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THESIS

Thesis submitted in partial fulfillment of the requirements for the degree of

2nd **Cycle LMD Master**

In : Automatic and Systems

By : **BELHAMRA AYOUB and DEBABECHE AZZEDDINE**

Theme

Identity Recognition Using Deep Learning Techniques

Publicly sustained on : 13/06/2022 before the jury composed of:

Name and Surname	*Title*	*Affiliation*	*Quality*
F. CHARIF	*MCA*	*Univ. K. M. Ouargla*	*President*
R. CHELAOUA	*MCB*	*Univ. K. M. Ouargla*	*Thesis Director*
M. KOURICHI	*MCB*	*Univ. K. M. Ouargla*	*Thesis Co-director*
N. BETTAYEB	*MAB*	*Univ. K. M. Ouargla*	*Examiner*

بسم الله الرحمن الرحيم

وقل رب زدني علما

صدق الله العظيم

Dedication

I DEDICATE THIS PROJECT TO ALLAH, MY SOURCE OF INSPIRATION, WISDOM, KNOWLEDGE AND UNDERSTANDING, THE SOURCE OF MY STRENGTH THROUGHOUT THIS PROGRAM. TO MY MOTHER ALLAH YERHAMHA AND MY FATHER WHO HAVE PROVIDED ME WITH THEIR ENCOURAGEMENT, LOVE AND UNDERSTANDING. TO MY BROTHERS AND MY SISTERS FOR THEIR WHOLE-HEARTED SUPPORT. TO BELOVED PEOPLE WHO HAVE MEANT AND CONTINUE TO MEAN SO MUCH TO ME. ALTHOUGH THEY ARE NO LONGER OF THIS WORLD, THEIR MEMORIES CONTINUE TO REGULATE MY LIFE. TO MY UNCLES AND AUNTS AND ALL MY EXTENDED FAMILY. TO ALL MY FRIENDS AYOUB, FIRAS, KHELAF, SEBTI, OUSSAMA, BASSET AND TEACHERS IN EVERY INSTITUTION I DID STUDY AT. TO ALL WHO WERE THERE FOR ME, THANK YOU FOR YOUR HELP AND ENCOURAGEMENT.

DEBABECHE AZZEDDINE

Dedication

TO MY DEAR PARENTS, FOR ALL THEIR SACRIFICES, THEIR LOVE, THEIR TENDERNESS, THEIR SUPPORT AND THEIR PRAYERS THROUGHOUT MY STUDIES, TO MY DEAR SISTERS FOR THEIR PERMANENT ENCOURAGEMENT AND MORAL SUPPORT, TO MY DEAR BROTHERS, FOR THEIR SUPPORT AND ENCOURAGEMENT, TO ALL MY FAMILY AND FRIENDS(FETHI) FOR MY NIECE RANIME FOR THEIR SUPPORT THROUGHOUT MY UNIVERSITY CAREER, MAY THIS WORK BE THE FULFILLMENT OF YOUR SO-CALLED WISHES, AND ESCAPE FROM YOUR UNFAILING SUPPORT, THANK YOU FOR ALWAYS BEING THERE FOR ME.

BELHAMRA AYOUB

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Abstract

In the past two years, we've seen the spread of COVID-19. Which forced people to follow a strict health protocol against such epidemics as staying away, sterilizing, not touching and wearing protective masks, etc. Thus, it has become necessary to use identification biometric systems that comply with the instructions of health protocol. And reject a biometric systems that violate laws. In this thesis, we propose a recognition system based on iris of eye. Iris recognition is known for its accuracy, effectiveness and widespread applications. The proposed system is based on Principal Component Analysis Networks (PCANET) technology of deep learning. By training the model, extracting features and to classify it using the radial basis function (RBF) kernel. Which is considered a non-linear classifier.

The experimental results provide an overview of the performance of the proposed recognition system. As, it brings out the disparity between the performance of unimodal system and the performance of multimodal system.

Keywords: Security, Biometrics, Identification, Machine Learning, Deep Learning, Artificial Neural Networks, PCANet, fusion Level.

Résumé

Au cours des deux dernières années, nous avons été témoins de la propagation du COVID-19, qui a obligé les gens à suivre protocole sanitaire strict contre les épidémies telles que la distanciation, la stérilisation, le non-touchement et le port de masques de protection, etc. De ce fait, il est devenu nécessaire d'adopter des systèmes d'identification conformes aux instructions du protocole sanitaire et rejet des systèmes biométriques qui violent les lois. Dans ce thèse, nous proposons un système de reconnaissance basé sur l'iris de l'œil, qui est connu pour sa précision, son efficacité et ses applications étendues. Le système proposé est basé sur la technologie PCANET (Principal Component Analysis Network) (pour l'apprentissage). La fonction profonde est réalisée en formant le modèle et en extrayant les caractéristiques et en les classant par le noyau de la fonction de base Radial (RBF) qui est considéré comme un classificateur non linéaire.

Les résultats expérimentaux donnent un aperçu des performances du système proposé, et mettent également en évidence l'écart entre les performances du system unimodal et Le système multimodal.

Mots clés: Sécurité, Biométrie, Identification, Machine Learning, Deep Learning, Réseaux de Neurones Artificiels, PCANet, Fusion Level.

ملخص

في العامين الماضيين، شهدنا انتشار مرض كوفيد-19، الذي أجبر الناس على اتباع بروتوكول صحي صارم ضد مثل هذه الأوبئة كالابتعاد ، التعقيم، عدم اللمس وارتداء الأقنعة الواقية، الخ. بسبب ذلك، أصبح من الضروري اعتماد أنظمة تحديد الهوية التي تتوافق مع تعليمات البروتوكول الصحي و رفض الأنظمة البيومترية التي تنتهك القوانين. في هذه الأطروحة، نقترح نظام تعرف قائم على قزحية العين، المعروفة بدقتها و فعاليتها و انتشار تطبيقاتها. يعتمد النظام المقترح على تقنية شبكة تحليل المكونات الرئيسية (PCANET) للتعلم العميق من خلال تدريب النموذج واستخراج الميزات وتصنيفها بواسطة نواة دالة الأساس الشعاعي (RBF) التي تعتبر انها مصنف غير خطي.

النتائج التجريبية تقدم لمحة عن أداء النظام المقترح، كما تبرز التباين بين أداء النظام الأحادي و النظام المتعدد الوسائط.

<u>الكلمات المفتاحية:</u> الأمن، القياسات الحيوية، تحديد الهوية، التعلم الألي، التعلم العميق، الشبكات العصبية الاصطناعية، PCANet، الدمج مستوى.

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Abbreviations

AI	:	Artificial Intelligence
ANN	:	Artificial Neural Network
CMC	:	Cumulative Match Curve
CNN	:	Convolutional Neural Networks
CPU	:	Central Processing Units
DBN	:	Deep Belief Networks
DL	:	Deep Learning
DNA	:	Desoxyribonucleic Acid
DWT	:	Discrete Wavelet Transform
EER	:	Equal Error Rate
FA	:	False Acceptation
FAR	:	False Acceptance Rate
FR	:	False Rejection
FRR	:	False Rejection Rate
FTC	:	Failure To Capture
FTE	:	Failure To Enrol
GAR	:	Genuine Acceptance Rate
GPU	:	Graphics Processing Units
ML	:	Machine Learning
MMU	:	Multi-Media University
PCA	:	Principal Component Analysis
PCANET	:	Principal Component Analysis Networks
RBF	:	Radial Basis Function
RBM	:	Restricted Boltzmann Machine
ROC	:	Receiver Operating Curve
ROR	:	Rank One Recognition
RPR	:	Rank of Perfect Recognition
SVM	:	Support Vector Machine
TA	:	True Acceptance
TR	:	True Rejection

Chapter I

INTRODUCTION

In our current world, individuals are highly linked to each other. Especially with information technology, mobile devices and social networking, that have a significant impact on their everyday life. In such societies, the majority of services are supplied electronically via intelligent equipment that may be accessed remotely like as: citizen and healthcare services, banking, education, business, defense and military, etc. In online services, information is a basic building block. We can communicate it, store and refine it. Thus, if such information is lost or incorrect, it can have catastrophic consequences. Therefore, information is valuable and needs to be protected based on the only authorized persons may take part in it (confidentiality). In concern of security, the all users agree on the biometric technologies are more secure than traditional IT security methods, and it will be a good change to replace passwords, keys and ID cards, etc. There are strong reasons for biometrics to be implemented because there are many secure authentication devices that could secure data in best possible way. Due to the threats and challenges to traditional schemes. The biometric could provide many benefits in sense of providing security, access to right information and access to data from different locations.

I.1 General Context: Biometric System

Biometrics is a specialized branch of science that deals with uniquely recognizing individuals based on measurement of their intrinsic physical or behavioral properties. Biometric authentication systems are widely used as they have proved to be the most accurate way for identifying human beings based on their biometric traits [2, 3]. Biometric traits include face, fingerprint, retina, iris, knuckle, hand geometry, palmprint, signature, voice etc. These traits can be utilized based on the need of application.

The term “biometrics” is derived from the Greek words bio (life) and metric (measure). Interestingly, the term “biometrics” was not used to describe these technologies until the 1980s. The first reference found for the term “biometrics” was in a 1981 article in The New York Times [4], [5]. In the centuries after several types of non-automated biometrics methods used by a human being but “automated” biometric technologies are invented with the development of computers [4]. The first known reference to non-automated biometrics was in prehistoric picture writing of a hand with ridge patterns that were discovered in Nova Scotia [5]. Fingerprint recognition represents the oldest method of biometric identification, with its history going back as far as at least 6000 B.C [4]. The first modern study of finger-prints was done by Johannes Evangelista Purkinje, a Czech physiologist, and professor of anatomy at the University of Breslau. In 1823, he proposed a system of fingerprint classification [4]. After the start of 20th century, the lot of biometric techniques used by a human being in there daily life.

Biometric system is the automatic recognition of a persons by extracting a biometric features from the acquired data, and comparing this feature set against the templates feature set, which are previously stored in the database. Generally, the biometric system components are divided into three main parts. Fig. I.1 illustrates enrolment and recognition processes in a biometric system.

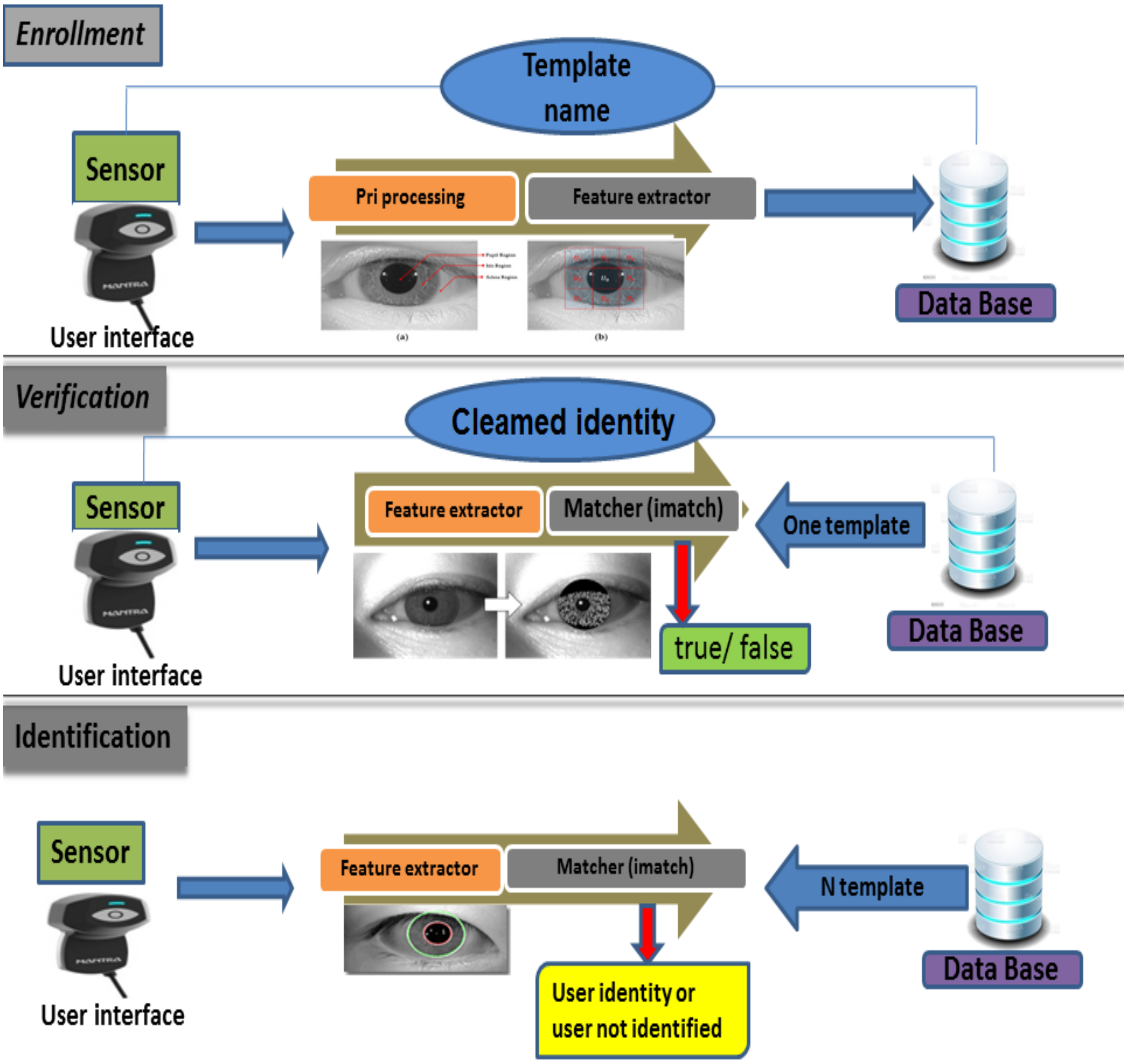


Figure I.1: Enrollment, Verification and identification in a Biometric system.

- **Biometric sensor**: it is responsible for capturing the biometric characteristics from the biometric subject and converting it to a digital form to be transferred to the subsequent module. The performance of the overall process depends heavily on the quality of the acquired raw data. In fact, this data is a result of transforming a real continuous phenomenon (such as a face) to a digital discreet form (face image) resulting in a loss of data. The quality of the acquired data depends on the technology of the reader, the added noise and the degree of the interoperability of the user with the system [6].

- **Enrollment**: the acquired raw data is first preprocessed to enhance its quality. After that, some relevant discriminatory features are extracted, by the extractor submodule, to generate a compact representation called "template" that efficiently resumes the biometric characteristics. The generated template is then sent to the storage system. Generally, the enrollment step allows the biometrics recognition system to learn the identities of the authentic persons in working environment [6].

- **Recognition**: Biometric systems typically operate in two modes: verification mode and identification mode [7]. Note that the terms "verification" and "authentication" they both indicate a protocol that runs in the verification mode of biometric systems. In the identification mode, a user provides the biometric information and the system needs to decide whether the user is valid. This model is close to the verification mode, but the difference is that the verification mode the comparison is made only against one template in the system by conducting 1 to 1 comparison. This is possible when we want to confirm the identity claimed by a user. While in the identification mode, the comparison is achieved against all records in the database by conducting 1 to many comparisons (1-to-N). This is the case when we want to know if the individual already exists in the database. So, the system try to answer the question "who is the user?" [6]. Biometric identification has been used in some scenarios such as criminal watching-list and identity management systems, because it is an intuitive method to solve the problem.

A biometric modality is a sort of biometric system that is categories are classified by the type of human attribute it uses as input. These categories can be classified are intrusive techniques need direct contact and non-intrusive techniques [8]. Furthermore, biometric modalities may be divided into two categories: physiological and behavioral features (show Fig. I.2). Physiological biometrics relate to the biological composition of the user being authenticated, like as face, fingerprints, iris, retina, hand geometry and DNA, etc [8]. Behavioral biometrics is related to measurable patterns in human activities such as keystroke dynamics, gait, voice and signature analysis and cognitive biometrics [8].

As the name depicts, all the biometric systems which take a single source of information for authentication, is called unimodal systems. The unimodal systems have to deal with various challenges such as lack of secrecy, non-universality of samples, the extent of user's comfort and freedom while dealing with the system, spoofing attacks on stored data, etc. These increasing operational and security demands are changing biometrics by

Physiological.

Behavioral.

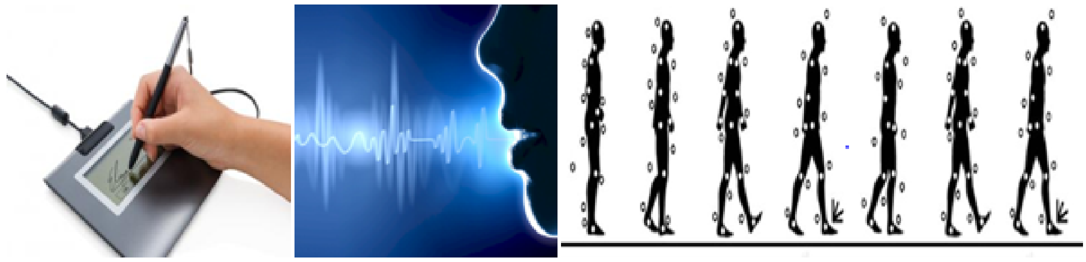


Figure I.2: The behavioral and physiological biometric modalities.

shifting the focus from unimodal to multimodal biometrics [9]. Multimodal systems are considered more suitable in terms of reliability, because a multimodal biometric system increases the scope and variety of input information taken from the users for authentication. As, there are several more reasons to employ a multimodal biometric system as in [10]. Within a multimodal biometric system, there can be variety in number of scenarios and components. They can be as follows [10]:

- Single biometric trait, multiple sensors.
- Single biometric trait, multiple classifiers.
- Single biometric trait, multiple units (say, multiple fingers).
- Multiple biometric traits of an individual (iris, fingerprint, etc.).

Before design any MBS, we need to consider a number of factors while designing a multimodal biometric system such as: Level of security, number of users, types of biometric traits and number of traits from the users. The fusion level at which multiple biometric traits need integration. The technique to be adopted to integrate the information. The trade-off between development cost versus system performance [10].

I.2 Research Objective

During the past few decades, the identification of personal identity has been active and widespread, including face recognition, finger and hand recognition. But due to the health protocol against Covid-19 that has recently swept the world, it has become necessary to avoid contact, adhere to distance and wear protective masks.

In this work, we aim to propose an identification system of persons based on the iris technology of the eye. Which is considered good choice, due to its wide applications in several fields. Also, it's more reliable and accurate. Currently, it is considered an active scientific research field. Furthermore, we present the PCANet as deep learning algorithm to apply it for our recognition challenge. Then to classify these deep features, we use Radial Basis Function (RBF) as non-linear classifier in our thesis.

I.3 Outline of Thesis

The rest of the thesis is organized as follows.

Chapter II describes a general overview of machine learning and it also gives a detailed idea about the different applications of artificial intelligence. After that, this chapter will present a description of deep learning. Which is a set of algorithms in machine learning that attempt to learn in multiple levels, corresponding to different levels of features.

In Chapter III, the proposed biometric methodology will be illustrated based on iris technology. Also in this chapter, we will justify our choice to deep learning methods and their structures, where can use for biometric applications. Then, all different processes of proposed system will be also described in more detail in this chapter.

Chapter IV will explain the outcomes of the experiments performed on MMU iris database. Also, this chapter will include an experimental setup to adapt our algorithms. In this chapter, fusion of data in multimodal biometrics will lead to improvement performance and accuracy in identifying, much more than unimodal biometrics.

Finally, Chapter V will provide the thesis summary, achieved contributions and a future works from this research.

Chapter II

THEORETICAL BACKGROUND: DEEP LEARNING

II.1 Introduction

CERTAIN functions performed by humans are so complex and it takes a lot of time and effort. But, with the progression of artificial intelligence (AI), these functions have become very easy. Machine learning (ML) is an application of artificial intelligence that involves algorithms and data that automatically analyses and make decision by itself without human intervention. Also, we can say in machine language artificial intelligence is generated on the basis of humane experience. Machine learning has become a highly successful discipline to apply in many different areas. Machine learning studies automatic methods for learning based on past observations and experience from big data. Machine learning has shown great success in building models for pattern recognition in domains ranging from Computer Vision [11], Pattern Recognition [12] and Signal Processing [13]. In addition to these domains, machine learning and in particular deep learning are increasingly important and successful in engineering and the sciences [14, 15, 16]. These success stories are grounded in the data-based nature of learning from a tremendous number of examples.

II.2 Machine Learning

Mitchell provides a definition, ML is "A computer program is said to learn from experiences with respect to some class of tasks and performance measure, if its performance at tasks improves with experience" [17]. ML uses an algorithm and statistical techniques to train the systems by themselves without using any explicit programs and provide us the system predicted results, we need to provide lots of data and more trained for predicting results Machine learning Types and which type and algorithm should be selected for applications. These different types and its applications are illustrated in the Fig. II.1. Many kinds of tasks can be solved by machine learning such as [18]:

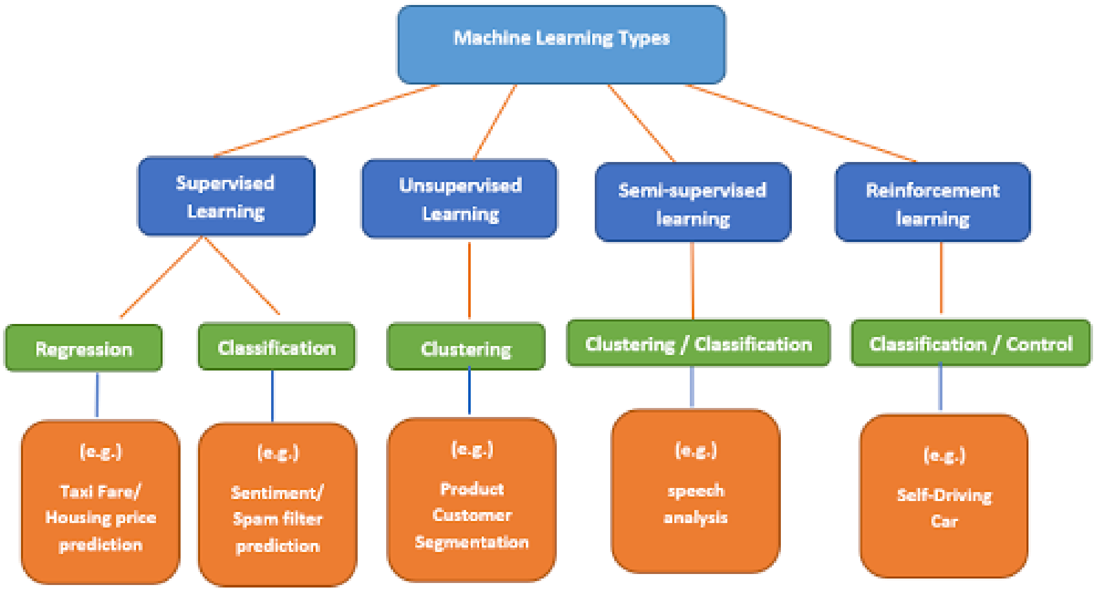


Figure II.1: Diagram of different types for machine learning.

II.2.1 Classification

The algorithm is asked to specify the categories which some input belongs. For this task, the algorithm is usually asked to produce a function when, the model assigns an input described by a vector to a category identified by numeric class. There are other variants of the classification task, where the outputs have a probability of distribution over classes.

II.2.2 Regression

The algorithm is asked to predict a numerical value given some input. For that, it's same to classification, except that the format of output is different. An example of a regression, is the prediction of the expected claim amount that an insured person will make, or the prediction of future prices of securities.

II.2.3 Clustering

The algorithm is asked to cluster a subset of data which are similar. Clustering is the process of dividing a dataset into groups such that the members of each group are as similar (close) as possible to one another, and different groups are as dissimilar (far) as possible from one another.

II.2.4 Density estimation

The algorithm is asked to learn a function model, where can be interpreted as a probability density function on the space that the examples were drawn. To do this, the algorithm needs to learn the structure of the data. Where examples cluster tightly and where they are unlikely to occur? Most of the tasks require the learning algorithm to at least implicitly capture the structure of the probability distribution.

II.3 Neural Networks

Neural networks are a set of algorithms, modeled loosely after the human brain such as shown in Fig. II.2. Artificial Neural Networks (ANNs) are machine learning-related computational approaches [19, 20, 17], are inspired from the biological neurons within the human body which activate under certain circumstances resulting in a related action performed by the body in response. A neural network [21, 22] is composed of simple processing units, or nodes, and connections between them. Also, contains networks consisting of layers and different interconnected elements that work in parallel. The weight of any link between two units is used to assess how much one unit will affect the other. A neural network performs a functional mapping from one set of values (assigned to the input nodes) to another set of values (retrieved from the output nodes). The mapping itself is stored in the weights of the network [23]. A subset of the units of the network acts as input nodes, and another subset acts as output nodes. By assigning a value, or activation, to each input node, and allowing the activations to propagate through the network.

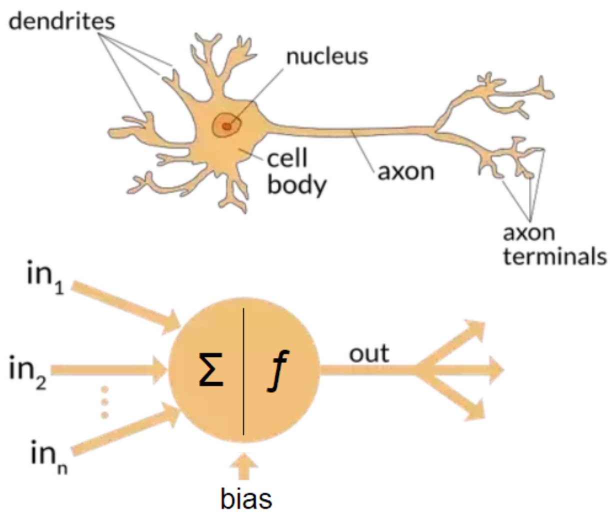


Figure II.2: The differences between artificial and biological neural networks.

Generally, neural network consist of a set of artificial cells, called Perceptron. That can be composed by basic elements like as:

- Input layer represents dimensions of the input vector.
- Weights are numeric values which are multiplied with inputs. They self-adjust depending on the difference between predicted outputs vs training inputs.
- Activation Function is a mathematical formula to activate the neuron.
- Hidden layer represents the intermediary nodes that divide the input space into regions with (soft) boundaries.
- Output layer represents the output of the neural network.

II.3.1 Neural Networks Types

Neural network algorithms can be categorized depending on the type of learning process. For that, we have:

II.3.1.1 Supervised learning

In supervised learning, the algorithm will get the labelled input and the desired output. In this type of learning both training and validation, which makes it pretty easier for us to predict. Supervised learning involves a observing several examples of a random vector x and an associated value or vector y, and learning to predict y from x, usually by estimating $p(y jx)$ [18].

II.3.1.2 Unsupervised Learning

In unsupervised Learning, the algorithm will get the input without the desired output. The main aim of this model is to find the structure in the inputs using clustering model. Unsupervised learning involves a observing several examples of a random vector x, and attempting to implicitly or explicitly learn the probability distribution $p(x)$, or some interesting properties of that distribution [18].

II.3.1.3 Semi-supervised learning

Semi-supervised learning traffic effect in making the most out of unlabeled data. And unlabeled instances, together with their predicted labels, are added to the training set, and the process repeats, to explore the un-known aspects [24].

II.3.1.4 Reinforcement learning

It is about taking suitable action to find the best possible behavior or path it should take in a specific situation. In simple term here the algorithm perform certain activity and learns from itself when gone wrong from its past experience (you can relate to human). Reinforcement learning differs from supervised learning in a way that in supervised learning the training data has the answer key with it so the model is trained with the correct answer itself whereas in reinforcement learning, there is no answer but the reinforcement agent decides what to do to perform the given task [25].

II.4 Deep Learning

From [26] and Fig. II.3, “Deep learning is a set of algorithms in machine learning that attempt to learn in multiple levels, corresponding to different levels of abstraction.

It typically uses artificial neural networks. The levels in these learned statistical models correspond to distinct levels of concepts, where higher-level concepts are defined from lower-level ones, and the same lower-level concepts can help to define many higher-level concepts. Deep learning is part of a broader family of machine learning methods based on learning representations."

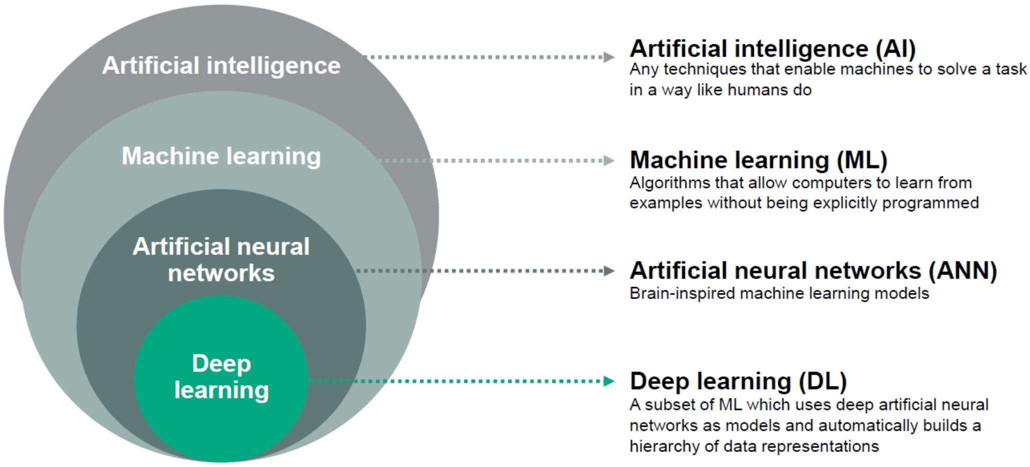


Figure II.3: The Simplifying of difference: Machine Learning vs Neural Networks and Deep Learning.

Deep learning has been around since the 1950s, but its elevation to apply in artificial intelligence field is relatively recent. In 1986, pioneering computer scientist Geoffrey Hinton (Google Researcher) and long known as the "Godfather of Deep Learning" was among several researchers who helped make neural networks progress again. Scientifically, by demonstrating that more than just a few of them could be trained using back propagation for improved shape recognition and word prediction. Actually, deep learning was being used in everything of consumer applications [27].

II.5 Deep Learning models

Deep learning methods are fast evolving to provide higher performance. The literatures include adequate review papers on the progressing algorithms of deep learning in particular application domains. The family of deep learning methods have been growing increasingly richer, encompassing those of neural networks models. In this section, we present the most important and most popular models in the field of deep learning. Where several basic definitions are summarized:

II.5.1 Deep Neural Network (DNN)

DNN is a neural network that incorporates the complexity of a certain level, which means several numbers of hidden layers are encompassed in between the input and output layers [28]. The deep design of a deep neural network (DNN) is made up of a number of hidden layers. This architecture seeks to build an abstract representation or high-level model from observation data. Which is then used to uncover highly nonlinear relationships mapping between the input data and the target values. DNNs have a long history of development, the Fig. II.4 give an example of image classification.

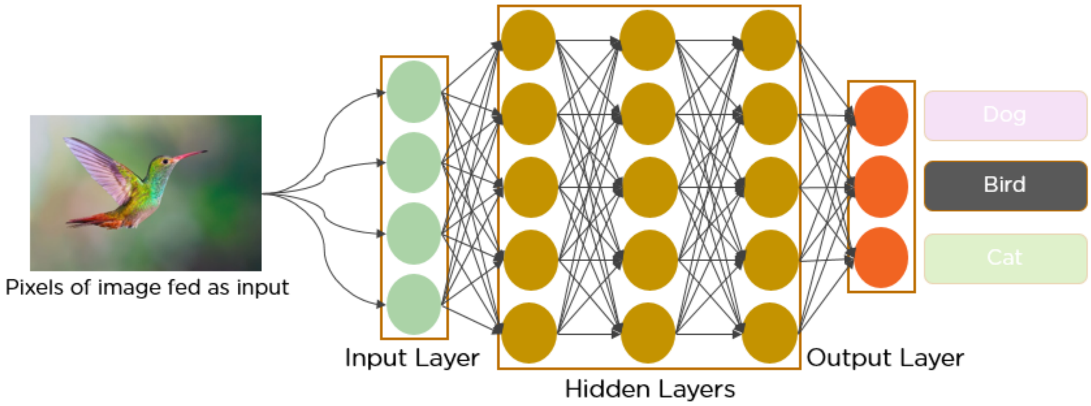


Figure II.4: Example of classification by Deep Neural Network (DNN).

II.5.2 Restricted Boltzmann Machine (RBM)

Restricted Boltzmann machine (RBM) plays a crucial role in building deep belief networks that are seen as the foundations in deep learning [15]. Basically, RBM is seen as a bipartite graph that can be represented by an undirected graphical model or equivalently a bidirectional graphical model in a two-layer structure [29]. Its two layers are visible layer $\boldsymbol{vv}$ and hidden layer $\boldsymbol{hh}$. The layers are connected by using symmetrically weighted connections. The name "restricted" is added because there are no connections between two neurons in the same layer, namely visible-visible or hidden-hidden connections do not exist. As shown in Fig. II.5, a restricted belief network whose visible layer has 4 nodes and the hidden layer has 3 nodes. It is different from the Boltzmann network in that there are no effects between nodes in a single layer of RBM [16, 30].

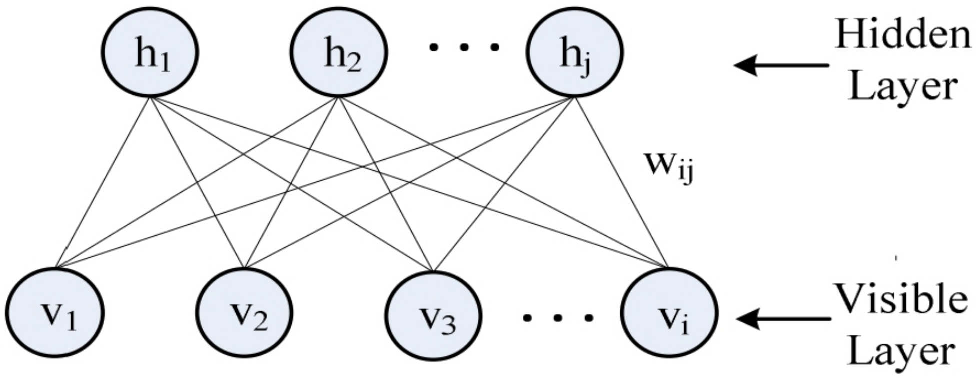


Figure II.5: An RBM with binary hidden units representing latent features and visible units encoding observed data.

Restricted Boltzmann Machine is unsupervised learning, it has the advantage of fitting the feature of the samples. So when we have an output of the hidden layer, we can use it as the visible layer's input of another RBM. This process can be regarded as further feature extraction from the extracted feature of our samples [29]. There are two different types of RBM that we usually use in DNN training. The difference between two types depends on the input data values. First, considers that both visible and hidden units are binary 0 or 1. Bernoulli distribution is used to represent the binary units. In the other hand, RBM is developed for the case that hidden units are binary while input units follow a linear model with Gaussian noise. This RBM deals with the real-valued data [29].

II.5.3 Deep Belief Network (DBN)

A Deep Belief Network (DBN) is a class of deep neural networks that comprises multi-layer belief networks. DBN is seen as a theoretical tool to train or initialize different layers in deep neural networks training. DBN is one of the most dependable deep learning algorithms, with high accuracy and computational efficiency [31]. DBN is probabilistic undirected vector graph models which include a group of stochastic variables [28]. DBN conducts unsupervised learning where the outputs are learned to reconstruct the original inputs [29].

DBN contains Restricted Boltzmann Machines (RBM) which are trained in a greedy manner. Each RBM layer communicates with both the previous and subsequent layers [32, 33]. From Fig. II.6, this model is consists of a feed-forward network and several layers of RBM as feature extractors [34]. A hidden layer and visible layer are only two layers of RBM [35]. The building method is based on a stack-wise and bottom-up style. Each stack is composed of a pair of layers that is trained by RBM. After training each stack, the hidden layer of RBM is subsequently used as an observable layer to train the RMB in next stack for a deeper hidden layer. Following this style, we eventually train a bottom-up deep machine in accordance with a stack-wise and tandem-based training algorithm [29]. DBN is successfully applied to all sorts of tasks including handwriting recognition [28, 11], speech recognition [36, 37], audio classification [38] and text classification [39].

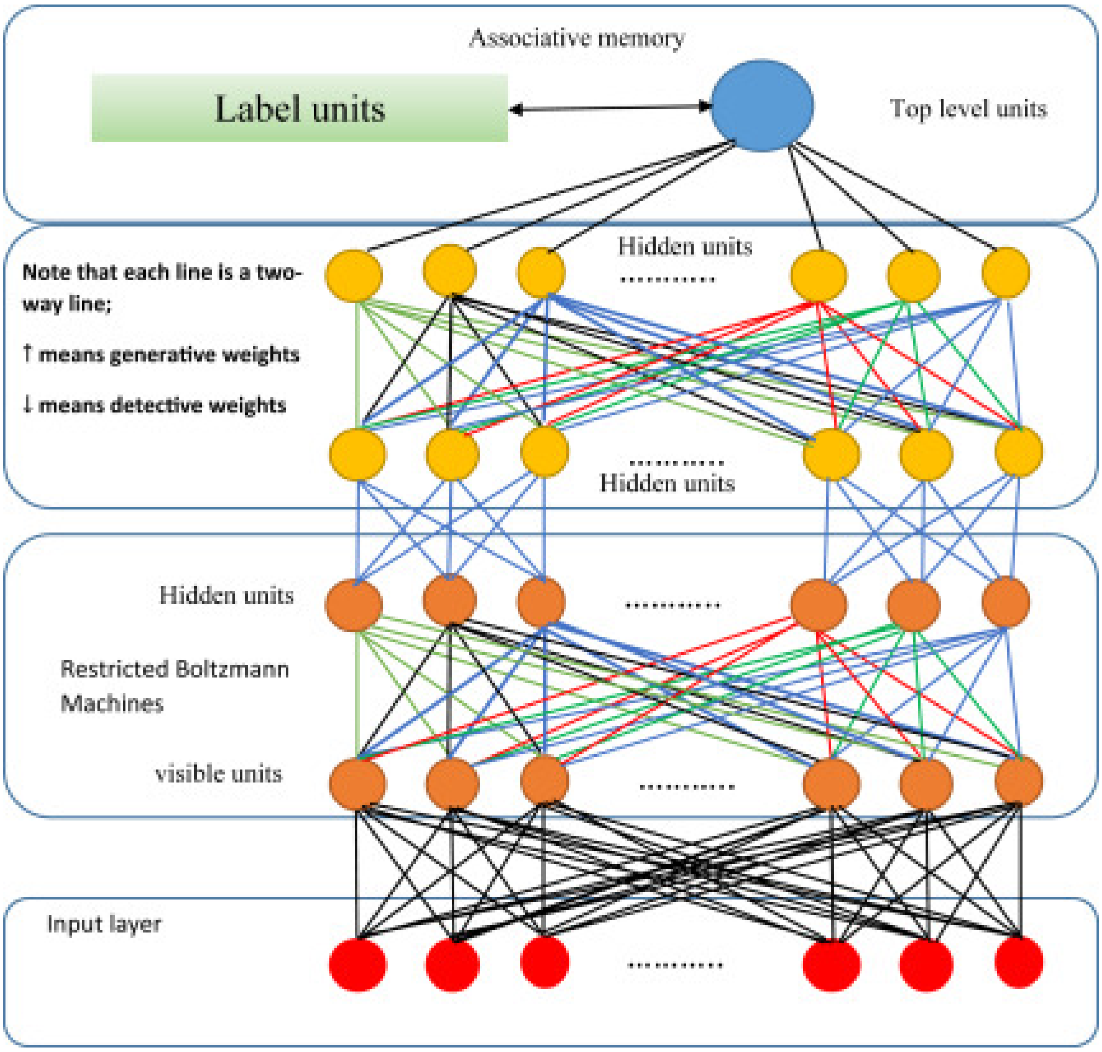


Figure II.6: The several layers of neural networks DBN.

II.5.4 Deep Autoencoder

One of the most often used building blocks in deep neural networks is the auto-encoder, which is also known as an auto-associator. It is made up of two modules:

- A encoder uses a deterministic mapping function:

$$f : h = f(x) \tag{II.1}$$

- A decoder uses another deterministic mapping function:

$$g : x = g(h) \tag{II.2}$$

The settings of the encoder and decoder may be learned for real-valued input by reducing the reconstruction error:

$$e = x - g(f(x)) \tag{II.3}$$

The hidden layer's output is then utilized as the feature for picture representation. It has been demonstrated that this type of nonlinear auto-encoder differs from PCA [40]. "Training an auto-encoder to minimize reconstruction error equates to maximizing a lower constraint on the mutual information between input and the learned representation," according to one study [41]. Where, Vincent et al. [41] offer a denoising auto-encoder that improves generalization by training with locally distorted inputs to improve the capabilities of auto-encoders for picture representation in deep networks.

A deep autoencoder is composed of two, symmetrical deep-belief networks that typically have four or five shallow layers representing the encoding half of the net, and second set of four or five layers that make up the decoding half. The layers are restricted Boltzmann machines, the building blocks of deep-belief networks. A schema of a deep autoencoder's structure is simplified in Fig. II.7.

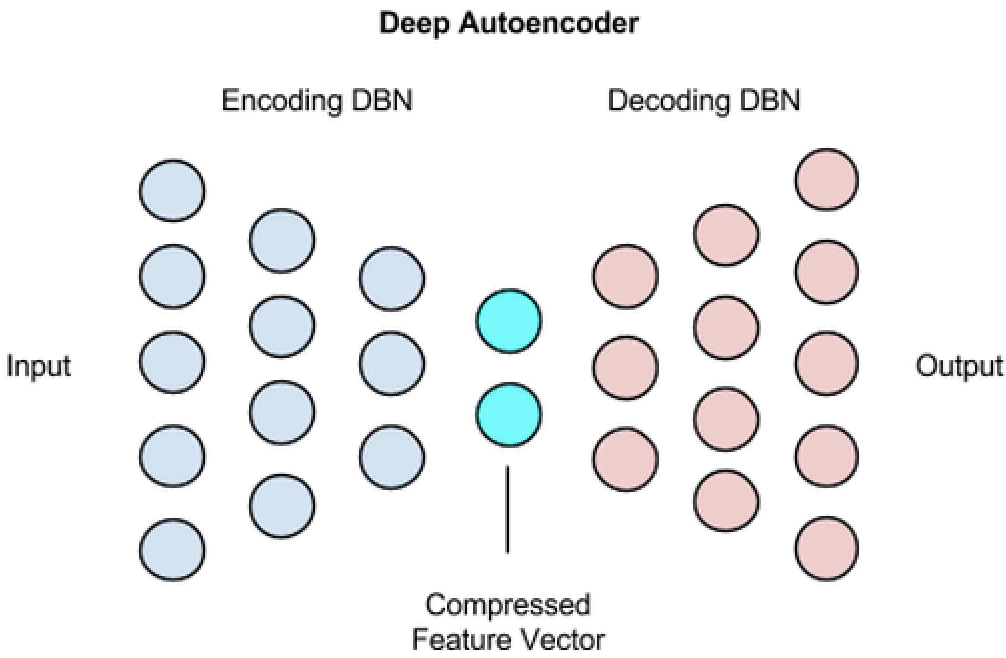


Figure II.7: The structure of deep auto-encoder.

The goal of an autoencoder architecture is to create a representation of the input at the output layer such that both are as close (similar) as possible. But, the actual use of autoencoders is for determining a compressed version of the input data with the lowest amount of loss in data. The autoencoders work in a similar way of the PCA concept. The encoder part of the architecture breaks down the input data to a compressed version ensuring that important data is not lost but the overall size of the data is reduced significantly. This concept is called Dimensionality Reduction. The downside to this concept is, cannot determine the structure of the compressed data.

II.5.5 Convolutional Neural Networks (CNN)

Convolutional Neural Network show in Fig. II.8 plays a vital role. In each CNN, there are two stages for the training process, the feed-forward stage, and the back-propagation stage. One key ingredient to the success of deep learning in image classification is the use of convolutional architectures [42]. A convolutional deep neural network (ConvNet) architecture [43, 44] consists of multiple trainable stages stacked on top of each other followed by a supervised classifier. Each stage generally consists of "three layers" – a convolutional filter bank layer, a nonlinear processing layer, and a feature pooling layer.

CNNs achieved high performance when applied in the activity recognition field. This goes back to the key advantages of CNNs, which are the local dependencies and the scale invariance. The local filters in CNN have the capability to capture local dependencies of neighboring sensor acceleration readings of an activity signal. In addition to that, scale invariance characteristic allows CNN to successfully learn hidden features regardless of their positions or scales. This is helpful in the recognition of human activities as people may do the same activity with different speeds and intensities [45]. The convolution operation applies each local filter over all subsets of the input where weights of these filters are shared across all subsets. Then, the pooling operation splits the output features and applies some functions to reduce the size of the previous layer to preserve the scale invariance property of features [45]. The output feature maps from this convolution can figure out different types of features at each temporal position. The most common CNN architectures are ZFNet [46], GoogLeNet [47], VGGNet [42], AlexNet [43] and ResNet [44].

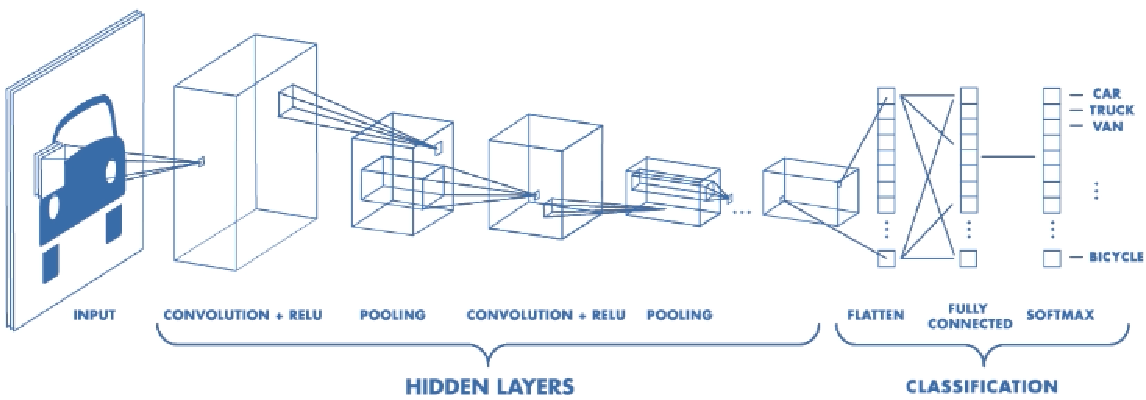


Figure II.8: A comprehensive guide to Convolutional Neural Networks (CNN).

II.5.6 Principal Component Analysis Networks (PCANET)

Recently, deep learning techniques have drawn much attention. Chan et al. [1] proposed a new variant of convolutional networks, namely, principal component analysis network (PCANet), which does not make use of backpropagation to obtain features from visual content or to visual classification tasks. Building the PCANet consists of only a cascaded linear map. Followed by a nonlinear output stage [1]. PCANet only deals with the most basic PCA filter for each stage of the convolution filter bank without further training, which can easily train and adapt to different data tasks without changing the network architecture [48]. The features of input visual content are extracted through three processing stages, i.e., principal component analysis (PCA) filter banks in convolution layers, binarization in nonlinear processing layers, and block-wise histogram in pooling layers, to avoid backpropagation. Many feature extraction methods based on PCANet shown their effect in the field of speech emotion detection [49], face recognition [1], hand-written digits, textures, and objects, etc.

II.6 Deep Learning Applications and Advantages

Deep learning is the last true developing of artificial intelligence. All recent artificial intelligence innovations, such as smart voice assistants, recommendation systems, image recognition, and even self-driving cars, are built on it. Deep learning algorithms power most intelligent using a computer vision such as self-driving cars, drones, and a host of biometric processes by comprehending a visual environment and deciphering its context. Also, these algorithms can analyze and interpret human language inputs in textual or verbal formats. Key applications include text classification, sentiment analysis, translation, speech recognition, and more. Deep learning is critical for knowledge application and knowledge-based predictions in the age of Big Data. All this is due to the advantages of deep learning technology, which can be summarized in:

1. Deep learning algorithms can generate new features from among a limited number of training dataset without additional human intervention.

2. Classical ML algorithms are limited in their ability to analyze unstructured data, but one of the biggest draws of deep learning is its ability to work with unstructured data.

3. Deep learning can perform complex tasks that often require extensive feature engineering, this means faster application and superior accuracy.

4. The multiple layers in deep neural networks allow models to become more efficient at learning complex features and performing more intensive computational tasks, it outshines machine learning in machine perception tasks.

5. Deep learning, when applied to data science, can offer better and more effective processing models. Its ability to learn unsupervised drives continuous improvement in accuracy and outcomes.

6. Parallel and distributed algorithms allow deep learning models to be trained at scale. With data or the model itself being distributed across multiple machines, training is faster.

7. While training deep learning models can be cost-intensive, once trained, it can help users cut down on unnecessary expenditure.

8. Deep learning is highly scalable due to its ability to process massive amounts of data and perform a lot of computations in a cost- and time-effective manner.

II.7 Conclution

Machine Learning is a technique of training machines to faster perform the activities a human brain can do. Machine learning is one of the applications of artificial intelligence. For more precisely, neural networks is a mathematical function that collects and classifies information according to a specific architecture and it can be a Supervised or Unsupervised. So, deep learning is a set of algorithms in machine learning that attempt to learn in multiple levels, corresponding to different levels of features.

This chapter includes overview on advanced algorithms of deep learning application such as: Deep Neural Network (DNN), Restricted Boltzmann Machine (RBM), Deep Belief Network (DBN), Deep Auto-encoder and Convolutional Neural Networks (CNN), etc. Recently, deep learning is the last true developing of artificial intelligence innovations such as smart voice assistants, recommendation systems, image recognition, and Auto-driving cars, etc.

Chapter III

OUR PROPOSAL RECOGNITION

III.1 Introduction

DEEP learning is a new subject in machine learning methods. It is the most efficient, supervised, time and cost-effective. The deep learning uses to solve difficult situations from the deep illustrative and distinguishing features. It is the finest option for pattern recognition using a sophisticated architecture able to process a big data. As far as deep learning is concerned has made remarkable progress and delivered outstanding results in a variety of applications such as: computer vision, object detection, facial recognition, handwriting recognition, speech recognition, and many more features applications.

Biometric recognition has been one of the most challenging and attractive areas of computer vision. The goal of biometric recognition algorithms is to answer the question, who is this person in a given image? Deep learning helps the Biometric recognition system to understand the complex perception tasks with the maximum accuracy to address two problems: verification and identification, generally.

III.2 Proposed Recognition

Persons recognition play a very important signification in our relationship, which is a process based on their biometrics trait, image processing and matching identification. Iris recognition is an automated biometric identification approach that uses mathematical pattern recognition algorithms of one or both of a person's irises, which include complex patterns that are distinctive, stable, and visible from a distance. Iris recognition allows for the avoidance of ”collisions” (False Matches) even in cross-comparisons across large populations. Its main flaw is that picture acquisition from distances more than a meter, or without collaboration, can be quite difficult [50].

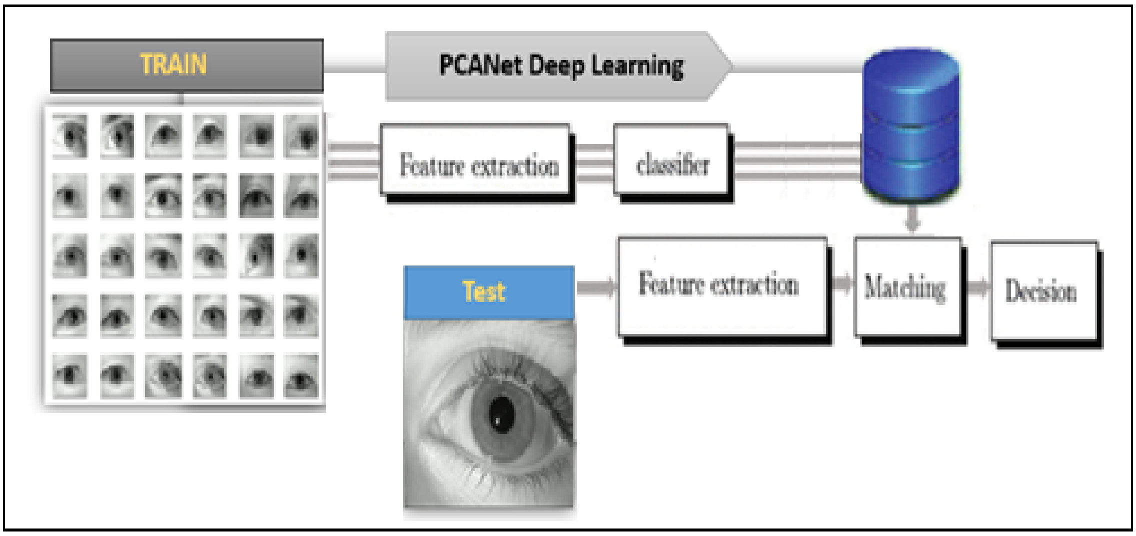


Figure III.1: Block-diagram of the proposed biometric recognition system.

In this work, we are based on iris recognition with PCANet deep learning technology. Where our work use a set of iris images from several people with different ages and poses, which makes the challenge strong. In Fig. III.1, we show the block-diagram of the proposed biometric system based on the iris modalities. For training phase, the features are extracted from the all images by deep learning network. After that, the feature vectors will be as a training data used to create models based on PCANet processing. In the test phase, the features are extracted from tested iris image, then is verified with models of database to identify person.

III.3 Our Contribution

With the outbreak of Covid-19, all humans in the world have been severely affected, including their communication and ways of Identify on each other. These impacts on developers in biometrics field are considered to be significant in the likely short and long-term period. What is clear is that biometrics is among the key technology like AI, machine learning, in responding to the pandemic. In order to contain the quick and widespread of Covid-19, several governments are exploiting biometric systems in public services to protect of individuals and to reduce the fast spread of this infectious disease.

In the past, there were several ways to identify people, including finger-print, palm-print and fkp recognition ..., which are known to be popular biometric techniques. Given the current situation of the Covid-19 epidemic, it is better not to use the previously mentioned biometric techniques because it needs contact and convergence. Therefore, they have become a danger to users due to the instructions of the preventive health protocol against Covid-19.

Consequently, we resort to relying on remote identification techniques such as face recognition, but it is not possible to identify the person based on this recognition technology because there is a protective personal mask to safe from infection is considered. In this thesis, we propose the biometric recognition system based on iris recognition. Iris technology is the best solution because does not require contact and not covered by mask as show in figure (Fig. III.2).

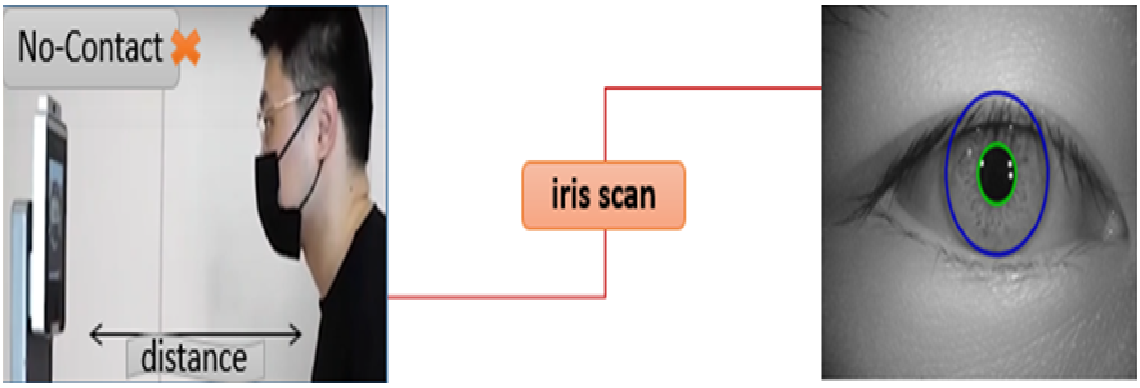


Figure III.2: Block iris recognition is the best solution against health protocol of Covid-19.

Iris is a colored ring shaped area surrounding pupil, providing detailed characteristics such as freckles, coronas, rings, stripes, crypts, etc [51]. Retinal identification has much higher user acceptance, it is the most reliable and most accurate biometric specifically. Iris recognition is considered as one of the best methods from security point because it have muscular patterns are almost impossible to steal and replicate.

In addition, one of the main reasons that drives to use the PCANet model to extract features with RBF classifier, is able to process the nonlinearly separable data. From [1], the SVM is applied to the linearly separable data. But in our case, we want to implement

RBF kernel classifier for nonlinear classification, which it means more generalization.

III.4 Deep Learning Feature

PCANet technique is one of simple deep learning techniques, this technique provides a reliable solution to extract the majority of information in image which can be used in a greater range of pattern recognition systems to discriminate the images. The PCANet model [52] cascades many filter bank convolutions with an intermediate mean normalization step, followed by two other steps which are the binary hashing and the histogram composition step. PCANet algorithm can execute multiple stages of PCA filters [1] to extract higher level feature vectors. The example of PCANet model is illustrated in Figure III.3.

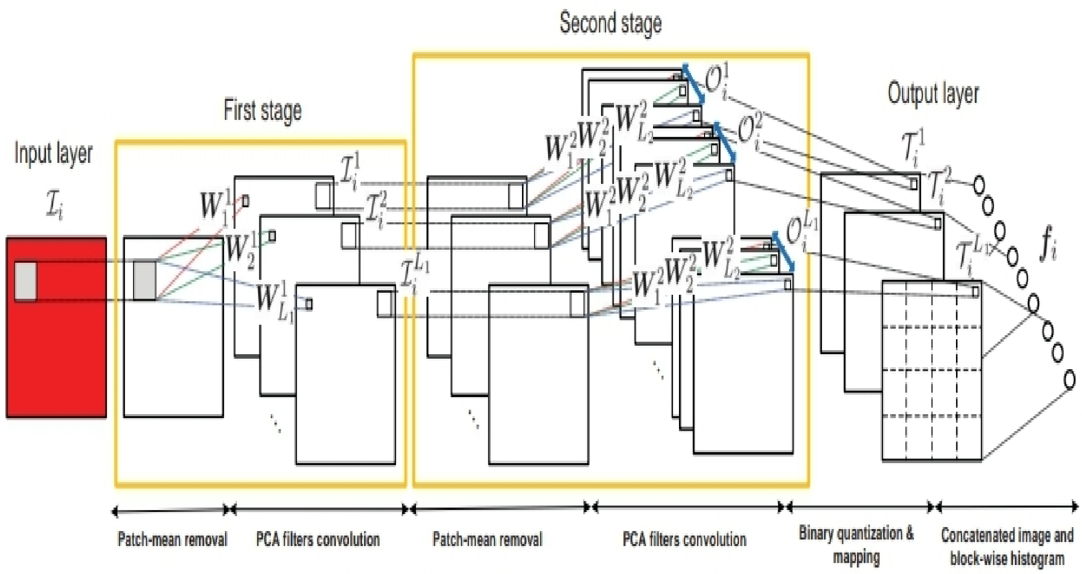


Figure III.3: The detailed block diagram of the PCANet (example of 2-stage) [1].

- In the first stage, the filter banks are estimated by performing principal components (PCA) technique over a set of vectors where each vector represents the $k_1 \times k_1$ points around each pixel. Before performing this technique, the mean of each vector must be subtracted from it (normalization process) [8].

- After applying PCA over the normalized vectors, a $k_1 \cdot k_1 \times L_1$ retained, where L_1 is the primary eigen vectors. Next, each principal component $(1 \ldots L_1)$ is a filter and may be converted to $k_1 \times k_1$ kernel which is convolved with the input image. So, using $L1$ vectors (L_1 convolution filter), we can convert the input image I into L_1 output filtered images [8]

$$I_{F_i}^{S_1}(x;y) = \left(I * F_i^{S_1}\right)(x;y); \tag{III.1}$$

Where $I_{F_i}^{S_1}$ $(i \in [1...L_1])$ denote the i^{th} filtered image using the $F_i^{S_1}$ filter for the first stage and $*$ denotes the discrete convolution.

- In the second stage, the same algorithm used in the first stage is iterated over each of the L_1 output filtered images (I_F^i) [8]

$$I_{F_{ij}}^{S_2}(x;y) = \left(I_{F_i}^{i} * F_j^{S_2}\right)(x;y); \tag{III.2}$$

Where $I_{F_{ij}}^{S_2}$ $(i \in [1...L_1]\, and\, j \in [1...L_2])$ denote the j^{th} filtered image using the F_j^{S2} filter (with size of $k_2 \times k_2$) for the second stage.

If the number of filters in second stage equal to L2, the output of the last convolution layer produce $L_1 \cdot L_2$ output filtered images.

Subsequently, the finally outputs ($I_{F_{ij}}^{s2}$) are converted into binary format by using a heaviside step function [53] which their value is one for positive entries and zero otherwise, this step called binary hashing step.

$$I_{i,j}^{B} = \begin{cases} 1 & if \quad I_{F_{ij}}^{S_2}(x,y) \geqslant 0, \\ 0 & Otherwise, \end{cases} \tag{III.3}$$

where I_{ij}^{B} is a binary image. After that, around each pixel, the vector of L2 binary bits is viewed as a decimal number

$$I_i^D(x,y) = \sum_{j=1}^{L_2} 2^{j-1} I_{ij}^B(x,y), \tag{III.4}$$

where I_i^D is an image whose every pixel is an integer in the range $[0; 2^{L_2-1}]$.

Finally, the histograms of the obtained images are computed and then concatenated to form a feature vector which represents the input image, this step called histogram composition. Thus, the feature vector of the input image I is then defined as [8]:

$$v_i = [v1; v2; ...vL_1] \tag{III.5}$$

where v_i denotes the histogram of the I_i^D image.

Lastly, it is important to note that in the PCANet technique it must choose the optimal values of the PCANet parameters which are the number of stages (N), the filters sizes in each stage ($k_1; k_2; ...k_N$) and the number of filters in each stage ($L_1; L_2; ...L_N$) [8].

III.5 Feature Classification and Matching

In machine learning and pattern recognition, a feature is an individual measurable property or characteristic of a phenomenon. A numeric feature can be conveniently described by a feature vector. Choosing informative, discriminating and independent features is a crucial element of effective algorithms in pattern recognition, classification, and regression [54]. Among the algorithms, Support Vector Machine (SVM) is a powerful and flexible supervised machine learning algorithm used for classification and regression [55]. Recently, SVM has become very popular due to its ability to handle many continuous and categorical variables. The linear support vector machine is an efficient algorithm for classification and regression in linearly structured data [56]. The main objective of SVM is to divide datasets into classes to find the maximum marginal. The SVM model consists of basic concepts [57], as we can see in Fig. III.4:

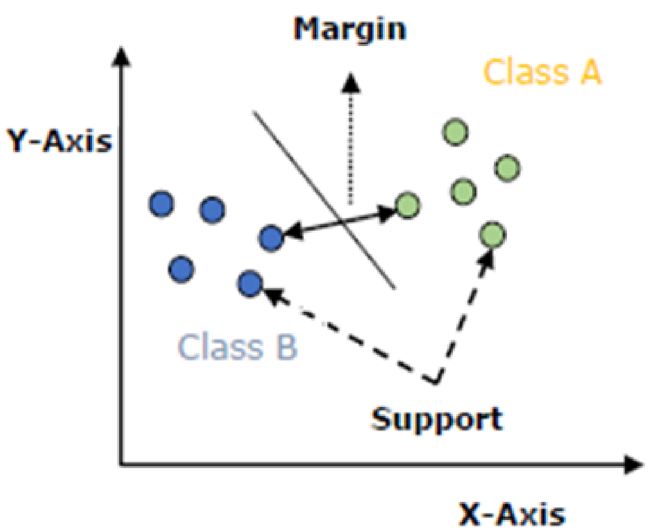


Figure III.4: A linear Support Vector Machine (SVM) algorithms.

- Support Vectors: The data points closest to the hyperplane are called support vectors.
- Hyperplane: A decision plane or space divided between a set of objects of different categories.
- Margin: It's the gap between two lines. It can be calculated as the perpendicular distance from the line to the support vectors. A large margin is a good margin.

The work on a SVM for non-linear datasets can't seem to class the right features. But can use the kernel trick is a typical and an easy way to extend the linear model to nonlinear model [58, 59]. SVM classifier becomes more robust for its kernel trick i.e. projecting the nonlinearly separable feature vectors into high dimensional feature space and making it linear and fitting an optimum hyperplane. reprojection of the hyperplane from a higher dimension back to the original feature space makes it curvy appearance rather than linear. The most important kernel functions is Radial Basis Function (RBF). RBF classifier is now widely used in many applications because of its robustness, efficiency, high sensitivity, specificity for non-linearly separable data [60]. For example, if we want to classify red and green dots it's impossible because it's non-linear form. The data is scattered and it's impossible to separate this data. As Fig. III.5, Kernel Trick uses the original feature space to separate this data.

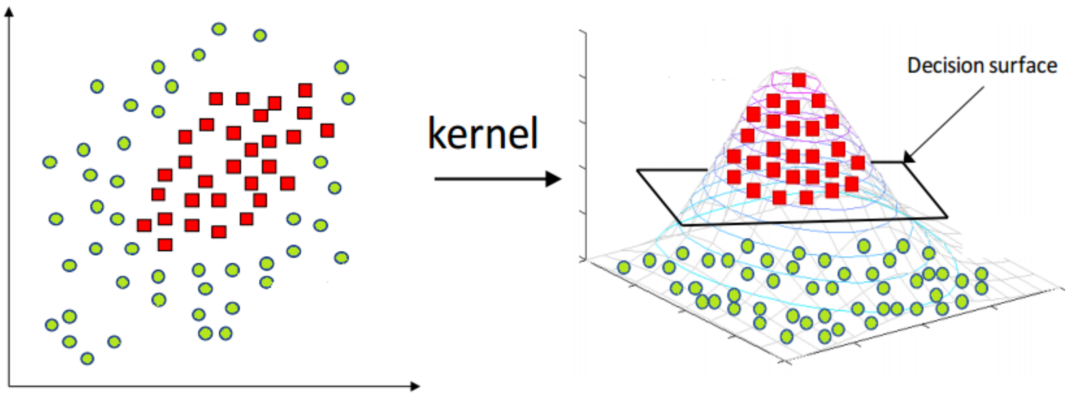


Figure III.5: A non-linear SVM based on Radial Basis Function (RBF) Kernel.

III.5.1 RBF Algorithm

A Radial Basis Function (RBF) is a real-valued function whose value depends only on the distance between the input and some fixed point. RBF Kernel algorithm is one of the more simple techniques used in machine learning. The RBF kernel, often used in classifying support vector machines, maps the input space to an indeterminate dimensional space. The main idea to use the RBF kernel is: A linear classifier or regression curve in higher dimensions becomes a Non-linear classifier or regression curve in lower dimensions. Radial Basis Function is given by [55]:

$$K\left(x,x^{'}\right) = e^{\left(-\frac{\left\|x-x^{'}\right\|^{2}}{2\sigma^{2}}\right)} \tag{III.6}$$

With x and $x^{'}$ are training and support vectors respectively.

A Gaussian RBF monotonically decreases with distance from the centre. In contrast, a multi-quadric RBF which, in the case of scalar input, is

$$h(x) = \frac{\sqrt{r^2 + (x-c)^2}}{r} \tag{III.7}$$

Monotonically increases with distance from the centre (see Fig. III.6) Gaussian-like RBFs are local (give a significant response only in a neighborhood near the centre) and are more commonly used than multi-quadric type RBFs which have a global response.

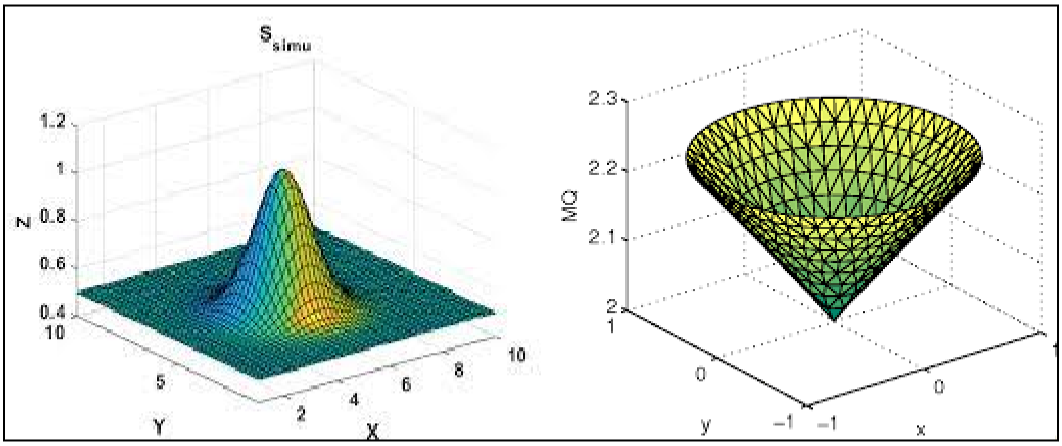


Figure III.6: Gaussian and multi-quadric RBF.

III.5.2 RBF networks

In principle, they could be employed in any sort of linear or nonlinear model, and any sort of network. However, RBF networks have generally been associated with radial functions in a single-layer network [61] such as shown in Fig III.7. An RBF network is nonlinear if the basis functions can move or change size or if there is more than one hidden layer. Some focus on single-layer networks with functions which are fixed in position and size. They use a nonlinear optimization but only for the regularization parameters and the optimal subset of basis functions [62]. That are employed in explicitly nonlinear networks.

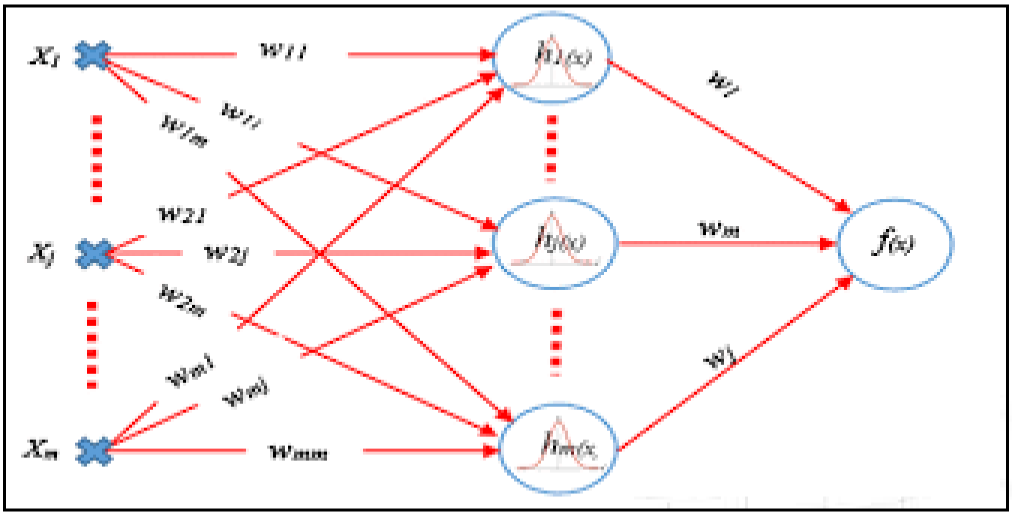


Figure III.7: The radial basis function network model.

III.6 Biometrics Fusion

According to [63], "Information fusion can be defined as an information process that associates, correlates and combines data and information from single or multiple sensors or sources to achieve refined estimates of parameters, characteristics, events and behaviors". In order to create multimodal system, we are proposed two types of fusion: Image level fusion and Match score level fusion.

III.6.1 Image level fusion

Image fusion is the process of integrating two or more pictures into a single image while maintaining the key characteristics of each original image. In this level, the trick used is Discrete Wavelet Transform (DWT) algorithm [64], which is a good example of image level fusion. We use the DWT transform to frequency discipline and analyze the signal of input image. The picture being processed is then broken down into different scales. Except for low–high, high–low, and high–high, there are many bands, namely low–high, high–low, and high–high. Low-low band that is sloppy and unevenly laid out. The wavelet changes can be used to characterize it in the denotation. X of the two enumerated input images $I1(x,y)$ and $I2(x,y)$ applying fusion operation u, at that point inverse wavelet change $x-1$ is figured out. Lastly, reconstructed image is output as $I(x,y)$. Fig. III.8 shows the DWT decomposition processes.

$$I(x,y) = x-1(u(x(I1(x,y)),x(I2(x,y)))) \tag{III.8}$$

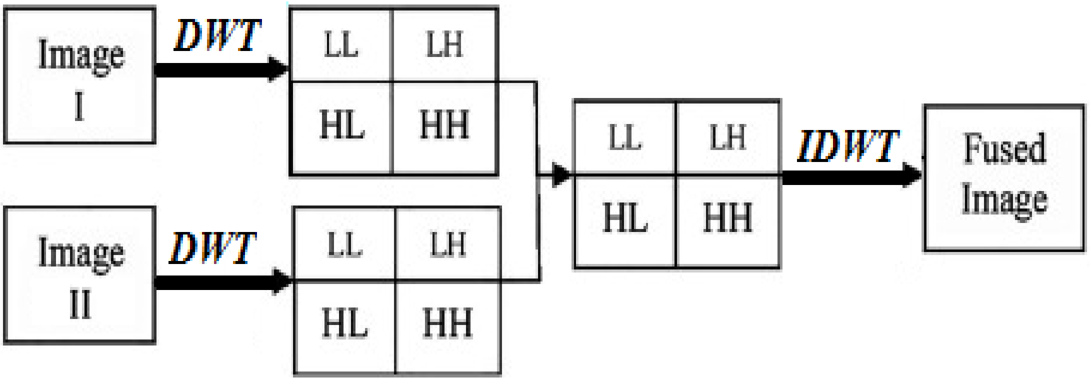


Figure III.8: DWT decomposition process.

III.6.2 Match score level fusion

Fusion at the matching score level appears to be the most useful fusion level because it's good performance and simplicity [65]. Score fusion is commonly used in multi-biometric systems which is sufficient to distinguish between a genuine and imposter scores. Firstly scores are obtained from a person, that scores can be either similarity scores or distance scores, it needs to convert these scores in a similar manner for making the final decision.

In our work, four different fusion schemes are experimented which are Sum-score, Min-score, Max-score and Weighted-score rules [66].

- **Sum-score (SUM):**

$$f_s = \sum_{i=1}^{k} \widetilde{d_\iota} \tag{III.9}$$

- **Min-score (MIN):**

$$f_s = min\left(\widetilde{d_1}, \widetilde{d_2}, ..., \widetilde{d_k}\right) \tag{III.10}$$

- **Max-score (MAX):**

$$f_s = max\left(\widetilde{d_1}, \widetilde{d_2}, ..., \widetilde{d_k}\right) \tag{III.11}$$

- **Sum-weighting -score (WHT):**

$$f_s = \sum_{i=1}^{k} w_i \widetilde{d_\iota} \tag{III.12}$$

where w_i denote the weight of each biometric subsystems.

III.7 Conclusion

In this chapter, the proposed system based identification is having several advantages, which is rich in texture features, easily accessible and stable features. The interest of biometric systems has lead to big advances in the field of security-enhancing technologies for biometric-based applications while it's safe to say that some of the sectors discussed above have benefitted from the use of iris recognition for quite a few years now. The deep learning is a relatively recent adopter of biometric applications but it's an area of rapid growth structure would have the potential to learn a redundant set of invariant features. In this work, it has been proposed and implemented a deep network with more hidden layers would best classification model that combines statistical features with PCANet based features.

An attempt has also been made to study the effect of RBF kernel function on system performance. Moreover, it can get the identification rate by directly extracting and matching feature from iris images. The proposed method has been successfully implemented for authentication system based on deep learning descriptors and evaluated its performance by using the universal iris database. This eligibility can be tested further after reviewing the results presented in the next chapter.

Chapter IV

EXPERIMENTATIONS AND RESULTS

IV.1 Introduction

In biometric authentication, a human being needs to be identified based on some physiological characteristic or behavioral characteristic such as face, fingerprints, handwriting and speech. As known theoretically, iris provide very robust performance and most accurate of recognition rates. But in order to test this technology requires a coherent structure and the appropriate conditions. In this chapter, we evaluate our iris recognition based on the MMU iris database to experiments and analyze the different results.In Biometric authentication, a human being needs to be identified based on some physiological characteristic or behavioral characteristic such as face, fingerprints, handwriting and speech. As known theoretically, iris provide very robust performance and most accurate of recognition rates. But in order to test this technology requires a coherent structure and the appropriate conditions. In this chapter, we evaluate our iris recognition based on the MMU iris database to experiments and analyze the different results.

It is noteworthy that:

1. The hardware that we used to conduct this experiment was very limiting. The specification is listed in the following:

   - Computer : HP probook 450 g5.
   - CPU : Intel(R) Core(TM) i3-7100U CPU @ 2.40GHz 2.40 GHz.

- Operating system 64 bits, processor x64.
- RAM: 4, 00 Go DDR3.

2. The software environment used to conduct this experiment is as follows:

- Math Works Matlab 2016a.
- Windows 10 operating system 64bit.

IV.2 Database

The proposed biometric system uses a personal authentication based on MMU iris database from Multi-Media University [67]. In the system-design, 3 images from 5 images of each person are randomly selected to use in the enrollment phase, to create the system database. The remaining 2 images are used to evaluate the system performance. Thus, a total of 4050 comparisons (database size equal to 45) were made. The genuine experiments were performed by comparing the 2 test images with the corresponding class in the database in which 90 genuine scores were made. Similarly, 2 images with each class, for impostor experiments, were compared with all references in database which give 3960 impostor experiments. The objective is to choose the best configuration of PCANet for iris recognition.

In our work to be accomplished, we select database of 45 person, and each person has 5 images of the right iris and 5 images of the left iris. The first 3 images for training the PCANet model, and the remaining 2 images for testing, and this is how to create an iris-based recognition system.

IV.3 Performance Evaluation

IV.3.1 Error Rates

For each type of decision, there are two possible outcomes, true or false. Therefore, there are a total of four possible outcomes: a genuine is accepted (True Acceptance (TA)) or a False Rejection (FR) occurred, and an impostor is rejected (True Rejection (TR)) or a False Acceptation (FA) occurred [68]. In evaluating the performance for any biometric based recognition system, there are mainly two types of factors: False Acceptance

Rate (FAR) and False Rejection Rate (FRR). A verification threshold, T_0 is needed in the overlap region as a reference to do the classification.

IV.3.1.1 False Accept Rate (FAR)

FAR is defined as the probability of an impostor being accepted as a genuine individual [68]. That is, in a biometric authentication system, the FAR is computed as the rate of number of people is falsely accepted FA over the total number of the impostor (NI) for a predefined threshold T_0. This is denoted

$$FAR = \frac{FA(T_0)}{NI} \times 100\%.$$

IV.3.1.2 False Rejection Rate (FRR)

FRR is defined as the probability of a genuine individual being rejected as an impostor [68]. That is, in a biometric authentication system, the FRR is computed as the rate of number of people is falsely rejected FR over the total number of total genuine user (NG) for a predefined threshold T_0. The formula for the FRR is denoted

$$FRR = \frac{FR(T_0)}{NG} \times 100\%.$$

IV.3.1.3 Genuine Accept Rate (GAR)

GAR is used to measure the accuracy of a biometric system [68]. It is measured as the rate of number of people is genuinely accepted over the total number of enrolled people for a predefined threshold. In other words, GAR can be obtained by subtracting the number of falsely rejected people from the total number of genuine people. The GAR is denoted

$$GAR = 1 - FRR(\%).$$

IV.3.1.4 Equal Error Rate (EER)

EER is a point defines the trade-off between the false rejects and the false acceptances, based on FAR and FRR. Thus, EER is a common way of evaluating the performance of a biometric system where low value of EER is considered to represent a biometric system with highly accurate performance. In general, the EER is the value on $FFR = FAR$.

IV.3.2 Performance Curves

Receiver Operating Characteristic (ROC): one of the standard method for expressing the technical performance of a biometric system in a specific application(generally in verification and open-set tasks) is the Receiver Operating Characteristic (ROC) curve. The ROC curve is A graphical representation giving a relationship between FAR and FRR (alternatively GAR against FAR) [69].

Cumulative Match Characteristic curve (CMC): a CMC curve is a graphical representation used to evaluate the performance of a biometric identification system under closed-set mode. A CMC curve plot the identification rate against the rank [69].

IV.4 PCANet Parameters Selection

The performance of PCANet algorithm depends on the best parameters of deep learning network. PCANet has generic parameters, such as: number of layers, number of filters and blocks size, etc. To select PCANet algorithm parameters, we need to conduct a set of tests that offer the necessary parameters for better performance.

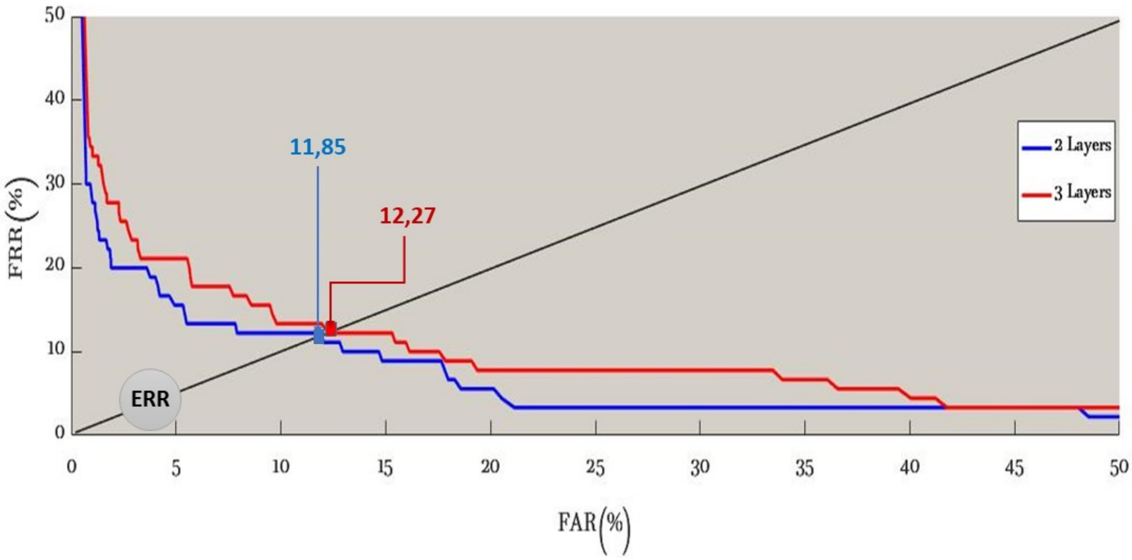
IV.4.1 Selection of Layers Number

Firstly, to select the number of layers in our deep method, this subsection describes a results of the proposed layers number parameter. When, we using a different Layers as 2 Layers, 3 Layers and 4 Layers, from left eye of each person. Thus, the test results are presented in table to select the best case for our iris recognition systems.

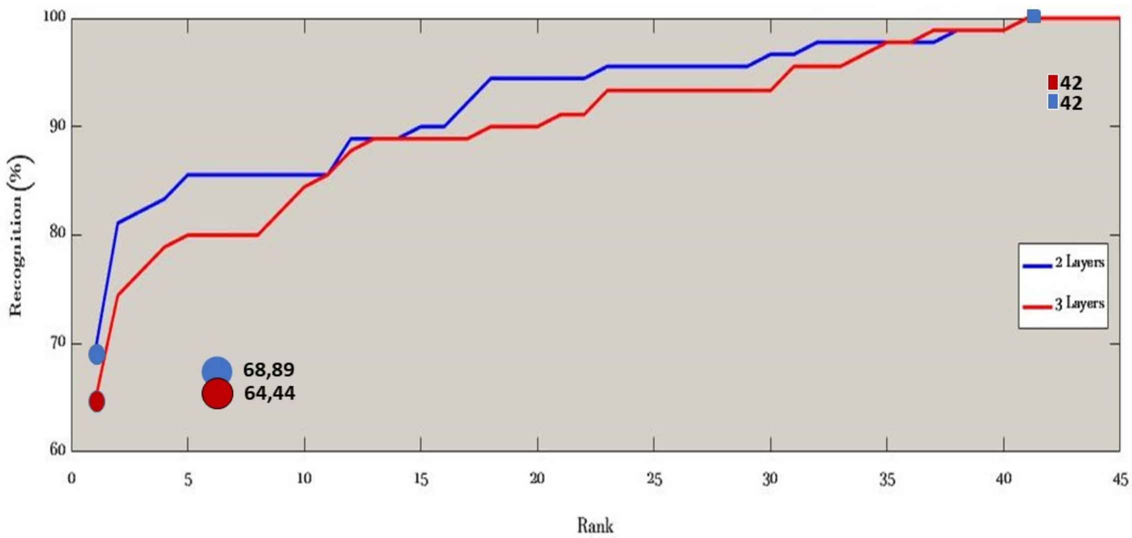
LAYERS NUM.	OPEN-SET IDENTIFICATION		CLOSED-SET IDENTIFICATION	
	EER	T_0	ROR	RPR
2 LAYERS	**11.79**	**0.603**	**68.89**	**41**
3 LAYERS	12.27	0.609	64.44	41
4 LAYERS	error (hardware)			

Table IV.1: Test results of PCANet for different layers number.

OPEN-SET: As seen in this table, PCANet with 2 layers can give lower error EER equal to 11.85% at a threshold $T_0 = 0.653$. Also from this table, we can observe that the 3 layers of PCANet gives EER =12.27% at a threshold T_0 = 0.609. In the case of using the 4 layers of PCANet, our system did not provide results because it requires more hardware features than our computer (note in section) such as: Processor, Memory and Graphics Card, etc. The ROC curves of cases of PCANet layers are shown in Fig. IV.1.(a), which plot the False Rejected Rate (FRR) against the False Accept Rate (FAR). The test results indicate that the case of 2 layers is very efficiency at the EER performances and better than the 3 layers.



(a)



(b)

Figure IV.1: Open/Closed-set identification test results of PCANet for different layers number. *(a)* The ROC curves (FRR against FAR), *(b)* The CMC curves.

CLOSED-SET: From looking at the table, we observe that the Rank One Recognition (ROR), equal to 64.44% with a Rank of Perfect Recognition (RPR) equal to 42 when we use the 3 layers of PCANet. The system can achieve accuracy in the 2 layers of PCANet compared with the other, because is produced ROR = 68.89% with a can produces same RPR equal to 42. To compare the performance of the different cases in closed-set identification mode, Fig. IV.1.(b) shows graphs of the Cumulative Match Characteristics (CMC) curves.

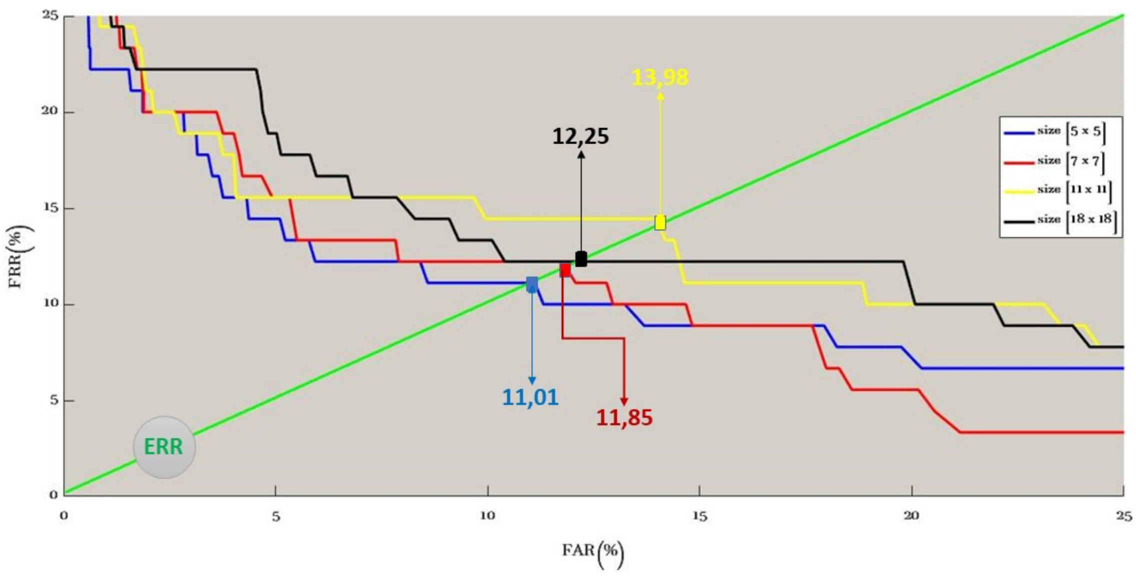
IV.4.2 Selection of Filters Size

For filters size, we use a different sizes as [5 × 5], [7 × 7], [11 × 11] and [18 × 18] in all layers. The Table. IV.2, present the all results of filters size performance at our recognition systems.

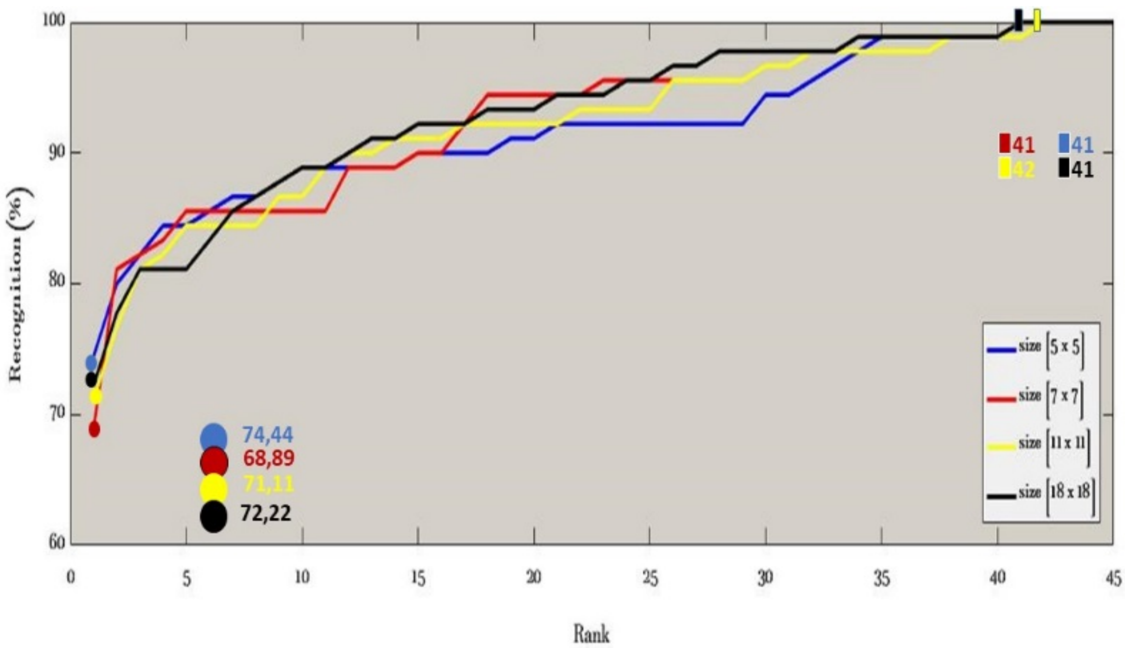
FILTERS SIZE	OPEN-SET IDENTIFICATION		CLOSED-SET IDENTIFICATION	
	EER	T_o	ROR	RPR
[5 × 5]	**11.01**	**0.675**	**74.44**	**41**
[7 × 7]	11.85	0.653	68.89	**41**
[11 × 11]	13.98	0.659	71.11	42
[18 × 18]	12.25	0.732	72.22	**41**

Table IV.2: Test results of PCANet for different filters size.

OPEN-SET: From looking at this table, it's clear that the size [5 x5] of PCANet filters give better results in terms of EER rate EER = 11.01% at threshold T_0 = 0.675. Also, we can see that the size [7 x 7] gives EER equal to 11.85% with threshold T_0 = 0.653, and the size [11 x 11] provides EER = 13.98% at threshold T_0 = 0.659, respectively. Lastly, in the case of using the size [18 × 18] , EER is 12.25% with T_0 = 0.732. So, the performance of open-set identification is weak compared with us aspirations in proposed system. The ROC curves of all cases are shown in Fig. IV.2.(a), which plot the FRR against the FAR. The test results indicate that the case of [5 × 5] is efficiency at the EER performances and better than the rest sizes.



(a)



(b)

Figure IV.2: Open/Closed-set identification test results of PCANet for different filters size. *(a)* The ROC curves (FRR against FAR), *(b)* The CMC curves.

CLOSED-SET: in this identification mode, we also see the system can achieve accuracy in the size [5 × 5] of PCANet filters compared with the other sizes. It has best value of ROR equal to 74.44% with a RPR equal to 41. The rest results are detailed in Table. IV.2. To summarize the closed-set identification experiments, graphs showing the Cumulative Match Characteristics (CMC) curves using all systems were generated in Fig. IV.2.(b).

IV.4.3 Selection of Filters Number

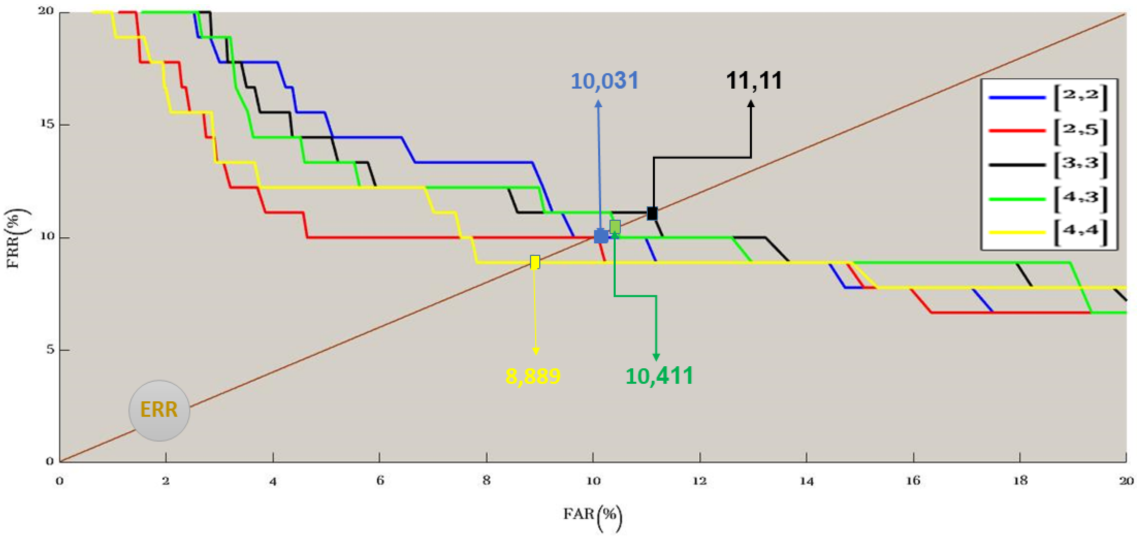
Thirdly, to select the number of filters in each layer, this subsection describes a results of the proposed filters number. When, we using a five different probability of numbers as [2, 2], [2, 5], [3, 3], [4, 3] and [4, 4] of each person. For that, the test results of the filters number are presented in Table. IV.3.

FILTERS NUM.	OPEN-SET IDENTIFICATION		CLOSED-SET IDENTIFICATION	
	EER	T_o	ROR	RPR
[2, 2]	10.031	0.735	71.11	41
[2, 5]	10.031	0.678	**78.89**	**38**
[3, 3]	11.110	0.678	74.44	41
[4, 3]	10.411	0.688	76.67	40
[4, 4]	**8.889**	**0.700**	**78.89**	**38**

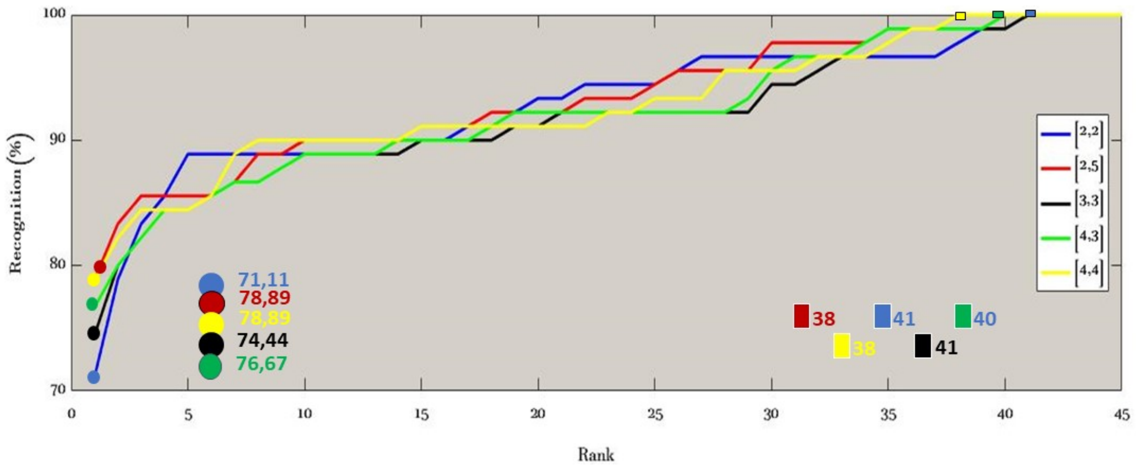
Table IV.3: Test results of PCANet for different filters number.

OPEN-SET: From the table, it's clear that the filters number [4, 4] of PCANet offer better results in terms of the EER. In this case, the open-set identification system can achieve a lower EER equal to 8.889% at a threshold T_0 equal to 0.700. Also in table, we note that the numbers [2, 2], and [2, 5] produces EER equal to = 10.031% at different thresholds T_0 = 0.735, and T_0 = 0.678 respectively. We can note again the number [3, 3] gives EER = 11.110% at a threshold T_0 = 0.678.

Finally, in the case of using the number [4, 3] presents EER = 10.411% with a threshold T_0 = 0.688. The ROC curves of all cases of filters number are shown in Fig. IV.3.(a), which plot the FRR against the FAR. The test results indicate that the case of [4, 4] is efficiency performances.



(a)



(b)

Figure IV.3: Open/Closed-set identification test results of PCANet for different filters number. *(a)* The ROC curves (FRR against FAR), *(b)* The CMC curves.

CLOSED-SET: At closed-set identification mode, we can see that the ROR is between 71.11% and 78.89% from this table who contains the results for all cases. The filters number [2, 2] gives the ROR = 71.11% and RPR = 41, followed by [4, 3] and [3, 3] which can produce a ROR equal to 76.67% with RPR = 40, and ROR 74.44% with RPR = 41, respectively. But, the filters number [4, 4] and the number [2, 5] of PCANet can achieve accuracy of recognition compared with the other, which is produced ROR equal to 78.89% with a RPR= 38. The closed-set identification experiments are showing in the Cumulative Match Characteristics (CMC) curves of Fig. IV.3.(b).

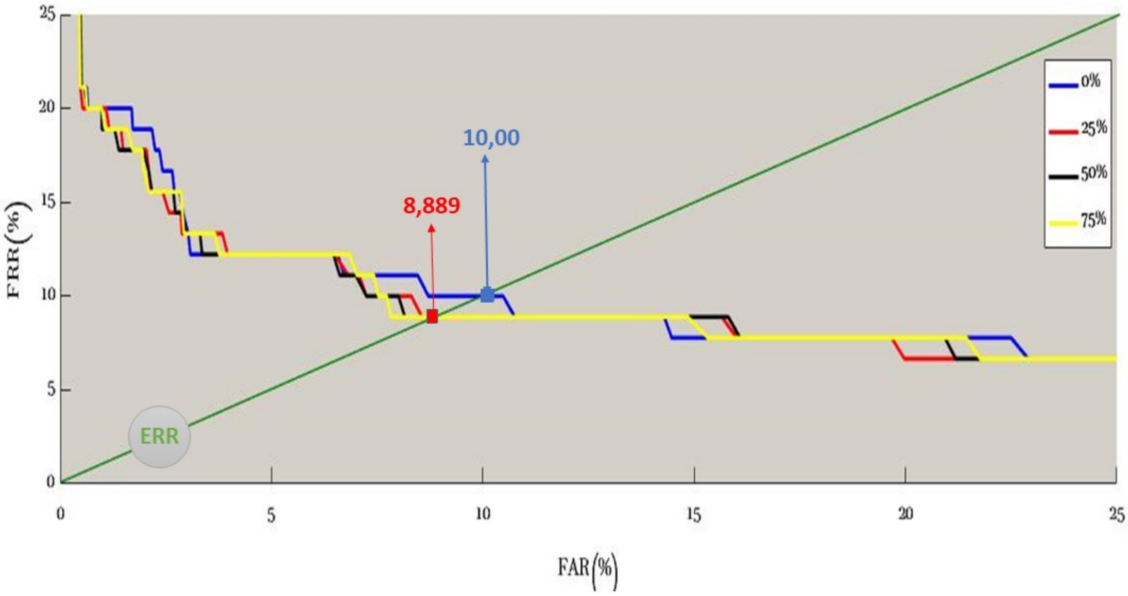
IV.4.4 Selection of Overlapped Rates

To choose the final parameter, this subsection describes a results of the cases of proposed overlapping rate. The results of open-set and closed-set identification are presented in Table. IV.4. For that, we using a four different probability of rates as 0% 25%, 50% and 75%.

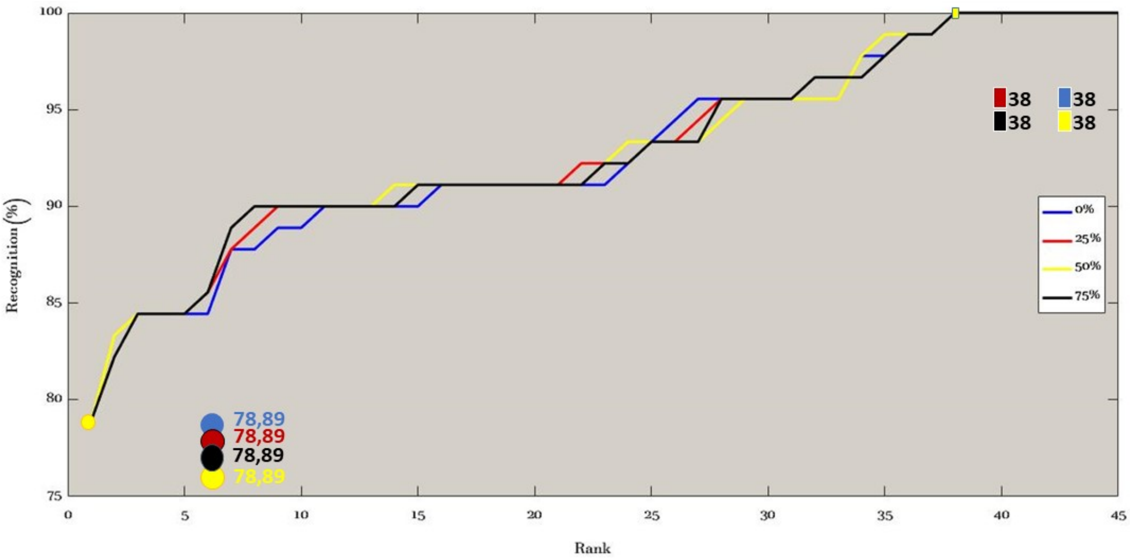
OVERLAPPED	OPEN-SET IDENTIFICATION		CLOSED-SET IDENTIFICATION	
RATES	EER	T_o	ROR	RPR
0	10.00	0.706	**78.89**	**38**
25%	**8.889**	**0.700**	**78.89**	**38**
50%	**8.889**	**0.700**	**78.89**	**38**
75%	**8.889**	**0.700**	**78.89**	**38**

Table IV.4: Test results of PCANet for different overlapped rates.

OPEN-SET: From this table, we see that the results of overlapping rate did not change in the open-set mode. For example, in the overlapping rate 25%, EER equal to 8.88% at a threshold T_0 equal to 0.700 that is the same in 50% and 75% cases, respectively. The ROC curves of all cases of filters number are shown in Fig. IV.4, which plot the FRR against the FAR.



(a)



(b)

Figure IV.4: Open/Closed-set identification test results of PCANet for different overlapped rates. *(a)* The ROC curves (FRR against FAR), *(b)* The CMC curves.

CLOSED-SET: From this table, it's clear that the results of overlapping rate also did not change in the closed-set identification mode. For example, the overlapping rates 0%, 25%, 50% and 75% provide the same ROR equal to 78.89% and the same RPR equal to 38. The Cumulative Match Characteristics (CMC) curves of Fig. IV.4.(b) is confirmed this results.

IV.5 Biometric System Evaluation

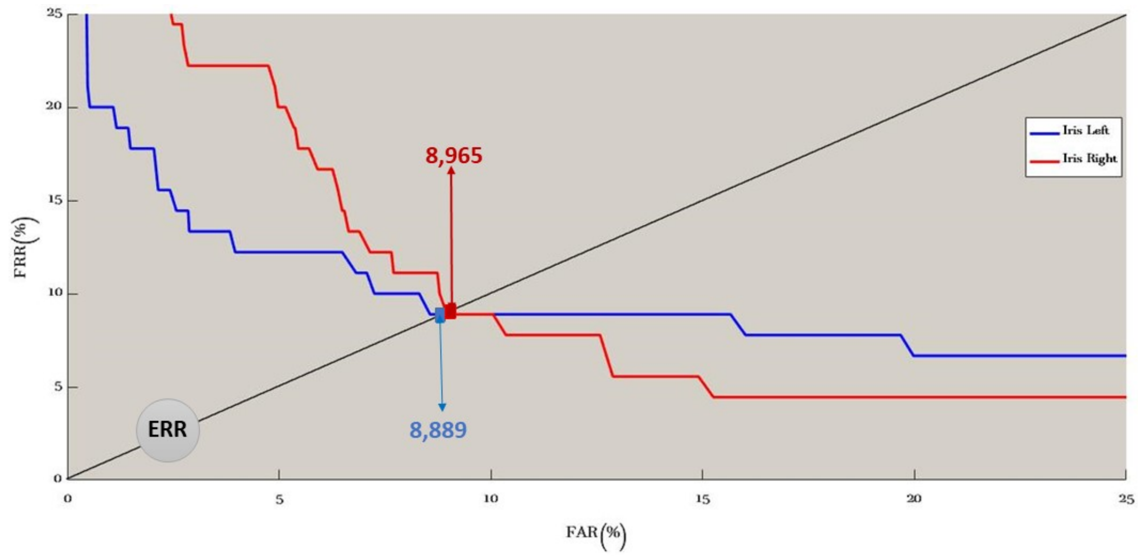
Depending on the preceding results, the PCANet algorithm can be set to the following parameters: the number of layers equal 2 layers, the filters number are [4, 4], 4 filters in each stage and the filters size is (5 x 5) with overlapped rate equal 50%. Therefore, we have decided to choose these parameters in the rest of test study.

IV.5.1 Unimodal Systems Test Results

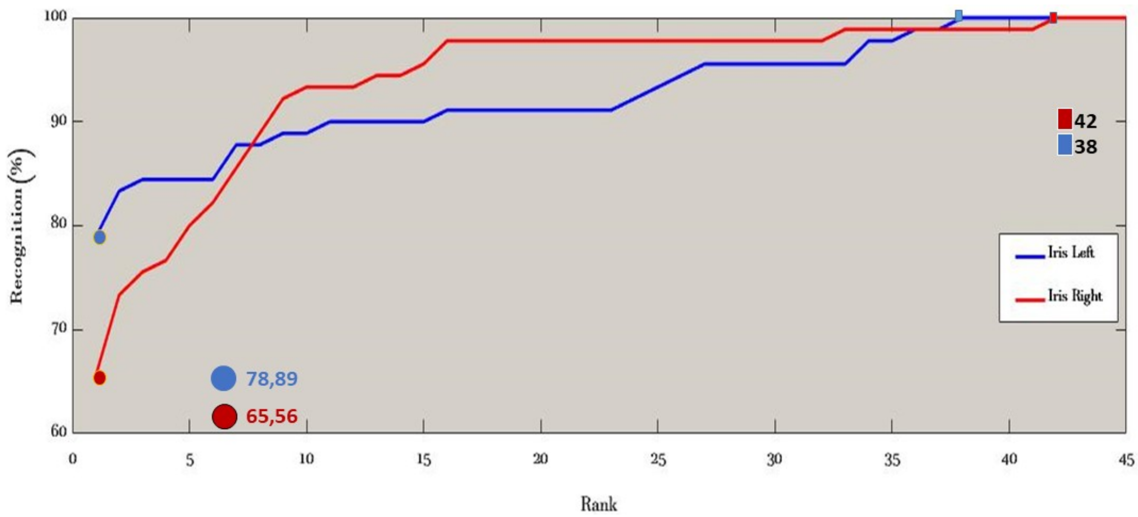
UNIMODAL	OPEN-SET IDENTIFICATION		CLOSED-SET IDENTIFICATION	
	EER	T_o	ROR	RPR
Iris left	**8.889**	**0.700**	**78.89**	**38**
Iris right	8.965	0.684	65.56	42

Table IV.5: Test results of PCANet for unimodal systems.

OPEN-SET: The table IV.5 presents the results of unimodal proposed systems based on PCANet algorithm. Where the left iris and the right iris were selected to experiment our system. In the open-set identification, we see that the left eye system achieves a better value for EER equal to 8.859% at a threshold T_0 = 0.708, than the right iris system provides EER equal to 8.965% at a threshold T_0 = 0. 684. However, the difference of two systems is negligible. The performance of proposed system for two samples are shown in the Fig. IV.5.(a), which plot the FRR against the FAR.



(a)



(b)

Figure IV.5: Open/Closed-set identification test results of PCANet for different unimodal systems. *(a)* The ROC curves (FRR against FAR), *(b)* The CMC curves.

CLOSED-SET: At closed-set identification test, the results are shown in the table IV.5 for different values of the two sub-systems. The right iris system provides the ROR value equal to 65.56% with RPR = 42. As, the system of left iris gives the best ROR equal to 78.89% and best RPR equal to 38. This means that the left iris system gives better results than the right iris system at open-set and closed-set identification tests. To summarize the closed-set identification experiments, the CMC curves in Fig. IV.5.(b) present the obtained identification rates.

IV.5.2 Multimodal Systems Test Results

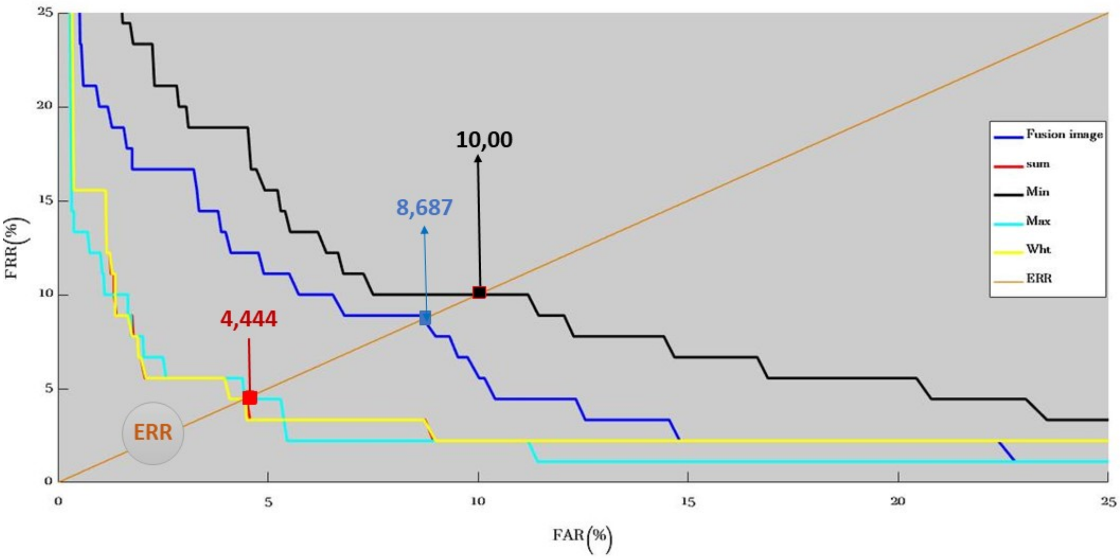
The unimodal biometric framework confronts numerous snags like dearth of distinctiveness, universality intra-class similarity. It can be improved with Multimodal Systems. The key to successful multi biometric systems is in development of an effective fusion scheme. In Multimodal Systems biometric information fusion can be accomplished at several different levels, including the sensor-level, feature-level, score-level, rank-level, or decision-level. Accordingly, to create our multimodal system, we choose two level of fusion like as Image and Matching Score Level Fusion.

In image level fusion, we used an efficient algorithm to fuse left and right images, with the help of DWT techniques. But in matching score level fusion, the idea is the combination of obtained scores from sub-system based on a simple rules Sum, Min, Max and Wht.

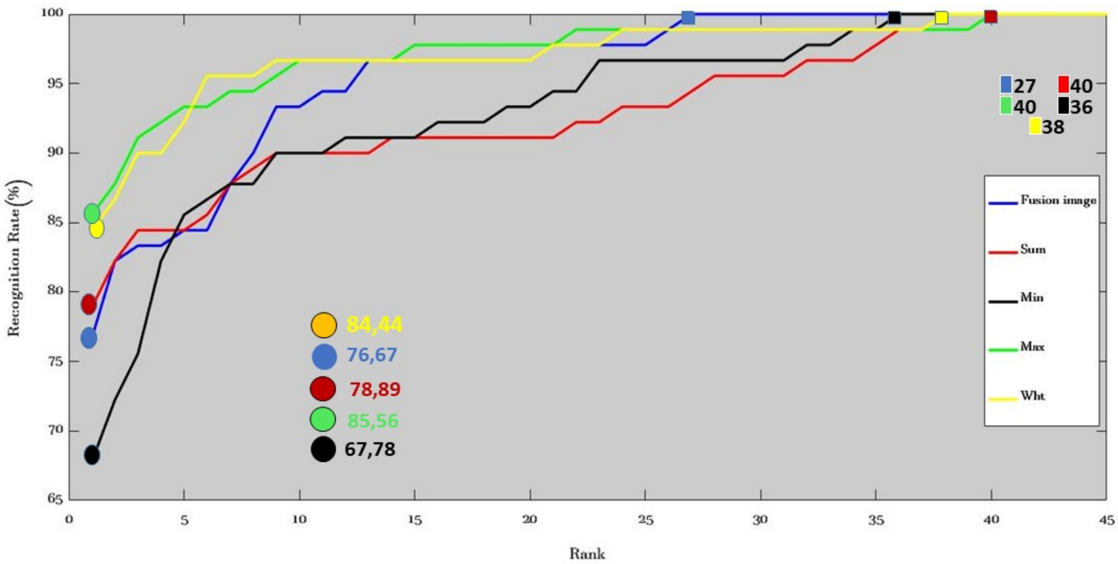
FUSION		OPEN-SET IDENTIFICATION		CLOSED-SET IDENTIFICATION	
		EER	T0	ROR	RPR
SENSOR-LEVEL	Image fusion	8.687	0.732	76.67	**27**
SCORE-LEVEL	**Sum**	**4.444**	**0.759**	78.98	40
	Min	10	0.724	67.78	**36**
	Max	**4.444**	**0.726**	**85.56**	40
	Wht	**4.444**	**0.762**	84.44	38

Table IV.6: Test results of PCANet for multimodal systems.

OPEN-SET: For the open-set identification mode, Table. IV.6 presents the test results of fusion. From this table, we can see that the fusion rules reduce the EER from 8.88% in unimodal to 4.44% in multimodal system. The case of image fusion achieves an EER equal to 8.687% with a threshold T_0 = 0.732. But in the Min case, EER equal only to 10% at a threshold T_0 = 0.724. As for the remaining three cases of fusion rules, Sum, Max and Wht, we see that the superiority is clear and it gives same result of the EER value (EER = 4.44%). The ROC curves in Fig. IV.6.(a) presents a direct comparison of the obtained performances by using the fusion.



(a)



(b)

Figure IV.6: Open/Closed-set identification test results of PCANet for different multimodal systems. *(a)* The ROC curves (FRR against FAR), *(b)* The CMC curves.

CLOSED-SET: For the closed-set identification mode, Table. IV.6 also contains the results of different combinations of fusion in our multimodal systems. This table shows the results of image fusion and score fusion rules Sum, Min, Max and Wht. At Max case, the ROR is much higher than in other cases, where the value of ROR is equal to 85.56% and the RPR is equal to 40. As for Wht case, the ROR is 84.44% with RPR is equal to 38. For image fusion level, the value of ROR is equal to 76.67%, with the best value of RPR equal to 27. In the rest of cases, the Sum and Min rules provide ROR = 78.89% with

RPR = 40, and ROR = 67.78% with RPR = 36, respectively. Finally, in Fig. IV.6.(b) , the CMCs curves plot the closed-set identification error rates for all cases and demonstrate the efficient of the matching score level.

IV.6 Evaluation of our Deep Learning Method

The purpose of this study is present biometric identification based on iris recognition by using the performance of deep learning algorithms. The obtained results indicated that the recognition rates are modest like as: 91.12% and 95.56% for our unimodal and multimodal system, respectively. Because, the conditions of work have a detrimental impact on the performance of deep learning methods. Some of the reasons can be summarized in:

- Preprocessing of database images needs more processing to eliminate the noise data.
- The training process was not sufficient due to the limited data. With reason that a deep learning algorithms require big data.
- In hardware side, the used processor unit (CPU) was very weak, until it was not able to process a four layers of deep.

IV.7 Chapter Summary

This chapter presents a test and evaluation of one of the deep learning algorithms to identification system. At first, we selected the left iris of only 45 people to test the PCANet algorithm. And we tried to adapt a PCANet parameters for best recognition performance. From previous experiences, the good and improved parameters for our system were represented in two layers and filter number [4, 4], 4 four in each stage, also filter size [5 x 5] with an overlap ratio of 50%. After choosing the best PCANet algorithm parameters, we experiment the right iris, and there was no significant difference with the left eye.

In the end of this chapter, the performance of multimodal biometrics much improved over unimodal biometrics. This is because the data fusion, including sensor-level fusion and fusion at matching score level. Thus, we summarize that the fusion of data in multi-modal biometric systems improves performance and accuracy in identifying, much more than unimodal biometrics.

Chapter V

CONCLUSIONS AND FUTURE WORKS

THIS chapter is a conclusion that summarizes all previous chapters, discussing the obtained results, and suggesting futures development based on this thesis.

V.1 Thesis Summary

This thesis can be summarized as follows:

At the beginning of thesis, Chapter I presented a general introduction to security, contributions and applications of biometrics. Chapter I also presented an overview of the characteristics of physiological and behavioral biometrics. How the biometrics system works?

As for Chapter II, we talked generally about the machine learning, which is an application of artificial intelligence. The artificial neural networks has been clarified to solve common problems in the field of artificial intelligence, machine learning. The main objective of this chapter was to present deep learning models, which is an important part or class of machine learning algorithms, used in image processing and recognition.

The proposed recognition system have been illustrated in the Chapter III. This chapter is important because presented the reason of choose iris recognition as biometric identification based on one of the deep learning method, the PCANet algorithm. In addition, the RBF kernel feature classification has been discussed in this chapter. Then, we presented the data fusion.

In Chapter IV, the various experimentations have been presented and discussed from MMU Iris database. Thus, we chose the parameters of the PCANet algorithm, to generalize in the training of proposed systems. Lastly, the end of this chapter provides a comparative study between unimodal and multimodal identification performance.

V.2 Contribution of Thesis

This study demonstrates that the IRS's future is bright, and it motivates scholars to perform more research to address the difficulties and propose appropriate answers. By creating a lot of neural networks, with the development of deep learning methods, and the diversity of dataset.

To improve recognition systems, this thesis presented a study of how to identify the persons based on iris trait using one of the deep learning algorithms. Based on the experimental results, the influences of network architecture and dataset type on the biometric recognition are summarized.

V.3 Future Research

The increasingly development of deep learning contributed to its use in the field of recognition tasks. Ranging from detection and pre-processing to feature representation and classification solutions. Research focus primarily on the development of powerful GPUs and the creation of big databases. Despite these advancements, there is plenty of room to improvement by suggesting network architects able to balance accuracy needs with time and the high computational cost.

Bibliography

[1] T.-H. Chan, K. Jia, S. Gao, J. Lu, Z. Zeng, and Y. Ma, "Pcanet: A simple deep learning baseline for image classification?" *IEEE transactions on image processing*, vol. 24, no. 12, pp. 5017–5032, 2015.

[2] V. Bharadi and P. Mishra, "Multidimensional clustering based feature vector extraction for hyperspectral face recognition‖," *IJAIS, Feb*, 2012.

[3] A. K. Jain and U. Uludag, "Hiding biometric data," *IEEE transactions on pattern analysis and machine intelligence*, vol. 25, no. 11, pp. 1494–1498, 2003.

[4] Biometric Technology Application Manual Volume One: Biometric Basics Compiled And Published by: National Biometric Security Project 2008.

[5] J. L. Wayman in Biometrics-Now and Then: The Development of Biometrics Over the Last 40 Years. New York Times article: Technology; Recognizing the Real You Pollack. September 24, 1981.

[6] F. Belhadj, "Biometric system for identification and authentication," Theses, Ecole nationale Supérieure en Informatique Alger, Feb. 2017.

[7] S. Prabhakar, S. Pankanti, and A. K. Jain, "Biometric recognition: Security and privacy concerns," *IEEE security & privacy*, vol. 1, no. 2, pp. 33–42, 2003.

[8] R. Chlaoua, "Combination of multiple biometrics for recognition of persons," PhD Thesis, University of Kasdi Merbah Ouargla, 2019.

[9] M. Singh, R. Singh, and A. Ross, "A comprehensive overview of biometric fusion," *Information Fusion*, vol. 52, pp. 187–205, 2019.

[10] Biometrics tutorial (tutorials point). [Online]. Available: https://www.tutorialspoint.com/biometrics

[11] P. P. Roy, Y. Chherawala, and M. Cheriet, “Deep-belief-network based rescoring approach for handwritten word recognition,” in *2014 14th International Conference on Frontiers in Handwriting Recognition*. IEEE, 2014, pp. 506–511.

[12] G. Hinton, L. Deng, D. Yu, G. E. Dahl, A.-r. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. N. Sainath *et al.*, “Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups,” *IEEE Signal processing magazine*, vol. 29, no. 6, pp. 82–97, 2012.

[13] A. Conneau, H. Schwenk, L. Barrault, and Y. Lecun, “Very deep convolutional networks for text classification,” *arXiv preprint arXiv:1606.01781*, 2016.

[14] K. T. Butler, D. W. Davies, H. Cartwright, O. Isayev, and A. Walsh, “Machine learning for molecular and materials science,” *Nature*, vol. 559, no. 7715, pp. 547–555, 2018.

[15] T. Ching, D. S. Himmelstein, B. K. Beaulieu-Jones, A. A. Kalinin, B. T. Do, G. P. Way, E. Ferrero, P.-M. Agapow, M. Zietz, M. M. Hoffman *et al.*, “Opportunities and obstacles for deep learning in biology and medicine,” *Journal of The Royal Society Interface*, vol. 15, no. 141, p. 20170387, 2018.

[16] J. N. Kutz, “Deep learning in fluid dynamics,” *Journal of Fluid Mechanics*, vol. 814, pp. 1–4, 2017.

[17] T. M. Mitchell, *Machine Learning*. New York: McGraw-Hill, 1997.

[18] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, http://www.deeplearningbook.org.

[19] J. Gabriel, *Artificial Intelligence: Artificial Intelligence for Humans*. CreateSpace Independent Publishing Platform, 2016.

[20] J. Kelleher, B. Namee, and A. D’Arcy, *Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies*. MIT Press, 2015.

[21] T. Verwoerd and R. Hunt, “Intrusion detection techniques and approaches,” *Computer Communications*, vol. 25, no. 15, pp. 1356–1365, 2002.

[22] S. Haykin and N. Network, "A comprehensive foundation," *Neural networks*, vol. 2, no. 2004, p. 41, 2004.

[23] C. Stergiou and D. Siganos, "Neural networks," Tech. Rep.

[24] X. J. Zhu, "Semi-supervised learning literature survey," 2005.

[25] Reinforcement learning (wikipedia). [Online]. Available: https://en.wikipedia.org/wiki/Reinforcement_learning

[26] L. Deng and D. Yu, "Deep learning: methods and applications," *Foundations and trends in signal processing*, vol. 7, no. 3–4, pp. 197–387, 2014.

[27] Deep learning: an in-depth look into the ai-based tech (builtin). [Online]. Available: https://builtin.com/artificial-intelligence/deep-learning

[28] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural computation*, vol. 18, no. 7, pp. 1527–1554, 2006.

[29] M. W. Mak, *Machine learning for speaker recognition / Man-Wai Mak, Hong Kong Polytechnic University, Jen-Tzung Chien, National Chiao Tung University.* New York: Cambridge University Press, 2020.

[30] R. Salakhutdinov, A. Mnih, and G. Hinton, "Restricted boltzmann machines for collaborative filtering," in *Proceedings of the 24th international conference on Machine learning*, 2007, pp. 791–798.

[31] A. Mosavi, S. Ardabili, and A. Varkonyi-Koczy, *List of Deep Learning Models*, 01 2020, pp. 202–214.

[32] Q. Zhang, Y. Xiao, W. Dai, J. Suo, C. Wang, J. Shi, and H. Zheng, "Deep learning based classification of breast tumors with shear-wave elastography," *Ultrasonics*, vol. 72, pp. 150–157, 2016.

[33] D. Wulsin, J. Gupta, R. Mani, J. Blanco, and B. Litt, "Modeling electroencephalography waveforms with semi-supervised deep belief nets: fast classification and anomaly measurement," *Journal of neural engineering*, vol. 8, no. 3, p. 036015, 2011.

[34] J. Patterson and A. Gibson, *Deep learning: A practitioner's approach.* " O'Reilly Media, Inc.", 2017.

[35] S. Vieira, W. H. Pinaya, and A. Mechelli, "Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications," *Neuroscience & Biobehavioral Reviews*, vol. 74, pp. 58–75, 2017.

[36] A.-r. Mohamed, D. Yu, and L. Deng, "Investigation of full-sequence training of deep belief networks for speech recognition," in *eleventh annual conference of the international speech communication association.* Citeseer, 2010.

[37] C. Huang, W. Gong, W. Fu, and D. Feng, "A research of speech emotion recognition based on deep belief network and svm," *Mathematical Problems in Engineering*, vol. 2014, 2014.

[38] H. Lee, P. Pham, Y. Largman, and A. Ng, "Unsupervised feature learning for audio classification using convolutional deep belief networks," *Advances in neural information processing systems*, vol. 22, 2009.

[39] T. Liu, "A novel text classification approach based on deep belief network," in *International Conference on Neural Information Processing.* Springer, 2010, pp. 314–321.

[40] N. Japkowicz, S. J. Hanson, and M. A. Gluck, "Nonlinear autoassociation is not equivalent to pca," *Neural computation*, vol. 12, no. 3, pp. 531–545, 2000.

[41] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, P.-A. Manzagol, and L. Bottou, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion." *Journal of machine learning research*, vol. 11, no. 12, 2010.

[42] L. Sifre and S. Mallat, "Rotation, scaling and deformation invariant scattering for texture discrimination," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2013, pp. 1233–1240.

[43] I. Goodfellow, D. Warde-Farley, M. Mirza, A. Courville, and Y. Bengio, "Maxout networks," in *International conference on machine learning.* PMLR, 2013, pp. 1319–1327.

[44] K. Jarrett, K. Kavukcuoglu, M. Ranzato, and Y. LeCun, "What is the best multi-stage architecture for object recognition?" in *2009 IEEE 12th international conference on computer vision*. IEEE, 2009, pp. 2146–2153.

[45] M. Zeng, L. T. Nguyen, B. Yu, O. J. Mengshoel, J. Zhu, P. Wu, and J. Zhang, "Convolutional neural networks for human activity recognition using mobile sensors," in *6th international conference on mobile computing, applications and services*. IEEE, 2014, pp. 197–205.

[46] T.-h. Chan, K. Jia, S. Gao, J. Lu *et al.*, "Pcanet: A simple deep learning baseline for image classification?" arxiv preprint arxiv: 1404.3606," 2014.

[47] Y. Zhou, W. Wang, and X. Huang, "Fpga design for pcanet deep learning network," in *2015 IEEE 23rd Annual International Symposium on Field-Programmable Custom Computing Machines*. IEEE, 2015, pp. 232–232.

[48] J. Wu, S. Qiu, R. Zeng, Y. Kong, L. Senhadji, and H. Shu, "Multilinear principal component analysis network for tensor object classification," *IEEE Access*, vol. 5, pp. 3322–3331, 2017.

[49] Z. Huang, W. Xue, Q. Mao, and Y. Zhan, "Unsupervised domain adaptation for speech emotion recognition using pcanet," *Multimedia Tools and Applications*, vol. 76, no. 5, pp. 6785–6799, 2017.

[50] J. Daugman, "Collision avoidance on national and global scales: Understanding and using big biometric entropy," 2021.

[51] H. Rai and A. Yadav, "Iris recognition using combined support vector machine and hamming distance approach," *Expert systems with applications*, vol. 41, no. 2, pp. 588–593, 2014.

[52] A. Meraoumia, L. Laimeche, H. Bendjenna, and S. Chitroub, "Do we have to trust the deep learning methods for palmprints identification?" in *Proceedings of the Mediterranean Conference on Pattern Recognition and Artificial Intelligence*, 2016, pp. 85–91.

[53] A. Meraoumia, M. Korichi, H. Bendjenna, and S. Chitroub, "Multispectral palmprint identification method using rotation invariant variance measures," in *2016 International Conference on Information Technology for Organizations Development (IT4OD)*. IEEE, 2016, pp. 1–6.

[54] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Berlin, Heidelberg: Springer-Verlag, 2006.

[55] A. Géron, *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems*. " O'Reilly Media, Inc.", 2019.

[56] M. Ring and B. M. Eskofier, "An approximation of the gaussian rbf kernel for efficient classification with svms," *Pattern Recognition Letters*, vol. 84, pp. 107–113, 2016.

[57] Tutorials point. [Online]. Available: tutorialspoint.com/machine_learning_with_python/machine_learning_with_python_classification_algorithms_support_vector_machine.html

[58] M. Pagani and A. Malliani, "Interpreting oscillations of muscle sympathetic nerve activity and heart rate variability," *Journal of hypertension*, vol. 18, no. 12, pp. 1709–1719, 2000.

[59] M. Bonnet and D. Arand, "Heart rate variability: sleep stage, time of night, and arousal influences," *Electroencephalography and clinical neurophysiology*, vol. 102, no. 5, pp. 390–396, 1997.

[60] K. Soman, A. Sathiya, and N. Suganthi, "Classification of stress of automobile drivers using radial basis function kernel support vector machine," in *International Conference on Information Communication and Embedded Systems (ICICES2014)*. IEEE, 2014, pp. 1–5.

[61] D. S. Broomhead and D. Lowe, "Multivariate functional interpolation and adaptative networks," *Complex Systems*, vol. 2, pp. 321–355, 1988.

[62] A. Esposito, M. Marinaro, D. Oricchio, and S. Scarpetta, "Approximation of continuous and discontinuous mappings by a growing neural rbf-based algorithm," *Neural Networks*, vol. 13, no. 6, pp. 651–665, 2000.

[63] J. Kludas, E. Bruno, and S. Marchand-Maillet, "Information fusion in multimedia information retrieval," in *International Workshop on Adaptive Multimedia Retrieval*. Springer, 2007, pp. 147–159.

[64] X. Liu and T. Chen, "Geometry-assisted statistical modeling for face mosaicing," in *Proceedings 2003 International Conference on Image Processing (Cat. No. 03CH37429)*, vol. 2. IEEE, 2003, pp. II–883.

[65] M. V. Karki and S. S. Selvi, "Multimodal biometrics at feature level fusion using texture," *International Journal of Biometrics and Bioinformatics (IJBB)*, vol. 7, no. 1, p. 58, 2013.

[66] M. Sudhamani, M. Venkatesha, and K. Radhika, "Revisiting feature level and score level fusion techniques in multimodal biometrics system," in *2012 International Conference on Multimedia Computing and Systems*. IEEE, 2012, pp. 881–885.

[67] The mmu iris database. [Online]. Available: https://www.kaggle.com/datasets/naureenmohammad/mmu-iris-dataset

[68] A. Ross, K. Nandakumar, and A. K. Jain, *Handbook of multibiometrics*. Springer, 2006.

[69] M. Korichi, "Biometrics and information security for a secure person identi cation," PhD Thesis, University of Kasdi Merbah Ouargla, 2019.