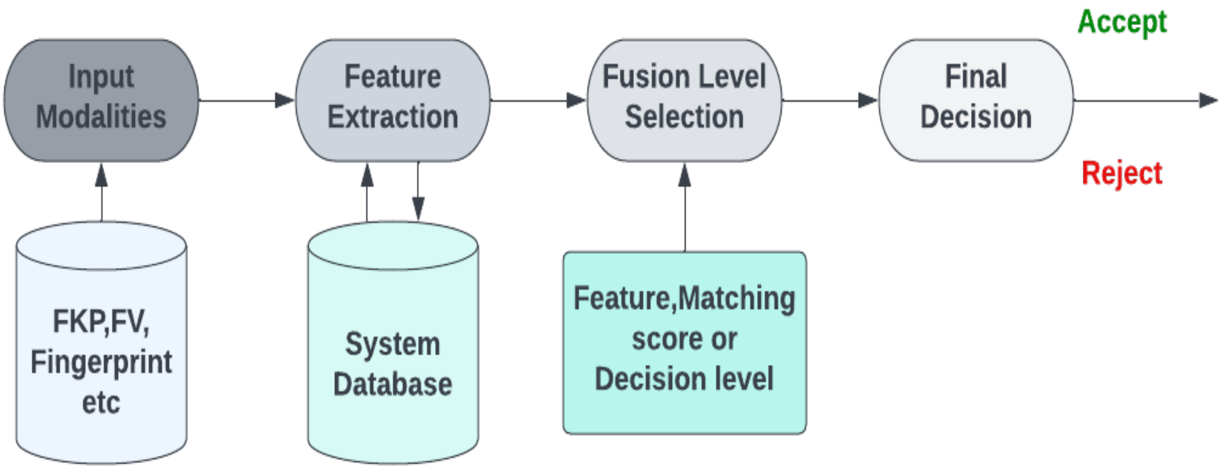


Figure 1.11: Diagram of general multimodal biometrics

1.8.3 Fusion Levels In Multimodal Biometrics

In a multibiometric system,there are four fusion levels in multimodal biometrics: Sensor-level fusion,feature level fusion, matching score level fusion and decision level fusion.

A) Sensor level fusion

The raw biometric data (e.g., a face image) acquired from an individual represents the richest source of information although it is expected to be contaminated by noise (e.g., non-uniform illumination, background clutter, etc.). Sensor-level fusion refers to the consolidation of (a) raw data obtained using multiple sensors or (b) multiple snapshots of a biometric using a single sensor [12] .

B) Feature Level Fusion

In the feature level fusion, signals coming from different biometric traits are first processed and feature vectors are extracted separately from each biometric trait. After that these feature vectors are combined to form a composite feature vector which is further used for classification. In case of feature level fusion some reduction technique must be used in order to select only useful features. Some of the researchers have applied fusion at feature level. Since features contain richer information of biometric trait than matching score or decision of matcher, fusion at feature level is expected to provide better recognition results [13] Figure1.12 Shows feature level fusion.

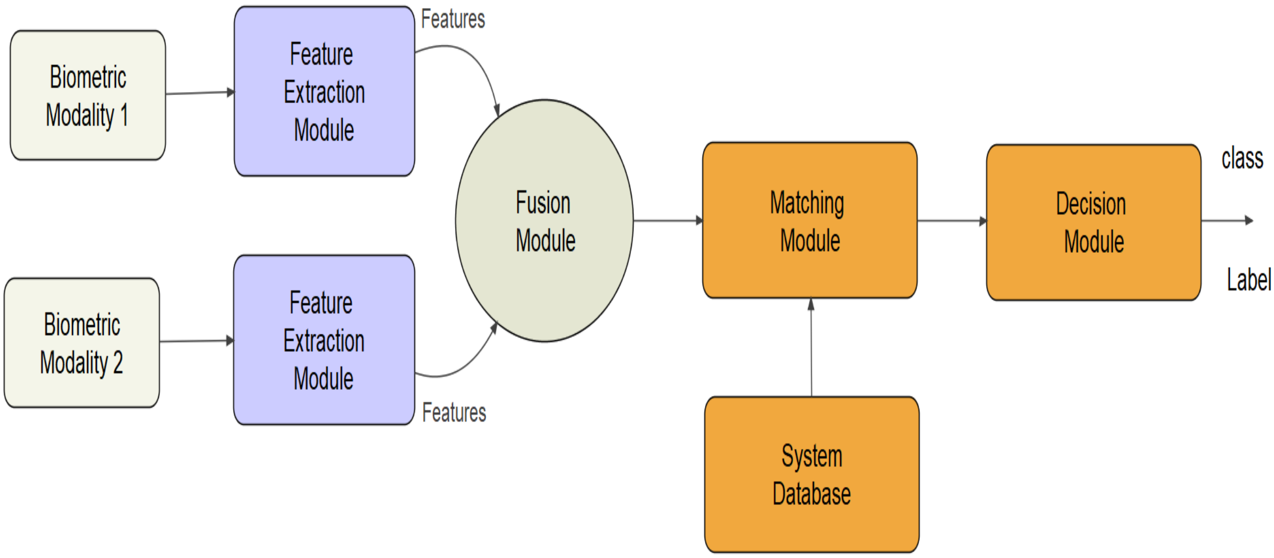


Figure 1.12: Feature level fusion

C) Matching Score Level Fusion

In this level, rather than combining feature vectors, they are processed separately and individual matching score is found and finally these matching scores are combined to make classification. Various statistical learning techniques may be used to combine match scores. [14] Figure1.13 show matching score level fusion.

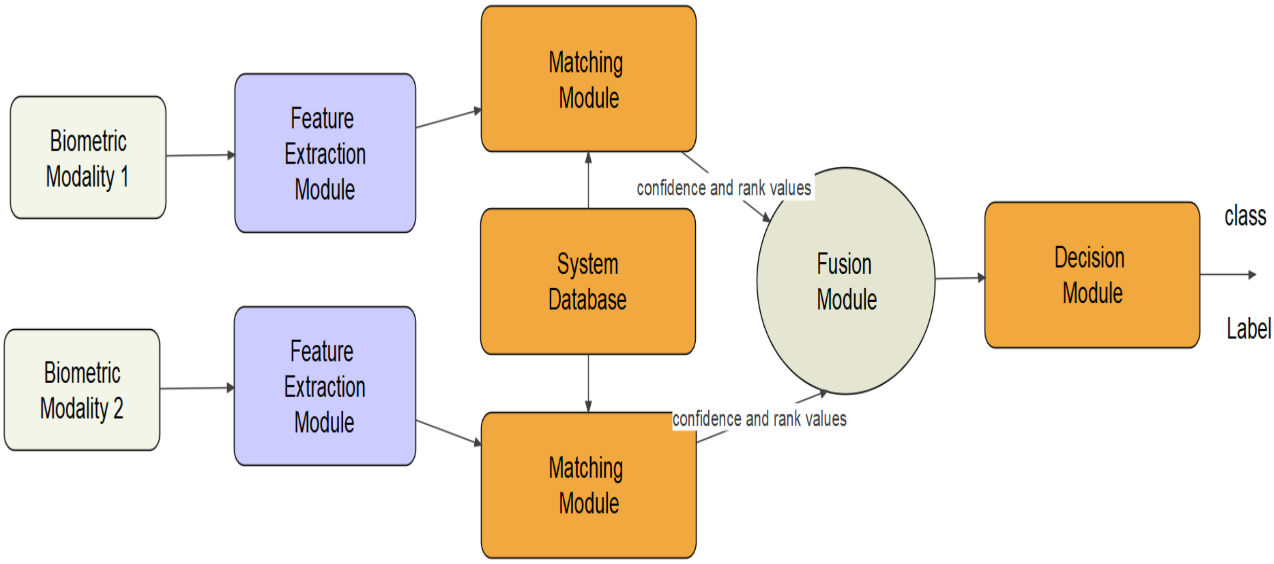


Figure 1.13: Fusion at matching score level

D) Decision Level Fusion

In decision level fusion each modality is first pre-classified independently i.e., each biometric trait is captured, then features are extracted from that captured trait, based on those extracted features. The final classification is based on fusion of the outputs of different modalities [14] Figure1.14 Shows decision level fusion.

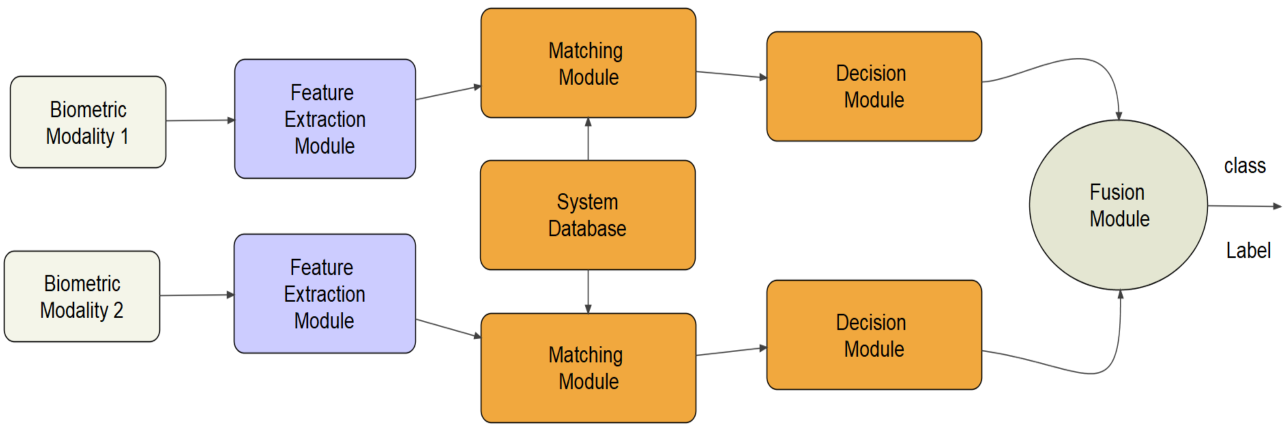


Figure 1.14: Fusion at decision level

1.9 Future Of Biometrics

Traditional biometrics have flaws that future technology may be able to solve.

1. The answer to the necessity of user participation with old technologies is to expand the spectrum of identification.

2. Multi-factor authentication can compensate for the drawbacks of individual technologies.

3. Behavioural biometrics evaluate people in real time and require users to re-identify themselves [2] .

1.10 Conclusion

In this chapter we offered a general overview of biometrics systems and the solved issues by using biometric systems, there are many needs for biometrics in numerous fields it helps overcome many difficulties faced in other person recognizing techniques.,and this chapter serves as an introduction to the next chapters. As a result, we must have introduced the many ideas in this biometric sector, as well as an overview of the features of biometric systems and the various approaches used to evaluate these systems. The next chapter introduces the various topics connected to Deep learning (DL) and CNN .

2

Deep-Convolutional Neural Networks (Deep-CNN) and Transfer learning

2.1 Introduction

In the last few years, the DL field has grown fast, and it has been extensively used to successfully address a wide range of traditional applications. The DL computing paradigm has been deemed the Gold Standard in Machine Learning (ML) [16] .
Moreover, it has gradually become the most widely used computational approach in the field of ML, thus achieving outstanding results on several complex cognitive tasks, matching or even beating those provided by human performance. One of the benefits of DL is the ability to learn from massive amounts of data [17] .

More importantly, DL has outperformed well-known ML techniques in many domains, e.g., cyber security, personal identification, biometric information, robotics and control, and medical information processing, among many others [17] . In this chapter we present the idea of deep learning methods CNN and we will be interested in the CNN pre-trained model .

2.2 Artificial intelligence

Artificial Intelligence (AI) is intelligence demonstrated by machines in the form of a computer process that mimics human intelligence and behavior while acting intelligently. A device that observes its environment and takes actions to enhance its chances of success at some goal is a computer accomplishing challenging tasks [18] . When a machine duplicates ”cognitive” functions that humans identify with other human minds, such as ”learning” and ”problem solving,” comprehending complex data and successfully understanding human thoughts, this is referred to as ”artificial intelligence” [19] . our AI application like as shown in figure . 2.1

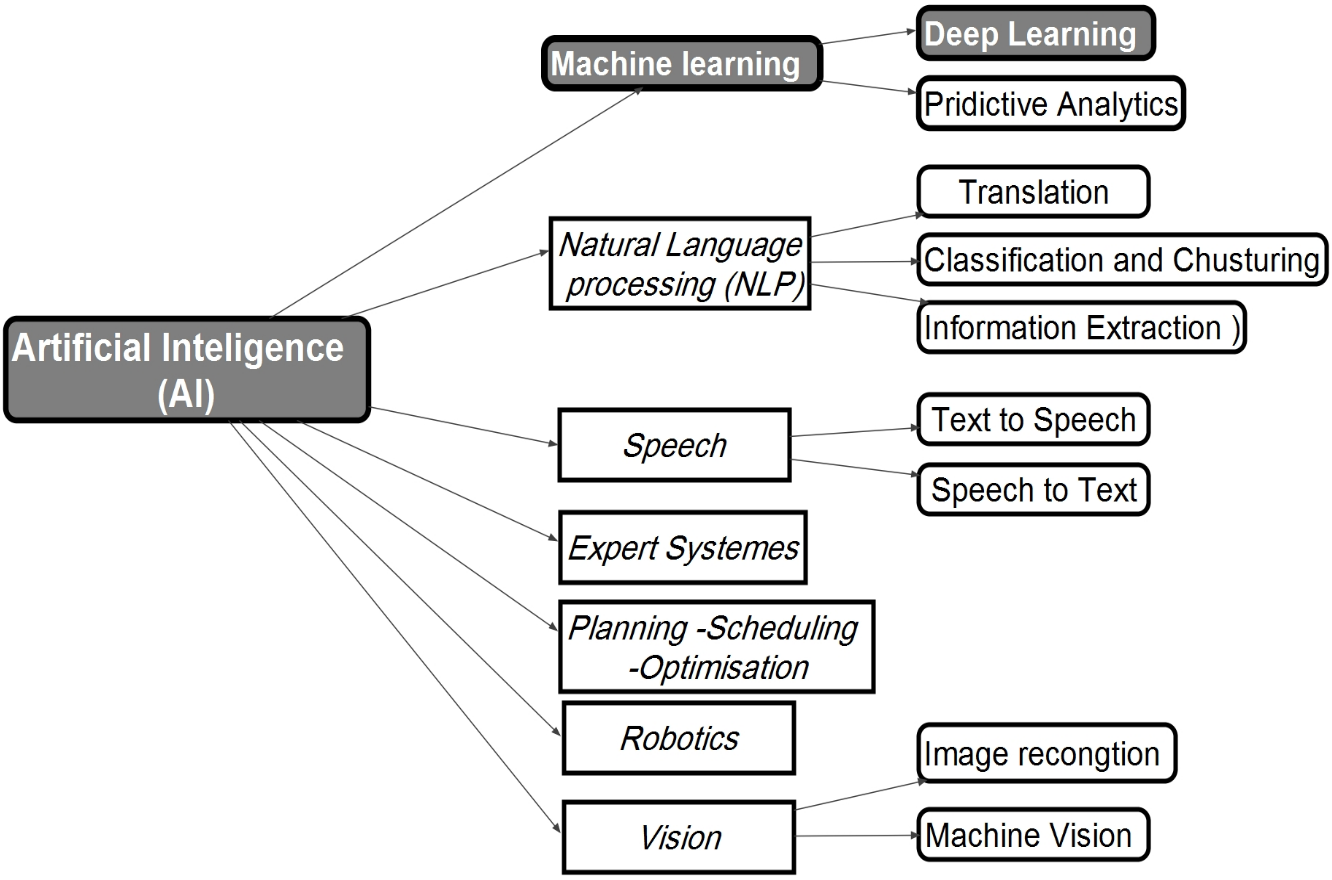


Figure 2.1: Structure-of-Artificial-Intelligence

2.3 Machine Learning

Machine learning is a computer science discipline that involves the capacity to learn without being explicitly programmed. ML investigates the study and design of algorithms that can learn from and make predictions on data learning theory in artificial intelligence, which evolved from the study of pattern recognition and computational learning theory in artificial intelligence. ML is used in a variety of computing jobs where creating and programming high-performing explicit algorithms is difficult or impossible. Some examples of uses are: email filtering, identification of network intruders or hostile insiders attempting a data breach, human recognition, automobile detection, and image processing. In addition, the method is put to the test to see how well it performs using the answers supplied before [18].as shown in figure 2.2 .

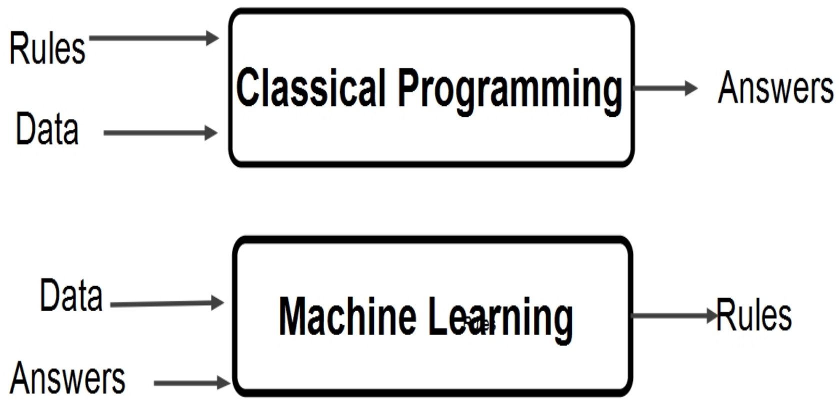


Figure 2.2: the difference between ML and classical programming

2.3.1 Machine Learning Methods:

Supervised and unsupervised learning are the most extensively used machine learning methods. Supervised learning accounts for 70% of machine learning, whereas unsupervised learning accounts for 10% to 20%. Other technologies that are occasionally used include semi-supervised and reinforcement learning [18].

A) Supervised learning

Algorithms are trained using labeled examples, such as an input where the desired output is known. For example, a piece of equipment could have data points labeled either ”F” (failed) or ”R” (runs). The learning algorithm is given a set of inputs and the proper outputs, and it learns by comparing its actual output to the correct outputs in order to detect errors. Some of the techniques used to adjust the model are classification, regression, prediction, and gradient boosting.

B) Unsupervised learning:

When the system does not have the ”right answer,” unsupervised learning is used against the data. The algorithm must explore the data and find some structure within it. Unsupervised learning is effective for segmenting text topics, recommending items, and detecting outliers in transactional data.

C) Semi-supervised learning

It is utilized in the same way that supervised learning is. However, it trains with both labeled and unlabeled data, usually a small quantity of labeled data and a large amount of unlabeled data (because unlabeled data is less expensive and takes less effort to acquire). Identifying a person’s face via a webcam is an early example of this.

D) Reinforcement learning

Robotics, gaming, and navigation all employ reinforcement learning. The program uses reinforcement learning to figure out which activities produce the most rewards through trial and error. The agent (the learner or decision-maker), the environment (everything the agent interacts with), and actions are the three main components of this sort of learning (what the agent can do). The agent’s goal is to select activities that maximize the predicted reward over a set period of time. By adopting a sound policy, the agent will get to the target much faster. In reinforcement learning, the aim is to learn the optimum policy.

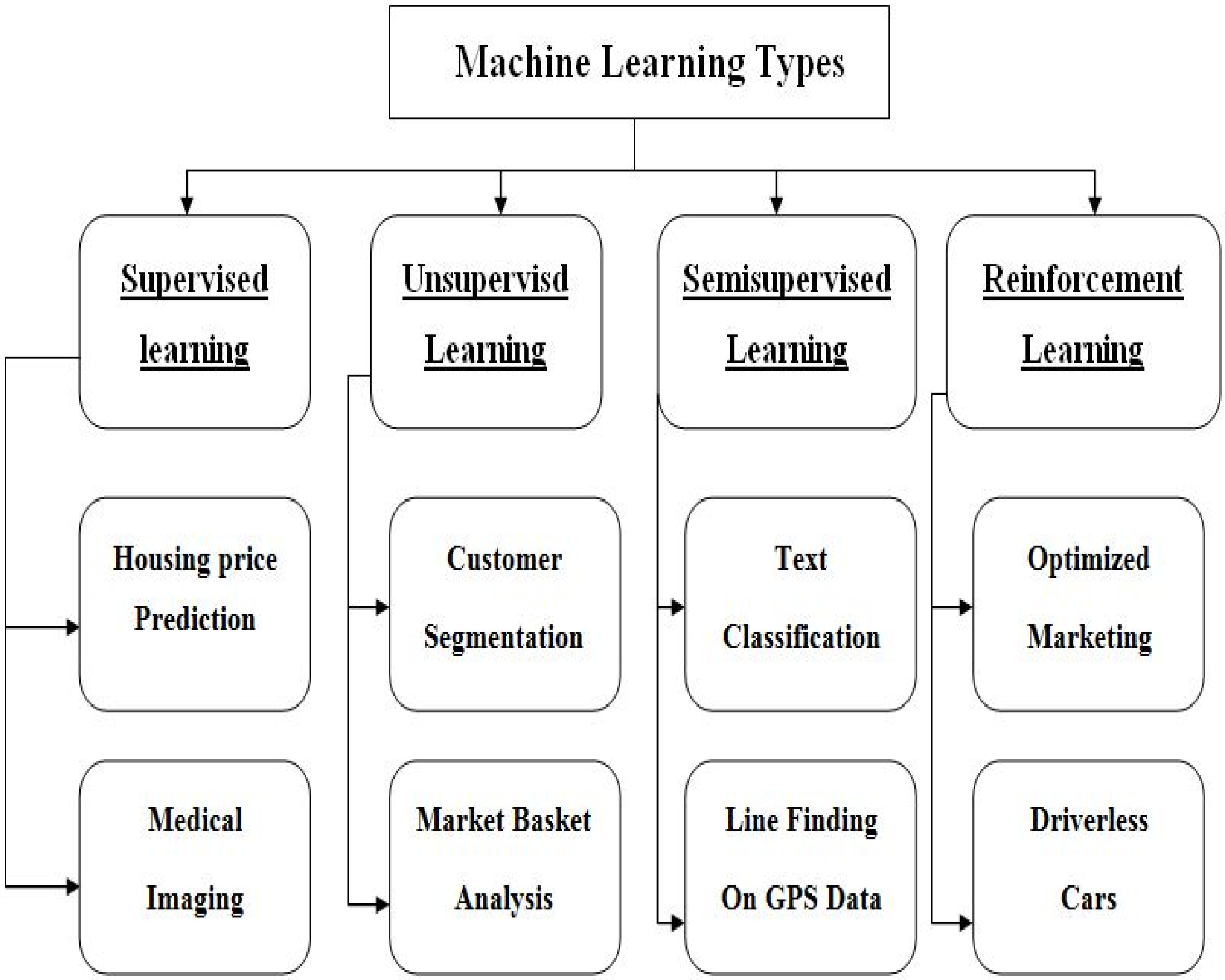


Figure 2.3: The Machine Learning Types

2.4 Deep Learning

The information processing patterns discovered in the human brain provide the inspiration for DL, a subset of Machine Learning . To work, DL doesn't need any human-designed rules; instead, it analyzes a massive quantity of data to map a given input to certain labels. Using traditional machine learning approaches, achieving the classification problem takes numerous sequential phases, including preprocessing and feature extraction, so DL is built with many layers of algorithms Artificial Neural Network (ANN), each of which delivers a unique interpretation of the data provided to it. Due to the enormous expansion and progress of the field of big data, DL has become an extremely popular sort of ML technique in recent years. It is still under development in terms of innovative performance for a variety of machine learning tasks, and it has eased the improvement of many learning domains, including picture super-resolution, object identification, and image recognition. Recently, DL performance has surpassed human performance on tasks such as image categorization. This technology has had an influence on nearly every scientific subject. The use of DL has already disrupted and revolutionized most sectors and enterprises.

2.5 Artificial Neural Network (ANN)

2.5.1 Biological Neurons:

They're a kind of cell that may be discovered in the cerebral cortex. As shown in Figure A 2.4 dendrites receive electrical impulses as weighted inputs. The inputs are used by the cell body to produce an output signal. The output signal flows through the axon wire, which is linked to other neurons through the synaptic terminal after it reaches a certain value [20].

2.5.2 Artificial Neurons:

The biological neuron is modeled after the artificial neuron. It takes a series of inputs, multiplies each by weight, and then adds all of these weighted inputs together with a constant value termed a bias. The weighted total is then given to an Activation Function, which sends its output to a different neuron as input [21]. The structure of an artificial neuron is show in Figure B 2.4 .

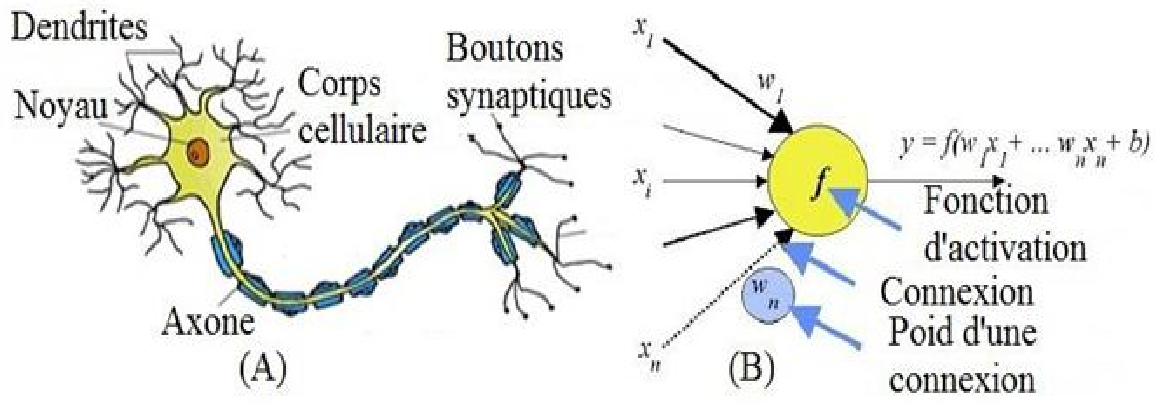


Figure 2.4: (A) Biological Neurons Network (B) Artificial Neurons Network

2.6 Convolutional neural networks (CNN)

The CNN algorithm is the most well-known and widely used in the field of deep learning. The fundamental advantage of CNN over its predecessors is that it automatically recognizes significant elements without the need for human intervention. CNN have been widely used in a variety of applications, including computer vision, audio processing, and facial recognition, among others. Similar to a traditional neural network, the construction of CNN was inspired by neurons in human and animal brains. In a cat's brain, the visual cortex is formed by a complicated succession of cells [22].

2.6.1 General architecture of a Convolutional neural network:

In a CNN model, the input x of each layer is structured in three dimensions: height, width, and depth, or m m r, where the height (m) equals the width. The channel number is another name for the depth. The depth (r) of an Red Green Bleu (RGB) picture, for example, is three. Each convolutional layer's available kernels (filters) are designated by k and have three dimensions (n×n×q) to the input image. Figure2.5 shows an example of the CNN architecture for image categorization [22].

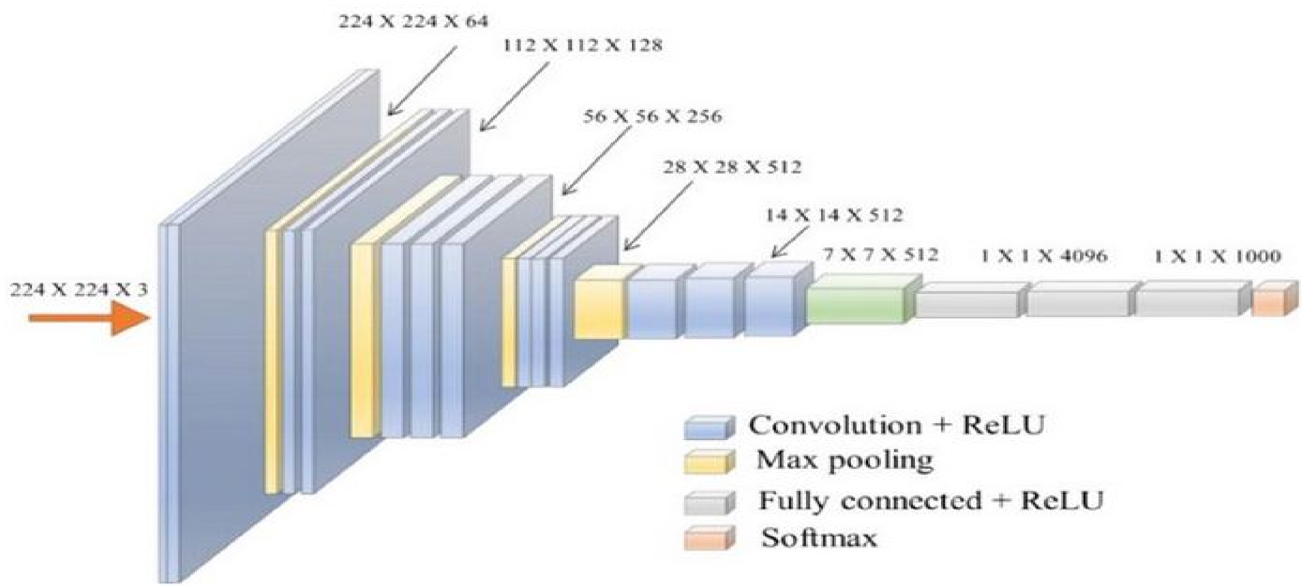


Figure 2.5: General architecture of a Convolutional neural network

2.7 CNN layers

Currently, CNN are the most effective image recognition models; the convolution layer, the pooling layer, Rectified Linear Unit (ReLU) layer, and the fully linked layer are the four types of layers in CNN. The several levels of a CNN will be described in depth in the subsections that follow:

2.7.1 Convolution Layer:

It is CNN most fundamental component. This layer must be the first in the CNN architecture (at least one Conv layer is required). The convolution layer in image processing tries to extract features from images by performing two-dimensional convolution between the input maps Z^m and the filters represented by the kernels k^m with n and m, where m and n are the level and map indices, respectively, and l is the filter index. Layer L, the output map f^m is calculated as show in equation 2.1 [22]:

$$[H]f_l^m = \sum_{n}^{N^{m-1}} k_{1,n}^m * z_n^m + b_l^m \tag{2.1}$$

Where N^m signifies the number of input maps, means convolution, and b^m denotes the bias of the m the level's L the output map. The values that define the kernels and biases are determined based on the work as show in figure 2.6.

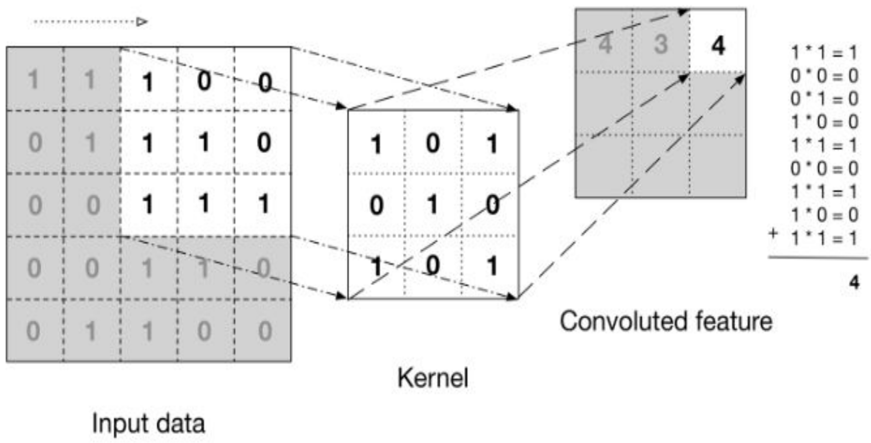


Figure 2.6: The convolution operation

2.7.2 ReLU layer:

The ReLU layer, also known as the activation layer, is a non-linear layer that is commonly applied after the Conv layer. The ReLU layer uses the function f (y) = max (0, y) to set all negative activations to zero. Due to the luck of feedback in the CNN, this layer renders the CNN non-linear without changing the receptive fields of the Conv layer [22].

2.7.3 pooling layer:

It takes numerous feature maps as input and pools them. By utilizing a filter (typically of size 2×2 and a stride of the same length), the pooling method reduces the picture sizes while keeping their significant characteristics. The most common pool layer is max pooling. It is applied to the input volume and produces the maximum value in each of the sub regions that the filter convolves around. Pooling layers using the average or L2-norms method is another option. In order to prevent over learning, the pooling layers minimize map parameter, which reduces network computations. -Max-pooling returns the maximum value of the receptive field, -Avg-pooling returns the average of the values [22].

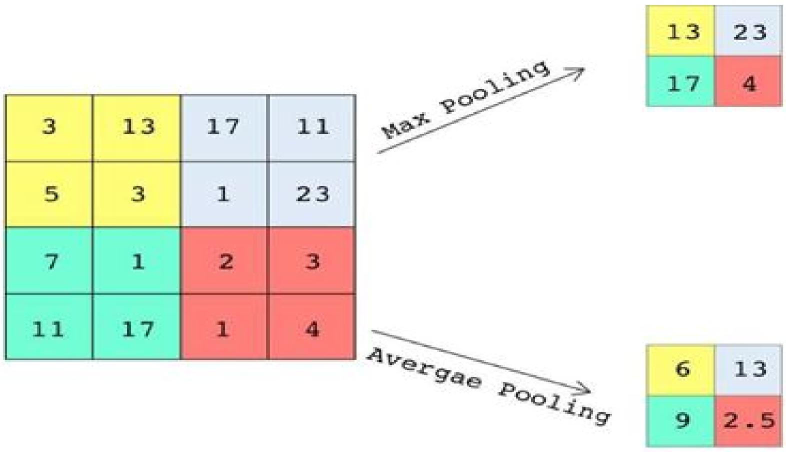


Figure 2.7: the Pooling operation

2.7.4 Fully connected (FC) layer:

The Fully Connected (FC) layer, also known as feed forward neural networks, is the CNN last layer. The convolution layer, pool layer, and/or ReLU layer might all be used as FC input. The FC input layers' characteristics are analyzed. The final pooling or convolutional layer output is flattened and then provided as input to the fully linked layer. The process of unrolling the values of a three-dimensional matrix into a vector is known as flattening, and then selected features are pooled and used for data categorization [22].

2.8 Transfer Learning

Transfer learning is a technique that allows you to apply what you've learned in the past to your current apprenticeship. Indeed, the parameters of a CNN network that had previously been determined (using a prior database) might be changed using a freshly obtained database. The key advantage of this method is that it saves time by merely using fresh data instead of a completely new database (with both old and new data) to update the parameter model. These strategies are especially effective when dealing with a pre-trained model that does not have access to a training database. To put it another way, transfer learning is a critical technique in deep learning for addressing the underlying problem of inadequate training data. For example, fine-tuning, which is based on pre-trained models AlexNet, GoogleNet and VGG, is one of the most models frequently used transfer learning techniques [22].

2.9 Pre-trained CNN networks

Several CNN designs pre-trained have been proposed in the last ten years. The architecture of a model is an important aspect in increasing the performance of many applications. From 1989 until the present, several adjustments to CNN architecture have been made. Structure re-formulation, regularization, parameter optimizations, and other changes are examples of such changes. On the other hand, it should be emphasized that the major improvement in CNN performance was primarily attributable to the restructuring of processing units and the development of new blocks. The utilization of network depth was used to conduct the most novel breakthroughs in CNN design. CNNarchitectures have made major contributions in a variety of domains. As a result, names like AlexNet, VGG, and Google Net as show in the table 2.1 became well-known. Currently, these networks are employed in a variety of recognition tasks [22]. As a result, we'll go through their designs in detail.

Table 2.1: Information about Pre-trained Models used .

Networks	Year	Depth	Size	Image Input Size
AlexNet	2012	25	227 MB	227 $\times$227$\times$3
Google Net	2014	22	112.9MB	224$\times$224$\times$3
VGG	2015	47	515 MB	224 $\times$ 224$\times$3

2.9.1 AlexNet

AlexNet is a well-known deep CNN architecture that has achieved groundbreaking achievements in the domains of image recognition and classification. This design was responsible for the most significant advancement in CNN performance. It took first place in the 2012-ILSVRC competition, which was one of the most demanding image recognition and classification tasks ever. AlexNet was created at the University of Toronto by Krizhevsky . and comprises five pairs of Conv layers, followed by ReLU, three max-pooling, and three fully connected layers FC. By increasing the depth of the CNN and adopting numerous parameter optimization procedures, the CNN learning ability may be improved.in the figure 2.8 illustrates the basic design of the AlexNet architecture [16].

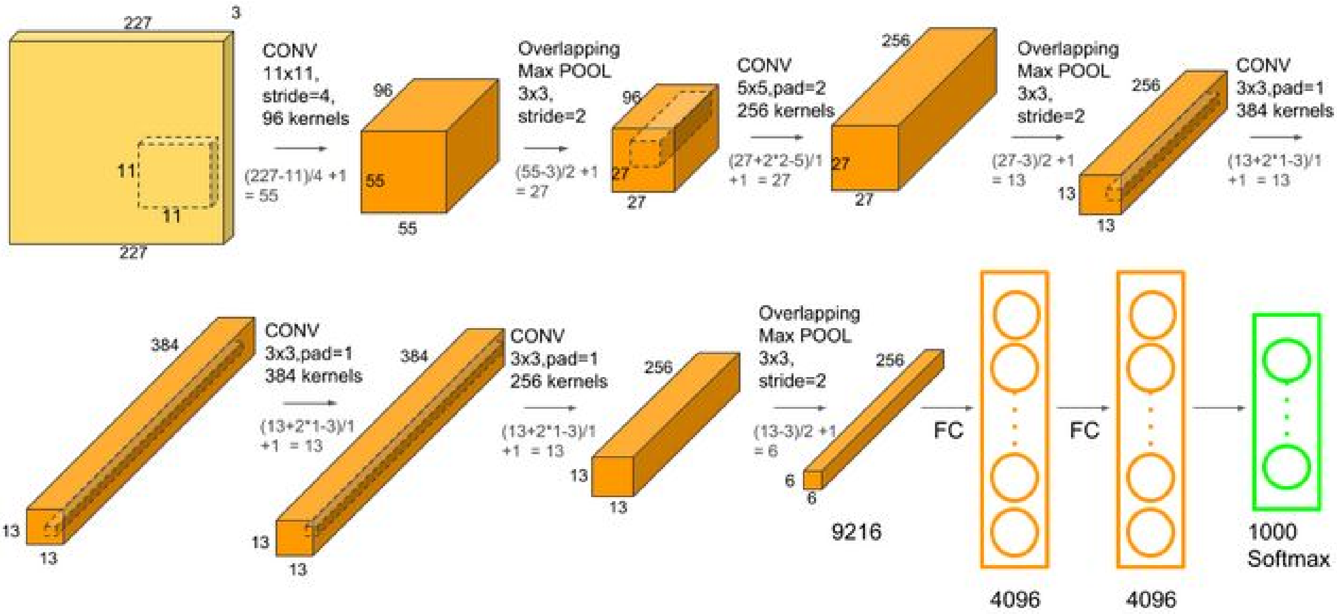


Figure 2.8: The AlexNet architecture

2.9.2 Google Net

Google Net (also known as Inception-V1) won the 2014 ILSVRC competition. The GoogleNet architecture's main goal is to achieve high-level accuracy at a low computing cost. It suggested a unique inception block (module) idea in the CNN context since it employs merge, transform, and split functions for feature extraction to integrate multiple-scale convolutional transformations [16]. The inception block architecture is depicted in the Figure 2.9 Filters are used in this architecture.

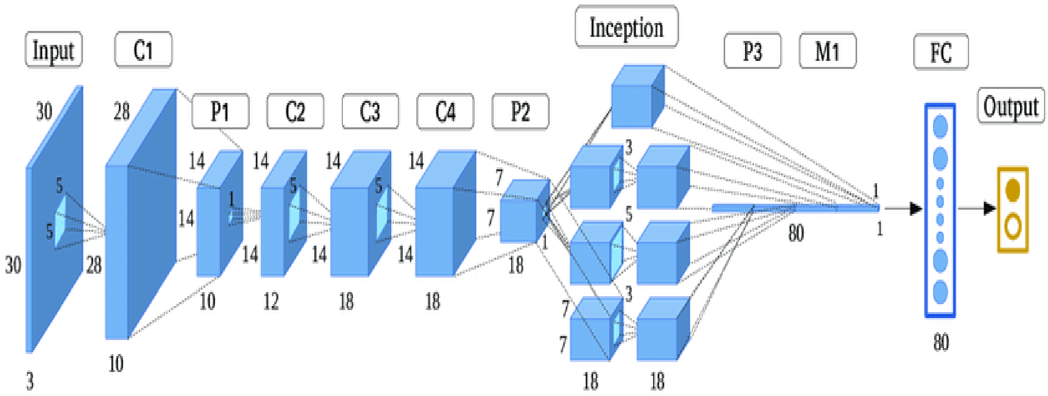


Figure 2.9: The Google-Net Architecture

2.9.3 Visual geometry group (VGG)

Visual geometry group (VGG) achieved substantial accomplishments in the areas of image classification and localization difficulties. Although it did not win first place in the 2014-ILSVRC competition, it gained a reputation for its increased depth, homogeneous topology, and ease of use. VGG computational cost, on the other hand, was exorbitant owing to its use of about 140 million parameters, which was its fundamental flaw [16]. The network's structure is depicted in the Figure 2.10 .

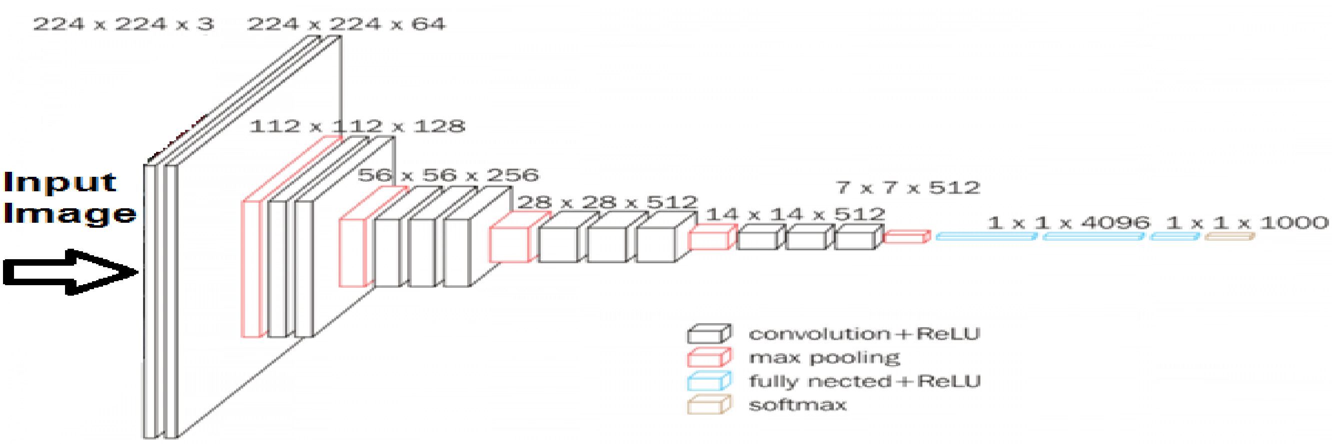


Figure 2.10: The VGG Architecture

2.10 Conclusion

In this chapter we presented the different principles connected about deep learning. DL networks are neural network-based machine learning ML techniques. Then we studied some fundamentals by deducing the precise structure of a CNN network and some CNN pre-trained model, as well as the layers of CNN, how they operate, and how to progress to the transfer learning process, which was the approach we employed in our research. Finally, we looked at various well-known Convolutional network designs CNN. The experimental results will be discussed in the next chapter.

3

Results and Discussion

3.1 Introduction

This chapter presents the final experimental results of the recognition of FKP and FV images in the database that contains several people, and then the identification of people, carried out by CNN networks' pre-trained models (AlexNet, VGG, and GoogleNet). The goal is to design a security system that uses biometric identification of people by FKP and FV based on Transfer Learning and their classifications. to improve the performance of our system.

3.2 The biometric system overview and block diagram

A simplified block diagram for the FKP and FV identification systems developed in this work is shown in the figure3.2. Several images are first acquired under different illuminations and the acquisition is automatically synchronized to the use of the respective lighting and a computer. The acquired images is show in the figure3.1 are then preprocessed and automatically segmented to extract the region of interest images. The features of the FKP and FV are then extracted and classified according to the proposed CNN network pretrained model. Concerning the multimodal system, we proceeded to the fusion at the level of the score of the modalities FKP and FV to see the decision of the system at the level of output.

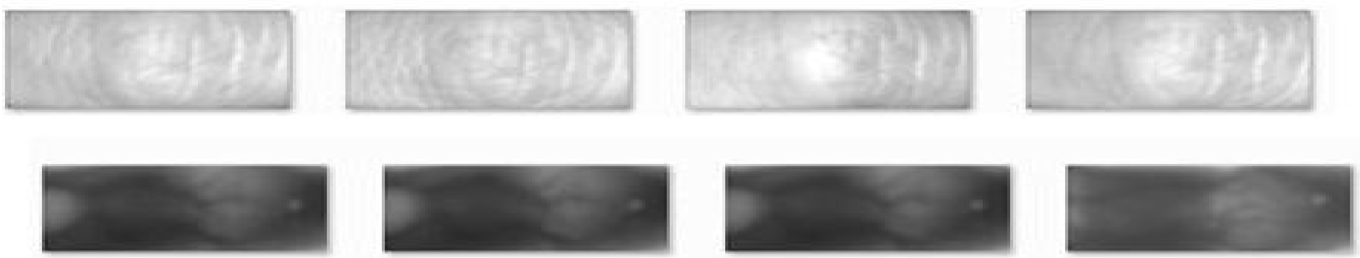


Figure 3.1: Examples of FKP /FV raw images acquired from different people

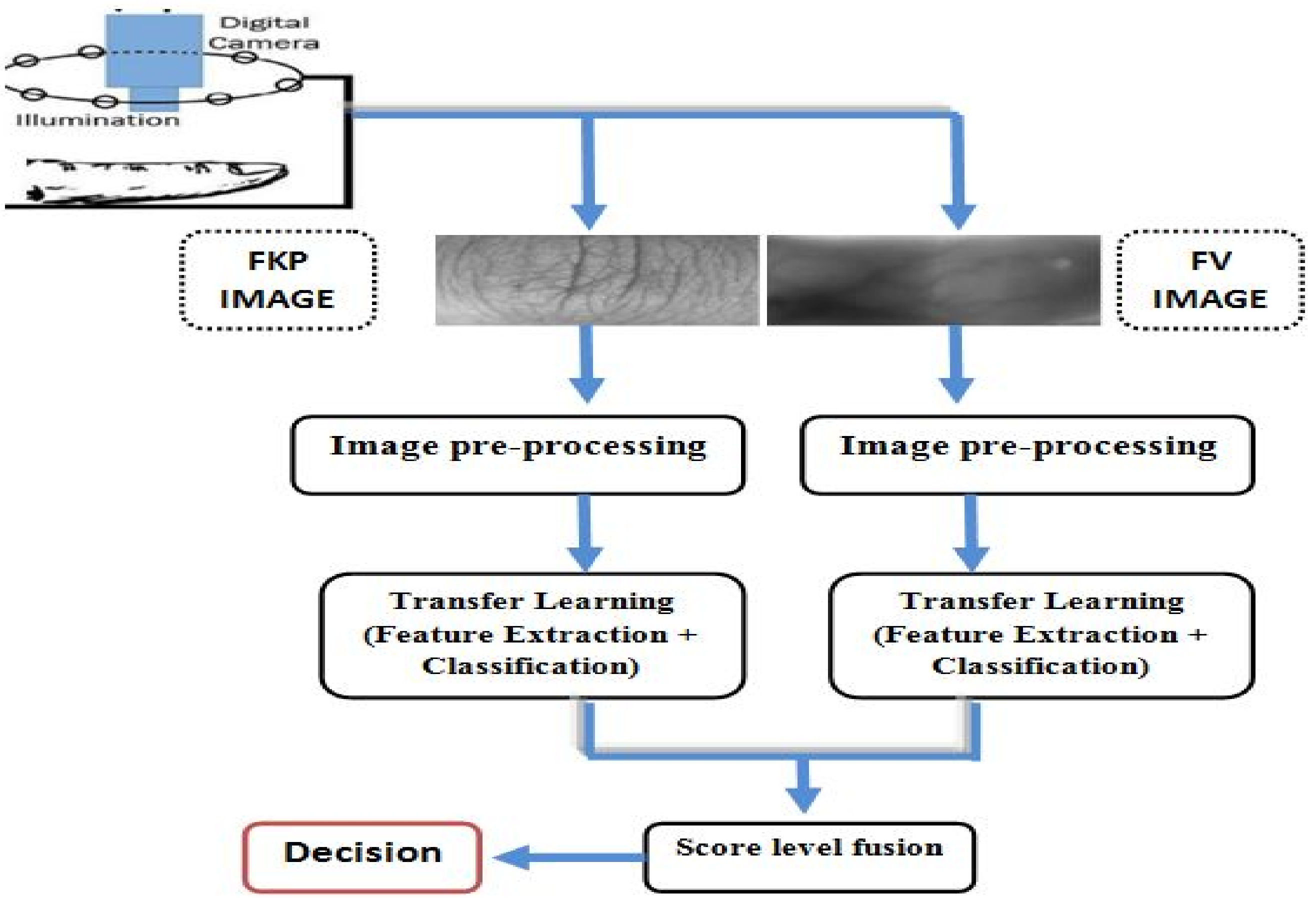


Figure 3.2: Block diagram of the FKP and FV identification multimodal system

3.3 Database

In this study, two databases (FKP and FV) were used for the evaluation of the performance of identification systems based on the proposed CNN networks.

The first one is the FKP database from (The Hong Kong Polytechnic University 2018) , was obtained from 165 different people. 12 images for the left index and 12 images for the left middle ,12 images for the right index and 12 images for the right middle for each person in each session.

The second one is the FV database from(The Hong Kong Polytechnic University 2018) , was obtained from 106 different people. 12 images for the index and 12 images for the middle, with 12 images for the ring for each person in each session. Figure3.1shows an example of the images in this database

3.4 Materials and work protocol

This section describes in detail the separation of the database (FKP and FV) exploited in our work and the CNN networks considered. In addition, Fine-Tuning, working environment, and implemented tool are provided. with the Transfer Learning (TL), the three CNN networks used: AlexNet, VGG, GoogleNet were trained for feature extraction and classification, then we compared the performance of the three CNN networks.

3.5 Database Separation

To develop an FKP and FV fingers recognition application, it is necessary to have two databases for each application, one to perform the learning and another to test the techniques and determine their performances, however that there is no rule to determine this share in a quantitative way. It often results from a compromise taking into account the amount of data available and the time to perform the learning ,the database was split in the following way:

3.5.1 Learning images (enrollment phase)

Is the first, third, fifth, seventh, ninth, and eleventh images of each person are used for the learning phase (Learning image = [1 3 5 7 9 11]).

3.5.2 Test images (Test phase)

Is the second, fourth, sixth, eighth, tenth, and twelfth image of each person were used to perform the various tests (test image = [2 4 6 8 10 12]). The goal is to evaluate the recognition rate of different algorithms (CNN networks) presented.

3.6 Used Convolutional Neural Networks (CNN)

CNN are well suited for image recognition or more broadly, data with spatial correlation. We need to effectively train a specific CNN architecture in order to tune its performance in a specific application scenario. In our work TL technique is used which involves fitting the deepest CNN layers to a new data set. As a result, new data containing previously unknown classes are introduced into an existing network and pre-training, once the network is in place, a new task, like FKP and FV classification in our case, can be performed. In our work we used the pre-trained networks, AlexNet, VGG16, VGG19, and GoogleNet, the table 3.1 show the most relevant characteristics of the CNN networks: AlexNet, VGG16, VGG19, and GoogleNet.

Table 3.1: The CNN networks used and their characteristics.

Networks	Year	Depth	Size	Image Input Size
AlexNet	2012	25	227 MB	227 ×227×3
Google Net	2014	22	112.9MB	224×224×3
VGG 16	2015	47	515 MB	224× 224×3
VGG 19	2015	47	515MB	224×777×3

3.7 Working environment

3.7.1 Hardware environment

• Computer: HP Z8 G4 Workstation

• Memory (RAM): **96.00 GB**

• Processor: Intel(R) Xeon(R) Silver 4108 CPU @ 1. 80 GHz 1. 80 GHz.

• Graphic Processing Unit: **(GeForce RTX 2080 Ti, GeForce RTX 3090)**

• System type: 64-bit operating system, x64 processor

3.7.2 Software Environment

The software tool used by our approach is: **Matlab R2021b**

3.8 Biometric Systems Evaluation

For a number of reasons, evaluating biometric systems is a difficult task in the field of biometrics. It first enables researchers to test and assess their systems more effectively. Additionally, it enables the definition of industrial applications for each system based on these capabilities. Here are some of the most frequently used metrics and curve types for evaluating the performance of a biometric system [23]:

3.8.1 False Reject Rate (FRR)

False Reject Rate (FRR) This rate determines the probability that a system will not recognize a person who should normally have been recognized. It is a ratio between the number of legitimate people whose access was refused and the total number of legitimate people who came forward [7] .

$$\text{FRR} = \frac{\text{number of rejected people}}{\text{total number of people accesses}} \times 100 \tag{3.1}$$

3.8.2 False Accept Rate (FAR)

False Reject Rate (FAR) This metric determines the likelihood that a system will recognize someone who would not normally be required to be recognized. It is a ratio of the number of people who have been accepted to the number of people who have not been accepted. and the total number of people not authorized to be accepted [24] .

$$\text{FAR} = \frac{\text{number of imposters accepted}}{\text{The total number of impostor entries}} \times 100 \tag{3.2}$$

3.8.3 Equal Error Rate (EER)

Equal Error Rate (EER) This rate is calculated from the first two criteria and constitutes a point of measurement of current performance. This point corresponds to where FRR = FAR. It is the best compromise between false rejections and false acceptances [7] .

$$\text{EER} = \frac{\text{number of false acceptances + number of false rejections}}{\text{The total number of entries}} \times 100 \qquad (3.3)$$

3.8.4 Genuine Acceptance Rate (GAR)

Genuine Acceptance Rate (GAR) The real acceptance rate (GAR) is a measure of the overall accuracy of the biometric system. It is calculated by the formula [7] :

$$\text{GAR (\%)} = 100 \text{ - FRR} \qquad (3.4)$$

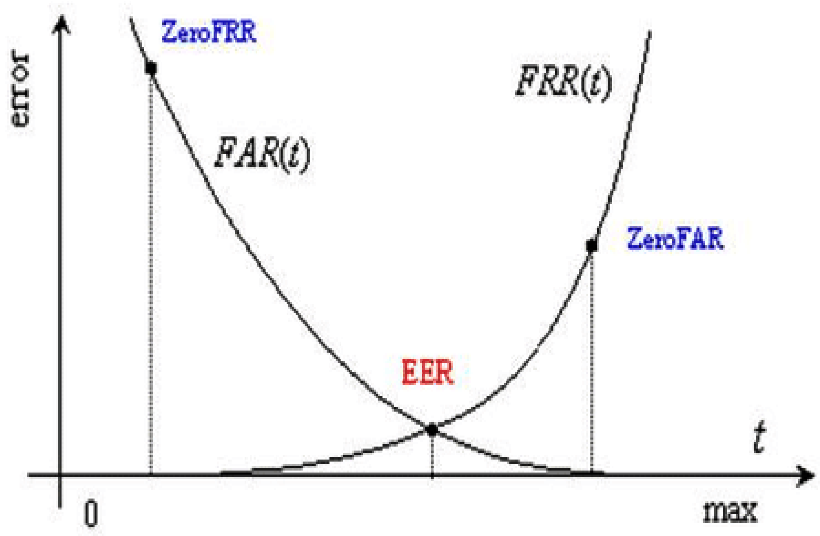


Figure 3.3: FRR and FAR illustrations example

3.8.5 Receiver Operating Characteristics ROC

Receiver Operating Characteristi (ROC) The performance of a biometric system can be presented graphically using the Receiver Operating Characteristic (ROC) curve [25]. This curve represents the values of FRR as a function of FAR. This is obtained by calculating the torque (FAR, FRR) for all the values of the test thresholds. This differs from the smallest value obtained to a higher value. This curve can be broken down into three zones: high security zone, compromise zone, and low security zone Figure3.4 [26] .

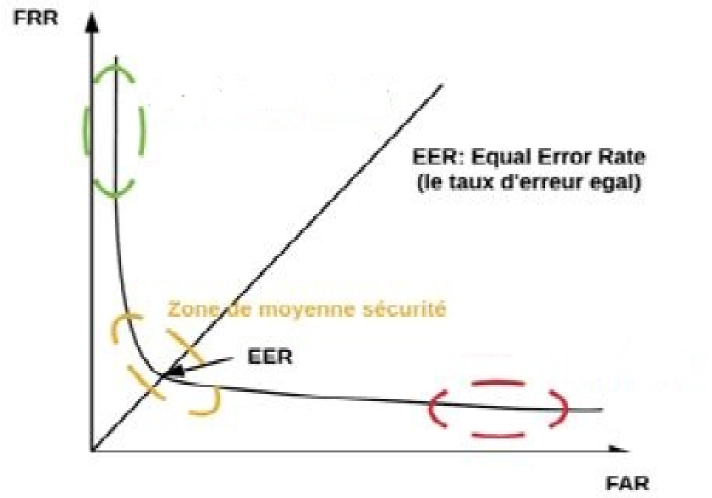


Figure 3.4: ROC illustrations example

3.8.6 Cumulative Match Characteristic (CMC)

Cumulative Match Characteris (CMC) This curve Figure3.5 gives the percentage of people recognized according(Matching Rate) to a variable called rank [27] .

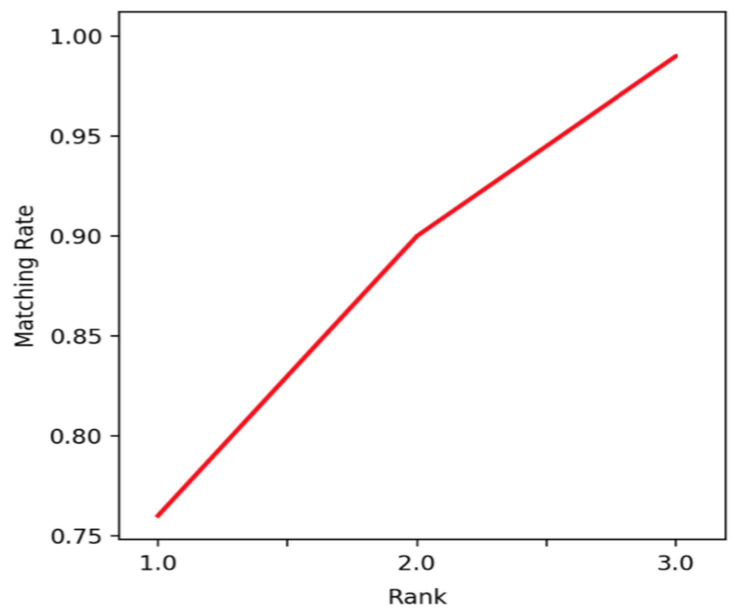


Figure 3.5: CMC illustrations example

3.9 Experimental results

3.9.1 Unimodal System

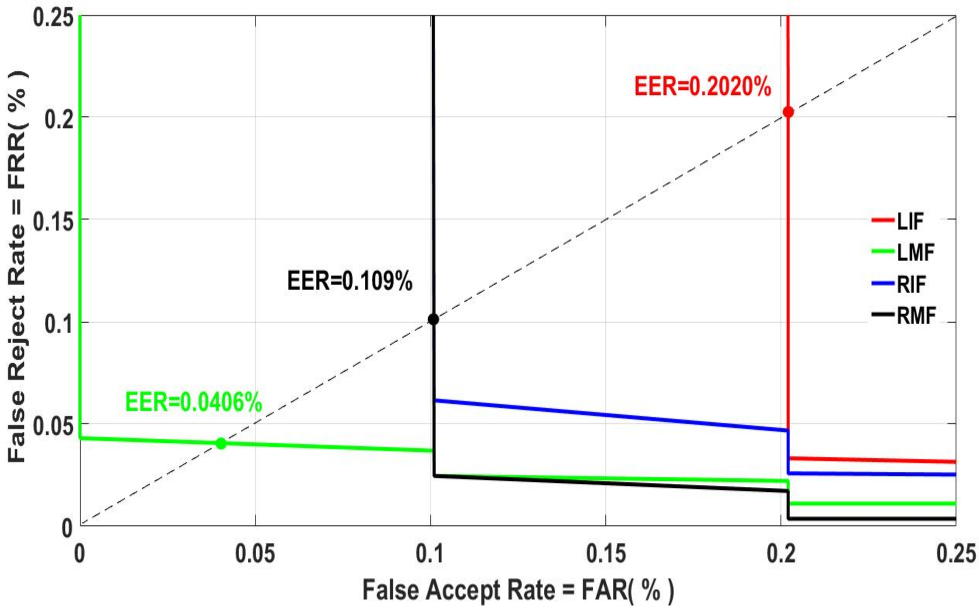
In our measure, there are two parts. The first one is the FKP part, and the second is the FV part. For each part, there is an open set. We measured the equal error rate (EER) and the Treshold (T_o) . and On the closed set, we measured the Rank One recognition ROR and the Rank of Perfect Recongtion (RPR) . The performances of the systems based on the four fingers (left index, left middle, right index, right middle) for FKP and three fingers (index, middle, right) for FV were evaluated after the parameters of each pre-trained network model (AlexNet, VGG16, VGG19, GoogleNet) were selected.

A) FKP Unimodal Results

Table 3.2: FKP Unimodal identification system results

Fingers	Open Set		Closed Set	
	T_o	EER(%)	ROR(%)	RPR
VGG 16 Features				
LIF	0.00299	0.1009	99.09	6
LMF	0.00299	0.0327	98.18	21
RIF	0.00299	0.3024	99.19	9
RMF	0.00462	0.1094	99.19	9
VGG 19 Features				
LIF	0.0033	0.2020	99.09	12
LMF	0.0010	0.0406	98.98	3
RIF	0.0029	0.1097	99.19	15
RMF	0.0029	0.1009	99.69	3
AlexNet Features				
LIF	0.011	0.0957	98.78	15
LMF	0.010	0.1010	99.09	3
RIF	0.061	0.0418	99.49	4
RMF	0.028	0.0625	99.19	4
GoogleNet Features				
LIF	0.0106	0.1010	99.59	11
LMF	0.029	0.3027	98.98	9
RIF	0.0204	0.0833	99.19	3
RMF	0.0223	0.0904	98.58	5

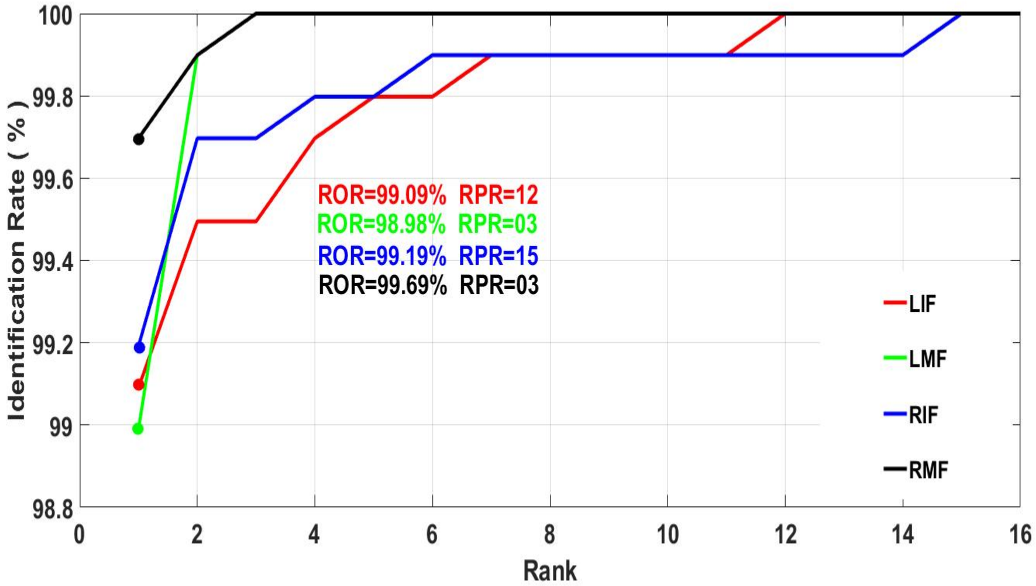
The goal of this experiment is to evaluate the system performance when we using the information from each modality (each finger). For this, in Open Set and Closed Set identification we found the performance under different modalities (LIF, LMF, RIF, RMF).
Table 3.2 shows the performance of the FKP Unimodal system using:
VGG16 classification with all the fingers giving in the open set a low value in Equal Error Rate (EER) (≥ 0.4)and in the closed set giving a high value of identification rate ($\leq 98.18\%$). In this case, the (Right Middle) finger gets the best results for $[ROR = 99.19, EER = 0.1094]$.
VGG19 classification with all the fingers giving in the open set a low value in Equal Error Rate (EER) (≥ 0.3) and in the closed set giving a high value of identification rate ($\leq 98.98\%$). In this case, the (Right Middle) finger gets the best result for $[ROR = 99.69, EER = 0.1009]$.
Alex net classification with all the fingers giving in the open set a low value in Equal Error Rate (EER) (≥ 0.2) and in the closed set giving a high value of identification rate ($\leq 98.78\%$). In this case, the (RIGHT Index) finger gets the best results for $[ROR = 99.49, EER = 0.0418]$.
GOOGLE NET classification is shown, with all fingers giving in open set a low value in Equal Error Rate (EER) (≥ 0.4) in the close set and a high value of identification rate ($\leq 98.58\%$) in the open set; in this case, the (Left Index) finger gives the best results for $[ROR = 99.59, EER = 0.1010]$.



;

Figure 3.6: ROC FKP Unimodal VGG19

Figure 3.6 shows a graph of ROC FKP Unimodal VGG19 for the open-set identification results. We observe a linear function between the EER of fingers (LIF, RMF, LMF, RIF). The LMF is better than others fingers in terms of EER. it gives $EER = 0.0406\%$ respectively.



;

Figure 3.7: CMC FKP Unimodal VGG19

Figure 3.7 shows a graph of the CMC FKP Unimodal VGG19 for the closed-set identification results. The system generates a Rank-One Recognition (ROR) equal to 98.98% up to 99.69% with a Rank of Perfect Recognition (RPR) equal to 3 up to 15 for all spectral bands.

B) FV Unimodal Results

The goal of this experiment is to evaluate the system performance when we use the information from the finger vein modality (each finger). For this, in Open Set and Closed Set identification we found the performance under different modalities (Index, Middle, Ring).

Table 3.3: FV Unimodal identification system results using

Fingers	Open Set		Closed Set	
	T_o	EER(%)	ROR(%)	RPR
VGG 16 Features				
Index	0.00299	1.71	93.23	65
Middle	0.0048	0.66	95.28	13
Ring	0.0054	1.25	92.45	48
VGG 19 Features				
Index	0.0029	0.785	96.54	23
Middle	0.0030	1.11	94.33	87
Ring	0.0029	1.09	95.59	25
AlexNet Features				
Index	0.0086	1.0078	95.28	70
Middle	0.0065	0.978	94.49	97
Ring	0.0075	1.101	95.59	28
GoogleNet Features				
Index	0.0013	0.945	92.45	41
Middle	0.0012	0.979	93.55	16
Ring	0.0079	1.04	92.76	38

Table 3.3 shows the performance of the FV Unimodal system using:

VGG16 classification with all the fingers giving in the open set a low value in Equal Error Rate (EER) ($\geq$ 2) and in the closed set giving a high value of identification rate ($\leq$ 92%). In this case, the (MIDDLE) finger gets the best result for [ROR = 95.28, EER = 0.66].

VGG19 classification with all the fingers giving in the open set a low value in Equal Error Rate (EER) ($\geq$ 2) and in the closed set giving a high value of identification rate ($\leq$ 94%). In this case, the (INDEX) finger gets the best result for [ROR = 96.54, EER = 0.785].

ALEX NETclassification, with all the fingers giving in the open set a low value in (EER) ($\geq$ 2) and in the open set giving a high value of identification rate ($\leq$ 94%). In this case, the (RING) finger gets the closed result for [ROR = 95.59, EER = 1.101].

GOOGLE NET classification with all the fingers giving in the open set a low value in Equal Error Rate (EER) ($\geq$ 2) and in the closed set giving a high value of identification rate ($\leq$ 92%). In this case, the (MIDDLE) finger gets the best result for [ROR = 93.55, EER = 0.979].

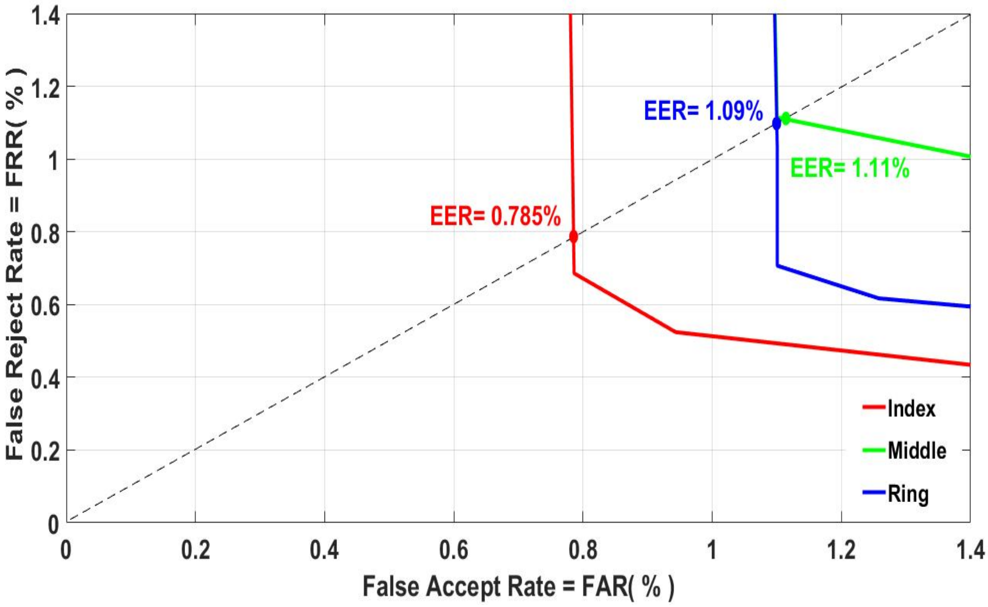


Figure 3.8: ROC FV Unimodal VGG19

figure 3.8 shows a graph of ROC FV Unimodal VGG19 for the open-set identification results. We observe a linear function between the EER of fingers (Index, Middle, Ring,). The index is better than others fingers in terms of EER. it gives "EER = 0.785" respectively.

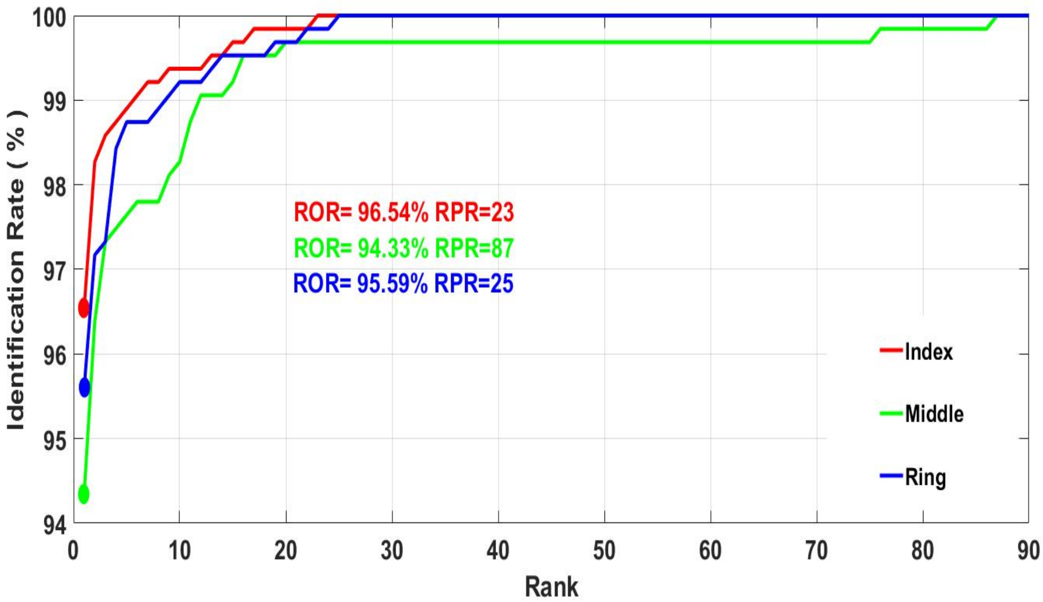


Figure 3.9: CMC FV Unimodal VGG19

figure 3.9 shows a graph of the CMC FV Unimodal VGG19 for the closed-set identification results. The system generates a Rank-One Recognition (ROR) equal to 94.33% up to 96.54% with a Rank of Perfect Recognition (RPR) equal to 23 up to 87 for all spectral bands.

3.9.2 Multimodal System

The objective of this subsection is to evaluate and improve the performance of a multimodal biometric identification system using information from multiple modalities coming from different types of fingers (knuckles and veins). Thus, by using various pre-trained CNN model networks for feature extraction and classification (AlexNet, GoogleNet, VGG19, and VGG16), many unimodel systems can be exploited. However, in our work we rely on a multimodal system. In our two databases, each person has two biometric modalities (knuckle and vein). Therefore, the combination of these modalities makes it possible to obtain a rate of identification (at most) higher than the rates of identification of the same methods taken separately. In our methodology, integration was tested at the outcome level. Several combinations can be obtained using each person's methods. In our study, for FKP we used three groups, is namely LIF+LMF combination, RIF+RMF combination, and the ALL (LIF+LMF+RIF+RMF) combination, and for FV we used one group, is namely index+middle+ring combination.

3.10 Fusion Rules

Different modes of fusion exist in the literature. The most important of them is the fusion at the matching score level known by its simplicity and good performances (Simple Sum Rule (SUM) ,Product rule (PROD) ,Maximum rule (MAX) ,Minimum rule (MIN)) . In our work, we fusion the four samples for FKP (LIF LMF , RIF, RMF) and for FV (Index , Ring , Middle) to improve the biometric identification system accuracy. Several rules of fusion can be used to yield a final matching score [28] :

3.10.1 The Simple Sum Rule

This rule makes the sum of the final matching scores. It is calculated as follows:

$$S = \sum_{i=1}^{N} S_i \tag{3.5}$$

3.10.2 The product rule

The Product rule is the product of all matching scores, it is calculated as follows:

$$S = \prod_{i=1}^{N} S_i \tag{3.6}$$

3.10.3 The Maximum rule:

It takes the minimum matching score, it is calculated as follows:

$$S = \max_{i} S_i \tag{3.7}$$

3.10.4 The Minimum rule:

It takes the minimum matching score, it is calculated as follows:

$$S = \min_{i} S_i \tag{3.8}$$

Tables 3.4 and 3.5 shows the system performance (open and closed group) for FKP and FV using the groups according to different fusion rules (SUM, PROD,MIN and MAX) with the methods based on the four networks: AlexNet, VGG19,VGG16 and GoogleNet.

A) FKP Multimodal results

Table 3.4: FKP Multimodal identification

Fingers	Open Set		Closed Set	
	T_o	EER(%)	ROR(%)	RPR
SUM				
LIF + LMF	0.184	0.0197	100	1
RIF+RMF	0.3200	0.00615	100	1
ALL	0.495	0	100	1
PRO				
LIF + LMF	0.1050	0.00123	100	1
RIF+RMF	0.00099	0.100	100	1
ALL	0.1170	0.00123	100	1
MIN				
LIF+LMF	0.335	0.00246	100	1
RIF+RMF	0.00125	0.0258	100	1
ALL	0.189	0.00123	100	1
MAX				
LIF+LMF	0.1842	0.0246	99.39	1
RIF+RMF	0.640	0.00615	98.78	1
ALL	0.519	0	100	1

Table 3.4 shows the performance of the FKP Multimodal system using different fusion rules: (SUM ,PROD ,MAX ,MIN) and different finger combinations LIF+LMF combination, RIF+RMF combination, and the ALL (LIF+LMF+RIF+RMF) combination.

we observe a better result from Multimodal, and in closed set we have ROR = 100% and RPR = 1 in every combination and every fusion rule, unlike in MAX rule the identification rate isn't always 100%. The best finger combination is (ALL) in every fusion rule with an EER =0 in SUM, EER=0.00123 in PROD, EER=0.00123 in MIN and EER=0 in MAX. In this case the best fusion rule is SUM and the worst is MAX.

B) FV Multimodal

Table 3.5: FV Multimodal identification

Fingers	Open Set		Closed Set	
	T_o	EER(%)	ROR(%)	RPR
SUM				
INDEX+MIDDLE+RING	0.877	0.0359	99.05	1
PRO				
INDEX+MIDDLE+RING	0.00638	0.00599	100	1
MIN				
INDEX+MIDDLE+RING	0.028	0.047	100	1
MAX				
INDEX+MIDDLE+RING	0.604	0.1557	88.67	2

Table 3.5 shows the performance of the FV Multimodal system using different fusion rules: (SUM, PROD, MIN and MAX), we used one group, which is (index+middle+ring) combination. The results are better than Unimodal, and the best fusion rule is PROD with the lowest value of EER=0.00599 and ROR=100% the bad results are MAX with high error rate EER= 0.01557 and low ROR.

3.11 Conclusion

This chapter. We presented the outcomes of a unimodal and a multi-modal biometric identification system. The final one is based on the matching score level fusion of the subsystem outputs. The first database utilized in this study is FKP, which includes the fingers LIF, LMF, RIF, and RMF, and the second database is FV, which includes the fingers Index, Middle, and Ring. In this case, we applied a deep learning approach based on CNN pretrained model networks (VGG16/19, GoogleNET, AlexNET). In our experiments, we found that integrating multiple finger image modalities yields the greatest outcomes when compared to using only one finger image modality. As can be seen, the EER for open-set identification is 0.00123% while the ROR for closed-set identification is 100% with an RPR of 1.

General Conclusion

In recent years, the field of biometric approaches has experienced tremendous growth. The work in this thesis contributes to the identification of people using their biometric descriptor. To implement the suggested monomodal and multimodal biometric systems, we based our work on a new biometrics technique called finger joint fingerprinting (FKP) and (FV). By providing core ideas regarding biometric systems in general and the techniques used to evaluate them, we first provided the background for the thesis subject.

Then, based on architecture, data sources, and integration levels, we described the various elements of multimodal biometric systems. The pre-trained models of the techniques we utilized in our study, Convolutional Neural Networks (CNN) and Transfer Learning (TL), were further discussed when we introduced deep learning.

Our experiments were conducted on the reference (poor data) FKP and FV databases, and we have suggested a novel deep learning-based method for multimodal selection. We investigated a CNN-based approach for this, utilizing four pre-trained networks (AlexNet, VGG19, VGG16, and GoogleNet). The data collected demonstrated that our strategy can deliver good outcomes in terms of equal error rate (EER), identification rate, and overall separation of the distributions of fraudsters and clients.

As an outlook, we suggest adopting other deep learning techniques, particularly transformers, in the future to significantly enhance the performance of our biometrics system.

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