جامعة محمد بوضياف - المسيلة
Université Mohamed Boudiaf - M'sila

جامعة محمد بوضياف - المسيلة
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Master's Thesis

To obtain the rank of

MASTER IN ELECTRONICS

Speciality :

ESEM

Presented and supported by

Bentahar Adel

Djouilem Aboubakar

Deep feature extraction and classification for finger vein images

Composition of the jury:

Name & First Name	Title & affiliate	Quality
Brik youcef	Associat Professor, University-Msila	President
Attalah Bilal	Associat Professor, University-Msila	Supervisor
Nadir chyema	PHD student, University-Msila	Thesis Co-Supervisor
Djerioui Mohamed	Associat Professor, University-Msila	Examiner

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To all the teachers of the electronic engineering department of M'sila.

Djouilem Aboubakr

Dedication

dedicate this modest work:

To my dear parents for their support throughout My life of studies and without

Which I would not have never become what i am now

To all the professors and teachers, I have had during All my school curriculum and

which allowed me to succeed in my studies.

To my family and all my friends to anyone who has contributed to this work

directly or from afar

Abstract

Cross-sectoral insecurity increased crime, and piracy is all major topics these days. Furthermore, people's movement, financial transactions, and access to services necessitate an urgent need to guarantee their identity. Traditional security solutions rely on previously learned information (PIN codes, passwords) or access tokens (keys, identifiers, badges). However, in many situations, these technologies are less reliable because they are unable to discern between legitimate persons and scammers. In this master's thesis, we chose a deep learning finger vein recognition system. This system is difficult to Falsification. There are numerous benefits, including ease of use and inexpensive cost. Our work can be divided into two stages. To start, data augmentation utilizing various geometrical techniques is used to compensate for the paucity of training samples required for the deep learning model's training. Second, the four CNN algorithms are used to execute feature extraction and classification tasks in order to validate the person's identity. The suggested model's performance is tested and evaluated using the SDUMLA dataset. With Vgg16 and 97.22 percent with Vgg19, 90 percent with the inception model, and 95 percent with MobilenetV2, our suggested technique for the SDUMLA database achieved an accuracy of 93 percent with Vgg16 and 97.22 percent with Vgg19, 90 percent with the inception model, and 95 percent with MobilenetV2. The proposed work achieves good performance when compared to existing methods, according to the findings of the experiments.

Keywords : Finger vein, recognition, classification, CNN, deep learning, data augmentation, feature extraction.

Table Lists

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Abreviations list

ID : identity document

ATM : automatic teller machine

FVR : Finger vein recognition

NIR : near infrared

CNN : convolutional neural network

ML : machine learning

DL : deep learning

AI : artificial intelligence

3D : three dimensions

2D : two-dimensional

ReLu : rectified linear unit

FC : fully connected

ILSVRC : ImageNet Large Scale Visual Recognition Challenge

VGG : Visual Geometry Group

4D : Four-Dimensional

PKU : Peking University

SDUMLA-HMT : Shandong University Machine Learning and Applications - Homologous Multi-modal Traits

HKPU : Hong Kong Polytechnic University

SVM : Support Vector Machine

MLP : multilayer perceptron

MCP : McCulloch-Pitts

SIFT : The scale-invariant feature transform

PCA : Principal Component Analysis

LDA : Linear Discriminate Analysis

LBPV : Local Binary Pattern Variance

LBP : Local Binary Patter

LLBP : line local binary pattern

LDC : linear discriminate classifier

LPQ-LDP : Local Phase Quantization-Local directional pattern

GWO-SVM : grey wolf optimization-Support Vector Machine

KNN : K-Nearest Neighbour

DNN : Deep Neural Network

FP : False Positive

TN : True Negative

FN : False Negative

TP : True Positives

BS : Batch Size

opt : optimizer

NE : Number of epoch

Lr : Learning rate

Summary

Introduction general

Today, with the development and deployment of Internet and networking technologies, modern society is increasingly interested in methods of verifying or identifying the identity of remote access users. Traditional security systems such as key locks or ID cards are also targeted for modernization, which can improve security in critical locations such as ATMs, banks, nuclear power plants, etc. These and other situations have prompted the development of more sophisticated systems based on biometric information, since it is impossible for a malicious person to copy this information.

These systems are often referred to as biometric systems. Pattern recognition systems can identify a person based on unique biometric characteristics. In theory, the ideal biometrics for identifying people should include : easy for individuals to extract, difficult to obtain, and difficult for others to replicate.Systems Biometric systems are widely used because the security of these systems has been proven. These systems have many advantages over other traditional identification systems.

Thèses biometric identification Methods fall into two categories , Extrinsic biometrics (palm prints, iris, fingerprints, face) and intrinsic biometrics (palm veins,hand and finger veins). finger vein enabled biometric technology due to its multiple benefits,such as non-contact implementation, effectiveness in living people, small equipment required, high safe, low cost.

In 2002, Japanese medical researcher Kono introduced the technique of detecting finger veins. Since then, these technologies have been widely used and implemented in hundreds of cities in Japan Other countries in the world have developed systems for the identification of finger veins. vein based Authentication system includes biometric templates for persons security and convenience. A typical framework for a Finger Vein Biometrics (FVR) system . Veins are part of an inherent feature and are therefore difficult to replicate and fake. Finger veins are typically illuminated with near-infrared (NIR) light (700–900 nm) Vein-based systems typically use various anatomical features such as finger veins, hand veins, foot veins, or hand veins for personnel verification. The finger vein is preferred because it is Imaging tools are the smallest, and fingers have more veins than palms and hands Furthermore, even among identical twins, the pattern of veins on each finger is unique and exists only in living people. Best of all, the vein pattern of each finger does not change for life. Finger vein detection is considered a challenging task due to low image contrast. Uneven lighting and temperature fluctuations. Finger vein detection systems are also vulnerable However, for spoofing attacks, the accuracy of personal verification is the most serious concern.Therefore, FVR still needs fast and efficient methods

We chose to articulate our study in three main chapters :

Chapter 01 :Biometrics Fundamentals In the first chapter, we have introduced the general concept of biometric systems , different methods and Fields of Application of Biometrics, overviews of unimodale and multimodale , and at the end of this chapter we will give an definition for deep and machin learning with an explanation to the Convolutional Neural Network

Chapter 02 : The proposed finger vein recognition system In this chapter we made a survey for deep and machine learning previous results with spotlight on deep learning feature extraction modalities and their architecture .

Chapter 03 : Results and discussions the third chapter presents the results of simulations, a description of the database used and followed by comparative study . And finally we end this work with a conclusion.

CHAPTER 1

BIOMETRICS FUNDAMENTALS

1 Introduction :

Its require people to be authenticated using two classic methods : the first is based on the a priori knowledge (password and activation code) and the second is based on the possession of an object (identity document, badge or key)[Chaari, 2009]. However, both of these methods have some drawbacks. Indeed, the password can be forgotten or spied on and the identity document risks being stolen or lost. In order to remedy the problems of the previous methods, biometrics seems to be a practical solution. [Toufik, 2016] In this part, we look at the definition of biometric, its applications, and the various types used in the world monomial and the multimodal, the difference between machine Learning and Deep Learning. with explanation of CNN that helps us in our theme,

2 Biometric Recognition Overview

Definition of biometric concept

Biometrics consists of the mathematical analysis of a person's biological characteristics and aims to determine their identity. Unlike what we know or possess, biometrics is based on who we are. And this avoids duplicates, theft, forgetting or loss. The characteristics used must be

Universality	common to all individuals
Uniqueness	to be able to differentiate between two individuals
Permanence	invariant over time for each individual
Collect ability	collects the characteristics of an individual with the agreement of this one
Performance	Security,speed,accuracy and robust.

TABLE 1.1 – *characteristics of biometrics[Sabhanayagam et al., 2018]*

3 Internal structure of a biometric system

The architecture of a biometric system is composed of five main modules. To have more details, we will explain the operation of each module as follows[Morizet, 2009]

Biometric sensor module

It is defined as an interaction interface between man and machine, it allows the reading or acquisition of certain biometric characteristics of an individual using a sensor (camera, microphone, reader fingerprint,etc.).

Data extraction module

Its principle is based on the evaluation of the biometric data acquired by the biometric sensor to extract the relevant information. To improve the quality of the acquired data, it must be passed through a restoration algorithm.

Signature creation module (storage)

Consists of creating a digital model to represent the acquired biometric data. This model will be saved on a database.

Comparison Module

It performs a comparison between the biometric characteristics extracted from an individual with the models stored in the database. This mod can work either in authentication mode to determine a claimed identity, or in mode identification to determine a sought identity.

Database module

It is the recording and storage of biometric models of enrolled persons

4 Operating modes of a biometric system

There are two types of biometric recognition systems : those based on verification and those based on identification. Verification, also called authentication, consists of confirming or denying a person's identity (am I who I claim to be ?) This is a one- to-one comparison ; the individual's characteristics are compared to those presentedin a reference record. As for identification, it makes it possible to establish the iden-tity of a person from a database, it is a one-to-many comparisons. Generally, biometric systems operate in three main modes : enrolment, authentication and identification[El-Abed, 2011]. We are present in the following the whole process for more details :

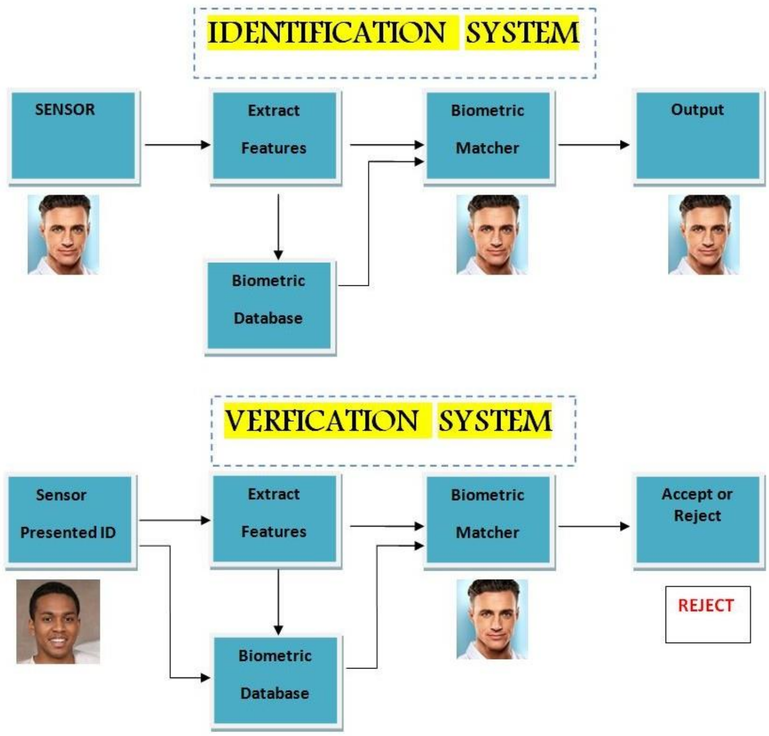

FIG 1.1 – *Block diagram of Identification and verification[Byrd et al., 2009]*

Enrollment

It is considered the first phase of any biometric system that serves to create a reference database. During this phase, the user is registered for the first time in the system by capturing a biometric

authentication

This is a step that verifies the authenticity of a person. Indeed, the system consists in checking the identity of an individual by making a comparison between the biometric data acquired with the own biometric model stored in the database, it is a " one against one " type comparison. A biometric system in verification mode must answer the question, "am I really me ?".This mode is used for the purpose of preventing the use of the same identity by several people.

Identification

It is a mode of recognition of individuals. The biometric system will compare the identity of an unknown person with the models of all the people registered in the database, so we are talking about a 1 : N match by answering the question"am I well known to the system ?" Typically, the person will be rejected if their identity does not match the identity models of the database, which means that the user was not among the people enrolled by the system. Otherwise, the person will be accepted.[Sabhanayagam et al., 2018].

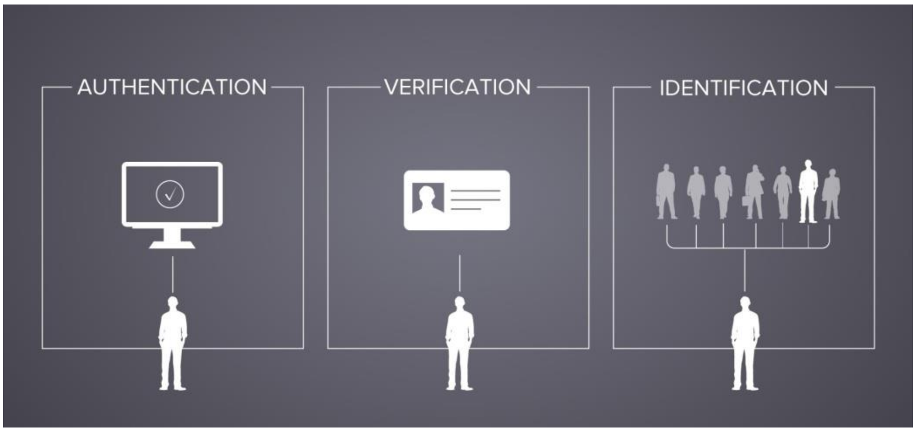

FIG 1.2 – *Authentication vs. Identification vs. Verification*

5 Fields of Application of Biometrics

Biometric techniques are presented in the fields of security where it is necessary to know the identity of the persons. Its applications can be divided into three main groups which are [Jain et al., 2007] :

Government Applications

Military (enemy/ally identification), passport control social security Border, migration control (traveller/migrant/passenger identification) driver's license, ID card, etc.

Commercial applications

consumer/customer identification ,control internet access, cell phones, use of bank credit cards, distance learning, management of medical records, etc.

Forensic applications

Such as criminal search(criminal/suspect identification), corpse identification, human body identification, etc.

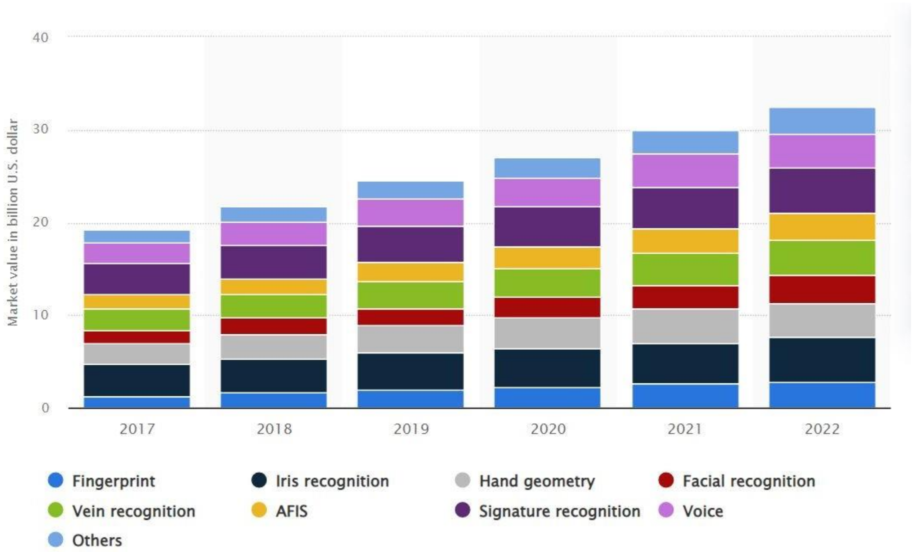

FIG 1.3 – *Global biometric system market revenue forecast from 2017 to 2022, by technology(in billion U.S. dollars)*

6 Unimodal and Multimodal Biometrics System

For recognition systems , biometric uses a one trait of the person is called as unimodal biometrics multimodal biometrics. The most well-known techniques include finger vein ,face , iris and other recognition systems multimodal biometrics combines several biometrics to increase security and accuracy of our system . It usually requires more than one biometric credentials for identification, such as combine finger vein and fingerprints, instead of one . They can overcome restrictions commonly experienced in unimodal systems. For many years , using several biometric features in combination, has considerably reduced error rates.

Unimodal Biometric System

The unimodal biometric systems have many advantages, it has to face a large number of problems like [Sanjekar and Patil, 2013] :

— Noisy data

— Interclass similarities

— Non-universality

— and Spoofing attacks

To solve this problem is to use a multimodal system which does not depend on one source of future extraction for the person [Sanjekar and Patil, 2013].

Multimodal Biometric System

The limitations unimodal biometrics has can be solved by including multiple source of information for creating the identity of the person[Ross and Jain, 2003]].

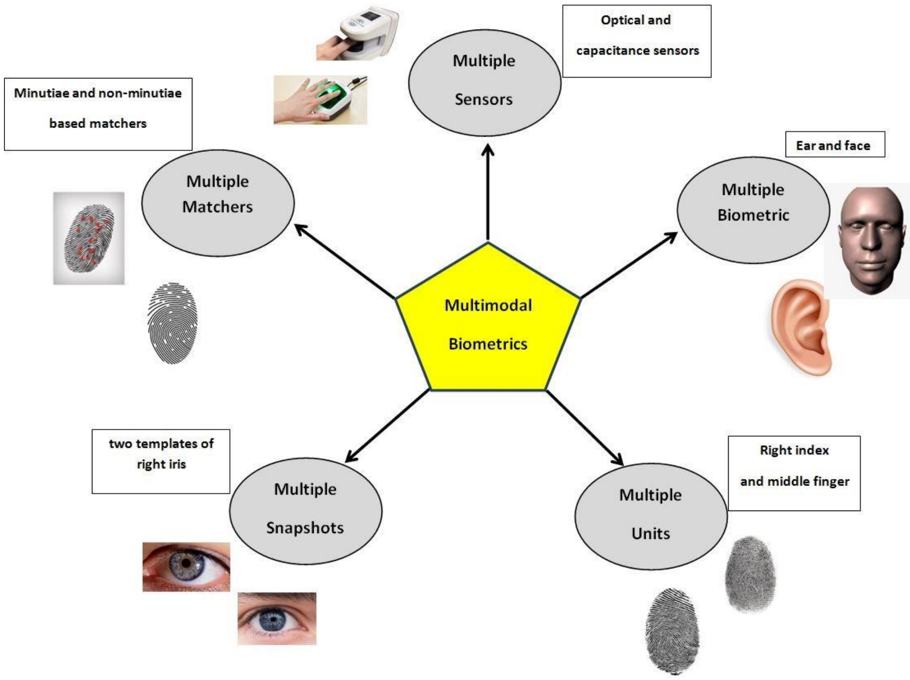

FIG 1.4 – *Multimodal Biometric Categories [Makinde et al., 2014]*

and this is some advantage and problems solved by multimodal [Kumar and Imran, 2010]] :

— improvement in the matching accuracy as compared to unimodal system.

— it can address the non-universality issue.

— less sensitive to imposter attacks.

— Insensitive to the noise on the sensed data.

— Help in continuous monitoring or tracking the person in cases when unimodal is not enough.

7 The different Biometric Modalities

Biometric techniques can be classified into two main categories, the first one is based on behaviour analysis methods. Concerns the study of repetitive and habitual actions of people. For example, the analysis of the human dynamics of the signature (speed of movement of the pen, accelerations, pressure exerted) or the way and speed of using a computer keyboard (typing speed, repetitive character sequences). On the other hand, the second category is based on the techniques of analysis of the human morphology. Use as means of analysis the fingerprints, the geometric shape of the hand, facial features, vain network, etc. These elements have the advantage of being stable during the life of the individual.

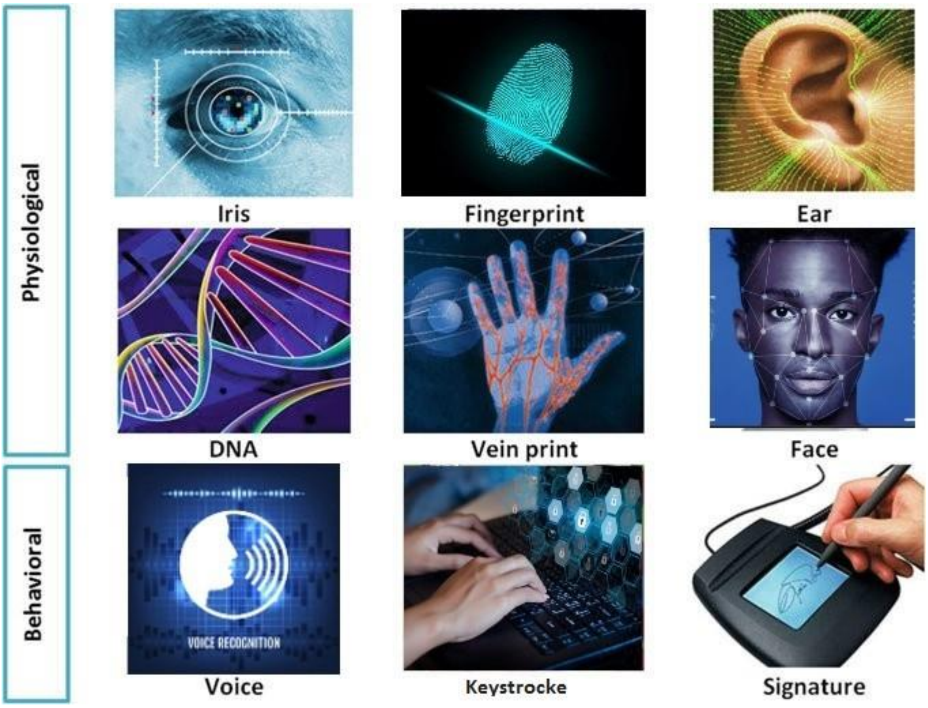

FIG 1.5 – *The different Biometric Modalities[Bouchrika, 2018]*

Physiological modalities

Finger Vein Recognition

Finger veins biometrics, also called vein matching or vascular technology, is a method for biometric authentication that precisely define and analyzes the patterns of blood vessels visible from the skin of fingers. This technique relies on capturing images of the veins inside oneâ€™s hand by using near-infrared light on their fingers.

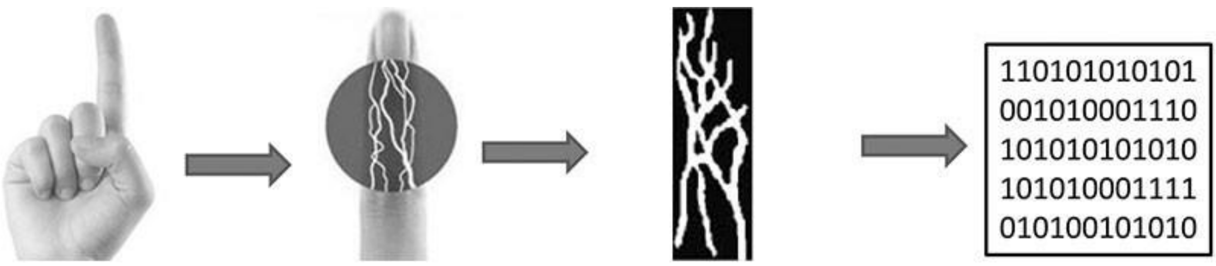

FIG 1.6 – *Finger Vein Recognition[Dargan and Kumar, 2020]*

Fingerprint recognition

The oldest identification technology. This technique requires the user to place a finger on a specific fingerprint sensor. Then, processing is performed on the image. This modality is resistant up to a certain threshold, it nevertheless presents some reliability problems. Indeed, the fingerprints of a manual worker make him resistant to any identification.

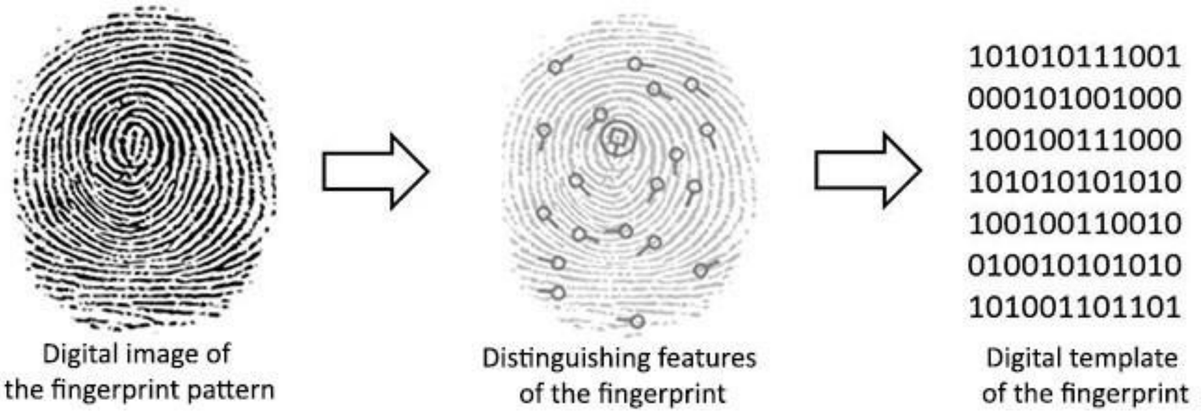

FIG 1.7 – *Fingerprint recognition [Dargan and Kumar, 2020]*

Face recognition

It is a technology that is rising. It is based on the main characteristics of the face, the distance between the eyes, the size of the mouth, etc., to build a map of the face[Gaur et al., 2012].

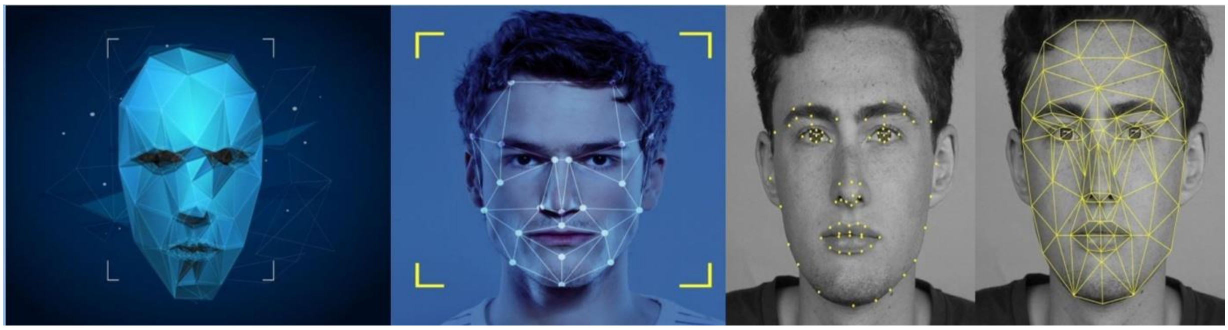

FIG 1.8 – *Face recognition*

Iris Recognition

It is the flagship of biometrics, our iris is unique and extremely complex. The error rate of products available on the market is close to 0/100. The iris is a region in the form of a ring, located between the pupil and the white of the eye, it is unique. The iris has an extraordinary structure and iris many textural characteristics that are unique to each individual. Iris recognition has been developed in the 1980s, it is therefore considered a recent technology. The image of the iris is captured by a device that contains an infrared camera when the person stands a short distance from the device[BENAGGA and TELIB, 2016]

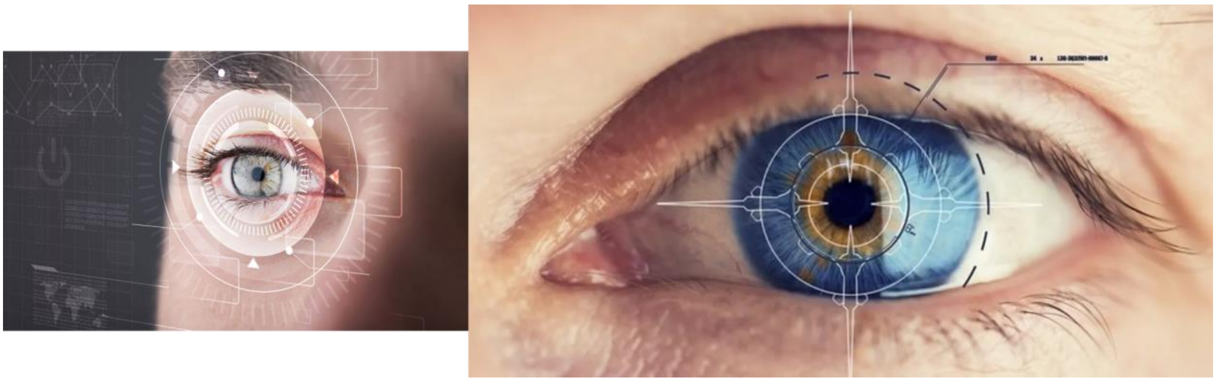

FIG 1.9 – *Iris's recognition*

Ear recognition

The human ear has been used as a means of forensic recognition, and its exterior morphology is relatively stable over a period of time that is acceptable for biometric applications. Ear recognition approaches are based on the correspondence of the distance between the different reference points of the ear. [Jain et al., 2004]

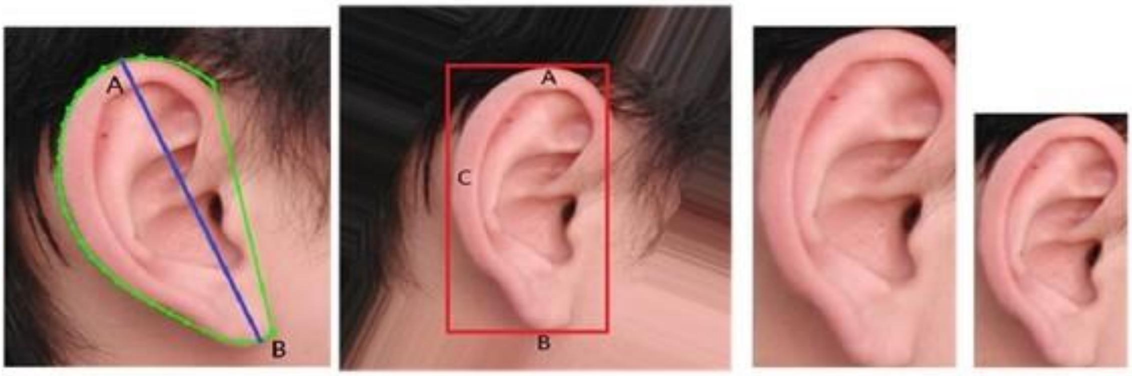

FIG 1.10 – *Ear recognition[Yuan and Mu, 2014]*

Behavioral Modalities

Voice Recognition

It is the only technology that currently makes it possible to recognize an individual remotely. However, speech recognition remains entangled in its limits : it is very difficult to record and reproduces a voice. Speech recognition requires excellent audio quality. It is a bad idea to install this technology in a place where background noise is very present. the low level of differentiation between two voices makes the technique unreliable

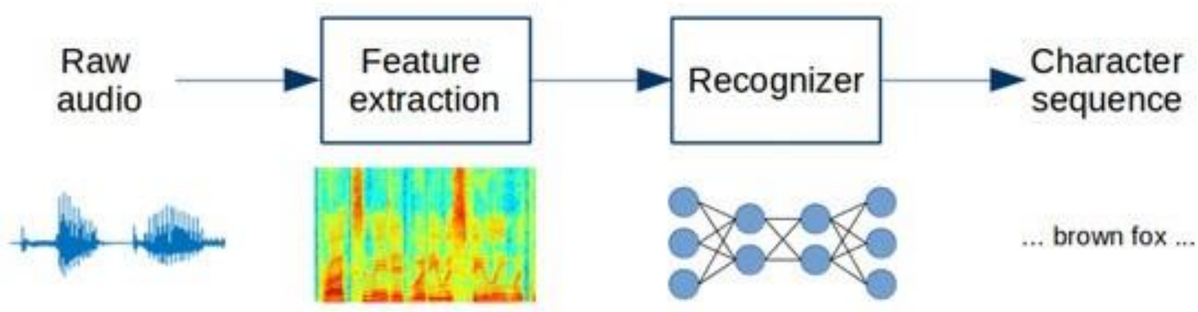

FIG 1.11 – *Voice recognition[Vazhenina and Markov, 2020]*

Handwritten signature

It is a personal writing of an individual, the verification of the signature is based on two modes : Static mode : the verification of the static signature emphasizes the geometric shapes of the signature, in this mode in general the signature is standardized to a known size then decompose into a single element. Dynamic mode : it uses dynamic characteristics such as acceleration[Sabhanayagam et al., 2018]

FIG 1.12 – *Handwritten signature[Sabhanayagam et al., 2018]*

8 advantage and disadvantage of biometric modalities

Biometric modalities	Advantages of Biometrics

Finger vein	- The distribution of finger veins is related to inner physiological characteristics and falsification is extremely hard so that it is trustworthy. - Vein vascular features are ordinarily more articulated, have a higher recognition rate. - It can realize non-contact verification and identification that is safe and healthy. - It belongs to the characteristics of under the skin veins. And it wonâ€™t be affected by dirt or stains on the surface of the fingers. - High recognition efficiency , fast speed, and easy to use.
Finger print	- Easy to use. - Famous technology and tested by the public. - Low cost. - High speed of processing. - Small Drive size.
Ear recognition	- Robust structure preserved throughout the lifetime of the individual. - Unlike facial expressions, ear structure does not alter. - Strong structure that is maintained throughout the life of the individual. - The obtained image size is small under the same resolution which is an added advantage when using portable media such as mobile phones. - Can be used in negative identification systems and covert operations. - Strong structure that is maintained throughout the life of the individual. - Unlike facial expressions, the structure of the ear does not change. - The obtained image size is small under the same resolution which is an added advantage when using portable media such as mobile phones. - Can be used in passive identification systems and covert operations.
Voice Recognition	- Inexpensive quick result and non-intrusive - Low-level spectral analysis.

Handwritten signature	- Easy - fast - low FRR - Low memory.
Iris Recognition	- Distinguish identical twins. - Large amount of information contained in the iris. - Reliability and durability.

TABLE 1.3 – *advantage of biometrics modalities[Sabhanayagam et al., 2018]*

Biometric modalities	Disadvantages of Biometrics
Finger vein	- The cost is high. - The collection method is limited. - The requirement for the image acquisition process of the finger vein cannot be miniaturized. - There are questions that the dissemination of finger veins may alter with age and physiological changes. - Lastingness has not, however, been confirmed.

Finger print	- Average acceptability. - Possibility of attack. - Some systems may accept finger cast or severed fingers.
Ear recognition	- feted by occlusion hair and ear piercing
Voice Recognition	- It has high average cost. - Failures in noisy surroundings.
Handwritten signature	- Can be forged easily - Users must be familiar with the usage of signing tablets. - The same individual can have inconsistent signature. - Signature of individual changes over time. - Has very limited. market

Iris Recognition	- Psychologically invasive aspect of the method. - Expensive. - Acquisition constraints. - Low acceptability.
Face Recognition	- Problem of distinguishing identical twins. - Low's efficiency. - Sensitivity to varying lighting and changing face position.

TABLE 1.5 – *disadvantage of biometrics modalities[Sabhanayagam et al., 2018]*

9 Machine learning

Machine learning (ML) is that computers offer different technologies that can learn from and predict data, by being able to learn without being explicitly programmed[Bakshi and Bakshi, 2018].A biometric comparison is considered an "unclear comparison." This is because the biometrics taken the second time around will never be as accurate as the first time. This biometric matching feature leads to the use of machine learning techniques such as neural networks, fuzzy logic, evolutionary computation in biometric algorithms, etc. The main characteristic of machine learning is that it is robust against noise and can effectively solve complex pattern recognition problems. In addition, machine learning is highly adaptive and often has parallel computing architectures. It simulates complex biological features well Use adaptively accurate mathematical models without making many assumptions. Using these properties, machine learning is proving to be an effective method for extracting and matching biometrics. Few studies have applied machine learning methods to vascular biometrics, and that's what we're talking about in this Servia.

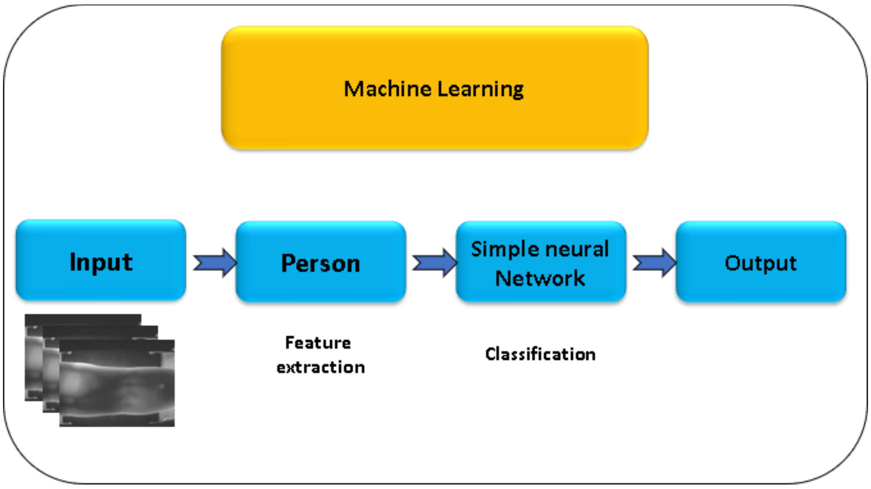

FIG 1.13 – *Machine learning[Najm et al., 2019]*

10 Deep learning

In recent years, deep learning (DL) has become feasible, and there are several developments that make it a useful option at a sufficiently large scale, such as the new amount of data available, new storage technologies that can store large amounts of data, and thus further enforced computing power, because it can handle a lot of information[Goodfellow et al., 2016]. Additionally, the availability of AI frameworks such as those offered by Kaggle and Google Cloud Platform offer even non-datum scientists the opportunity to develop AI-based solutions, even in the field of cybersecurity

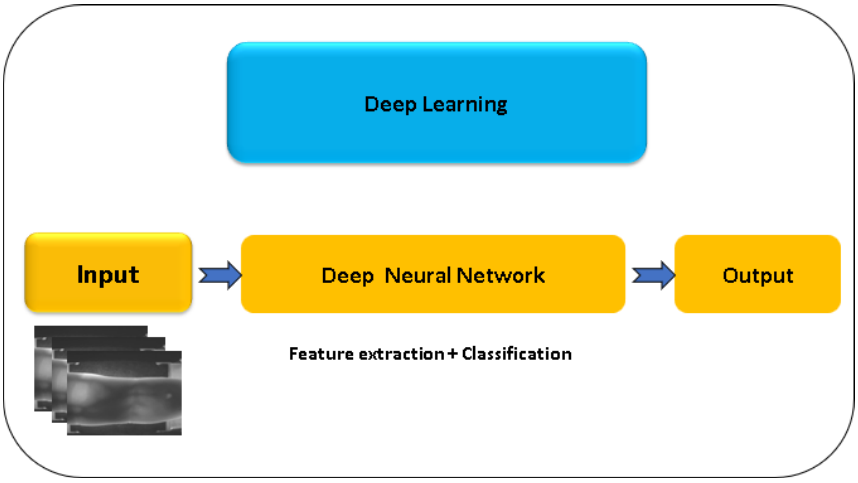

FIG 1.14 – *Deep learninge[Najm et al., 2019]*

11 Convolutional Neural Network

Definition

In deep learning, a convolutional neural network (CNN) is a class of deep neural networks, it's only used to analyze visual imagery. When we think of a neural network, we think about matrix multiplications but that is not the case with CNN. It uses a special technique called Convolution. in mathematics convolution is a mathematical operation on two functions that produces a third function that expresses how the shape of one is changed by the other[Li et al., 2021b]

CNN Architecture

CNNâ€™s basic architecture includes these layers , the main difference between the existing works that uses CNN as a base is the choice and the order of these layers and methods and its parameters

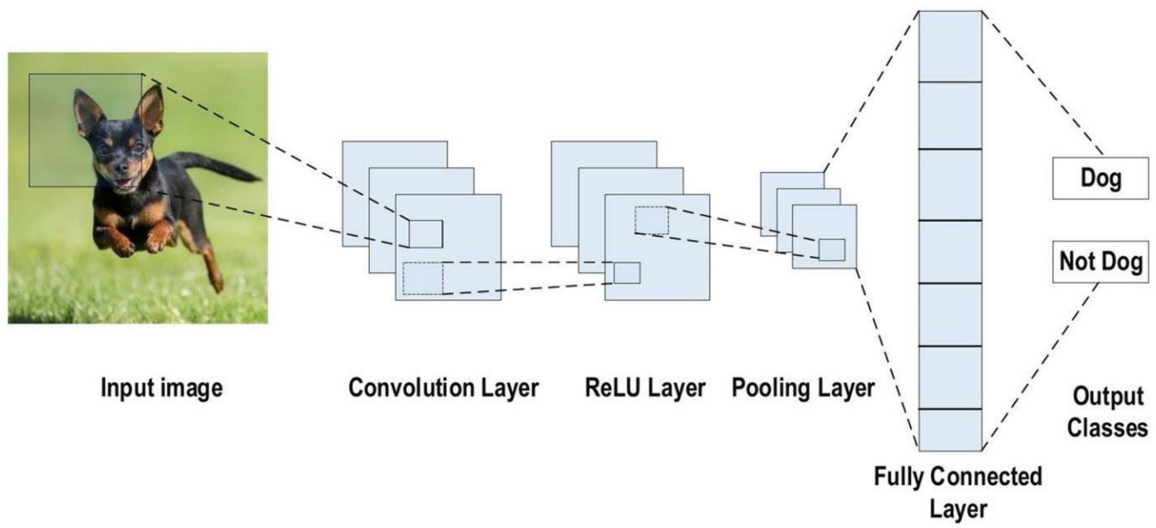

FIG 1.15 – *Basic CNN architecture[Laith et al., 2021]*

Input Layer

Input layers in CNN hold the raw pixel values of the image .our image data is represented by 3D matrix (width × height × depth).It needs to be reshaped into a single column. Like this example of image of dimension 28 × 28 =784, it needs to be converted into 784 x 1 before feeding it to the input layer. If there are " m " training examples then dimension of input will be (784, m). However, in CNN, the image remains in the shape matrix.

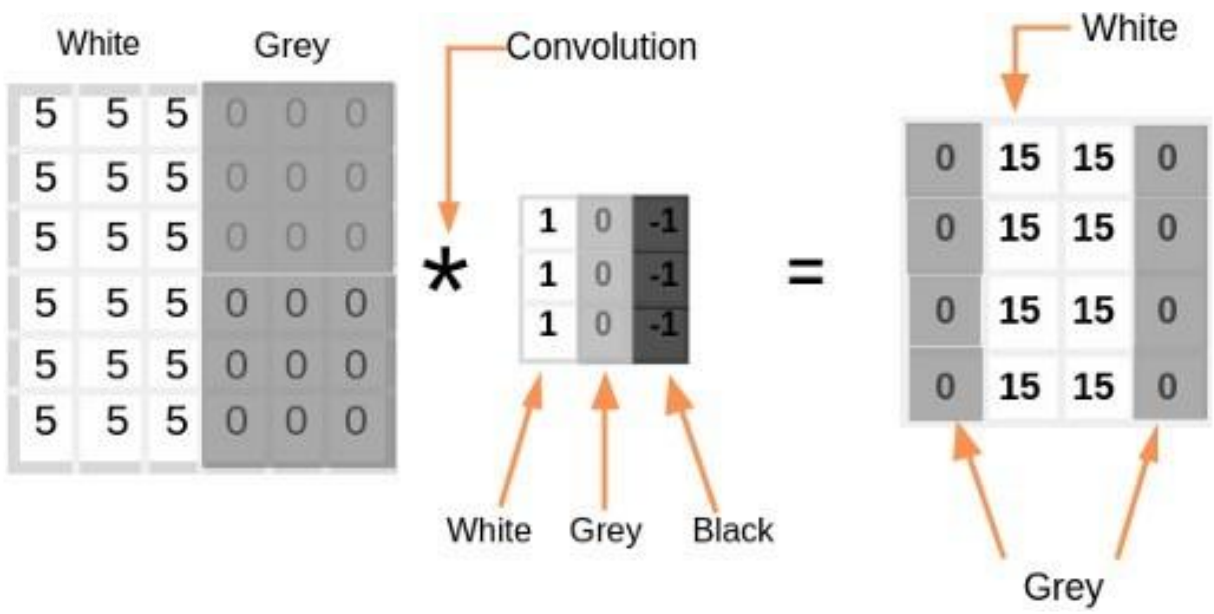

FIG 1.16 – *Example of convolution operation " Edge detection"*

Convolution operation

The convolution layer is sometimes referred to as the feature extraction layer because the features of the image are extracted in this layer. First, apart from the image is connected to the convolution layer to perform the convolution operation and calculate the scalar product between the receptive field (it is a local region of the input image which has the same size as the filter) and the filter. The result of the operation is a unique integer of the output volume. Then the filter glides over the next receiving field of the same input image by a Stride and performing the same operation again. This process is repeated again and again until the end of the image. The output will be the input for.

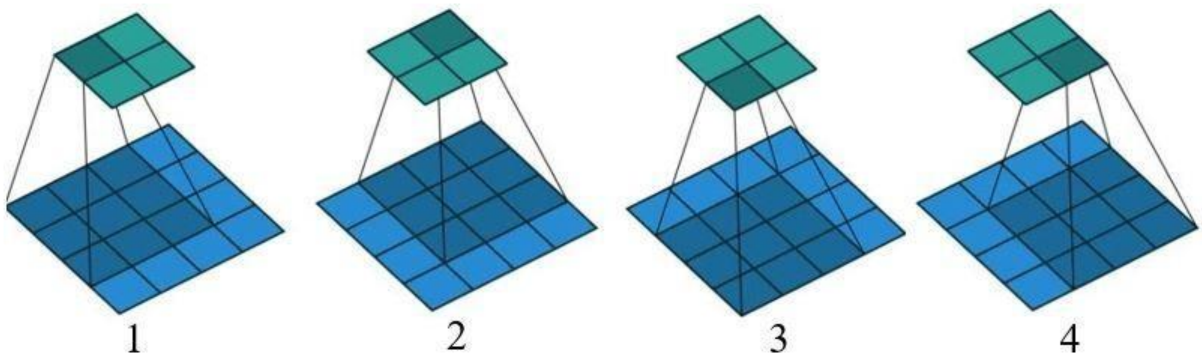

FIG 1.17 – *Example of Convolution Operation [Dumoulin and Visin, 2016]*

The next layer. The convolution operation can be visualized in here the image dimension is 4 × 4 and the filter is 3 × 3, so we get an output after the convolution is 2 × 2.

Filters

Convolution filters are sets of cube-shaped weights that are applied to the entire image. Each 2D slice of the filters is called kernels. These filters introduce translation invariance and parameter sharing.

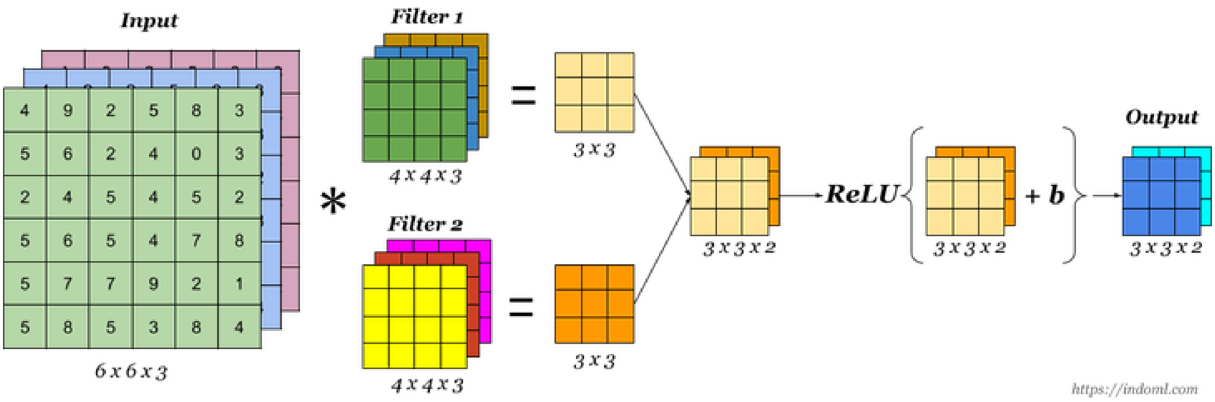

FIG 1.18 – *Visualization of the use of filters in Convolution Operation*

Padding

Applying convolutions to a normal image resizes the image by a total amount depending on the size of the filter. Here's why padding is used get rid of the loss of what could be an important part of an image.

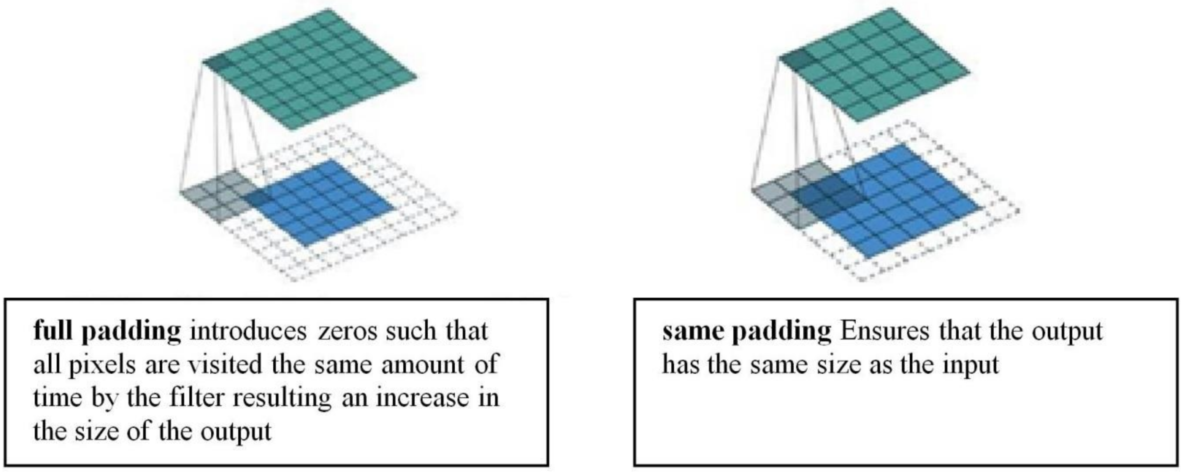

FIG 1.19 – *same and full padding [Kumar et al., 2020]*

The stride

The stride determines the number of cells whose filter will be shifted on the input to calculate the next cell in the result.

ReLU function

Rectified Linear Units is the most used activation function in deep learning models. The function returns 0 if it's a negative input, and for positive value x it returns the same value back. So it can be written as f(x)=max(0,x).

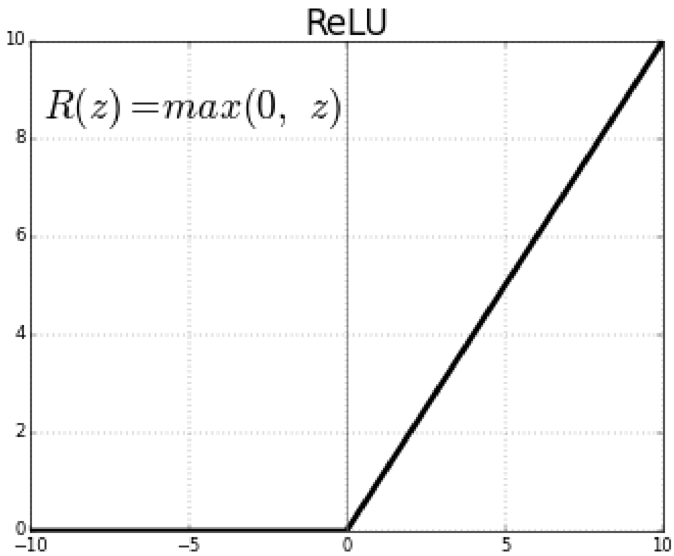

FIG 1.20 – *function of Rectified Linear Units[Sultan et al., 2019]*

Pooling Operation

Pooling is used to shrink the spatial volume of the input image after convolutions. It is utilized between two convolutions. If FC (fully connected) is applied after Convo without applying pooling or max pooling, at that point it'll be computationally costly. The max pooling is the only way to decrease the spatial volume of input pictures. In our example below, max pooling is applied in single depth slice with Stride of 2. the 4 × 4 dimension input is reduced to 2 × 2 dimensions.

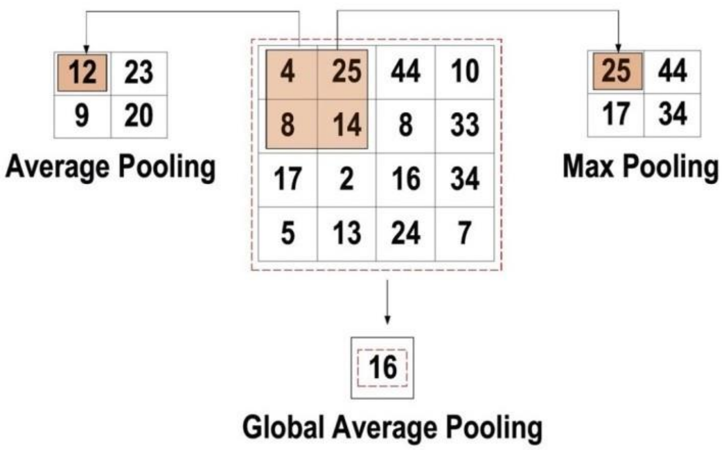

FIG 1.21 – *Example of Max and average and global Pooling in CNN [Laith et al., 2021]*

Fully Connected Layer

Connected Layer is fully a feed-forward neural network. FC Layers form the last few layers that are in the network. The input to the FC layer is the output from the final Pooling or Convolution Layer, which is flattened and then fed into the FC layer. FC layer computes the class scores, as with ordinary Neural Networks and as the name implies, each neuron in this layer will be connected to all the neurons in the past layer. As for the number of FC, it varies depending on the data we use. Example of famous CNN structure in ILSVRC, such as mobileNet, VGG16 and VGG19 ,etc. use 2 fully connected layer, followed by the output layer.

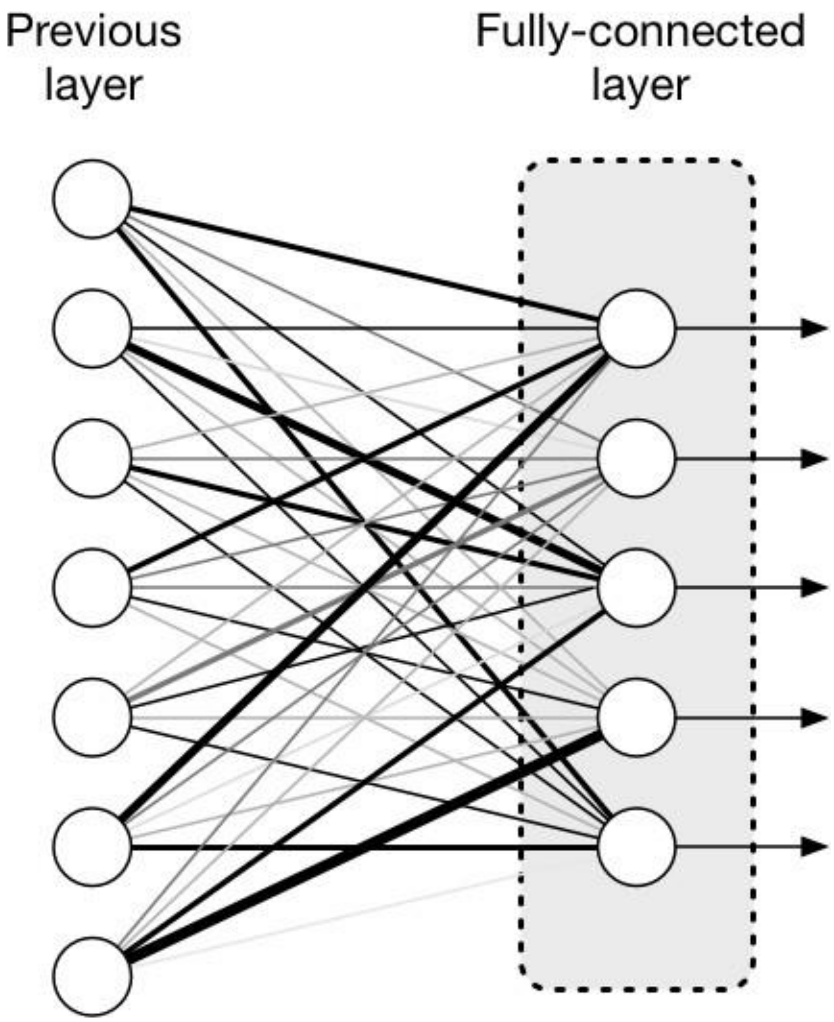

FIG 1.22 – *Fully Connected Layer [Kost, 2018]*

Soft max function

Soft max function exists within the final layer of CNN. It resides at the end of FC layer softmax is for multi-classification form of multinomial logistic regression that normalizes an input value into a vector of values that follows a probability distribution whose total sums is 1.

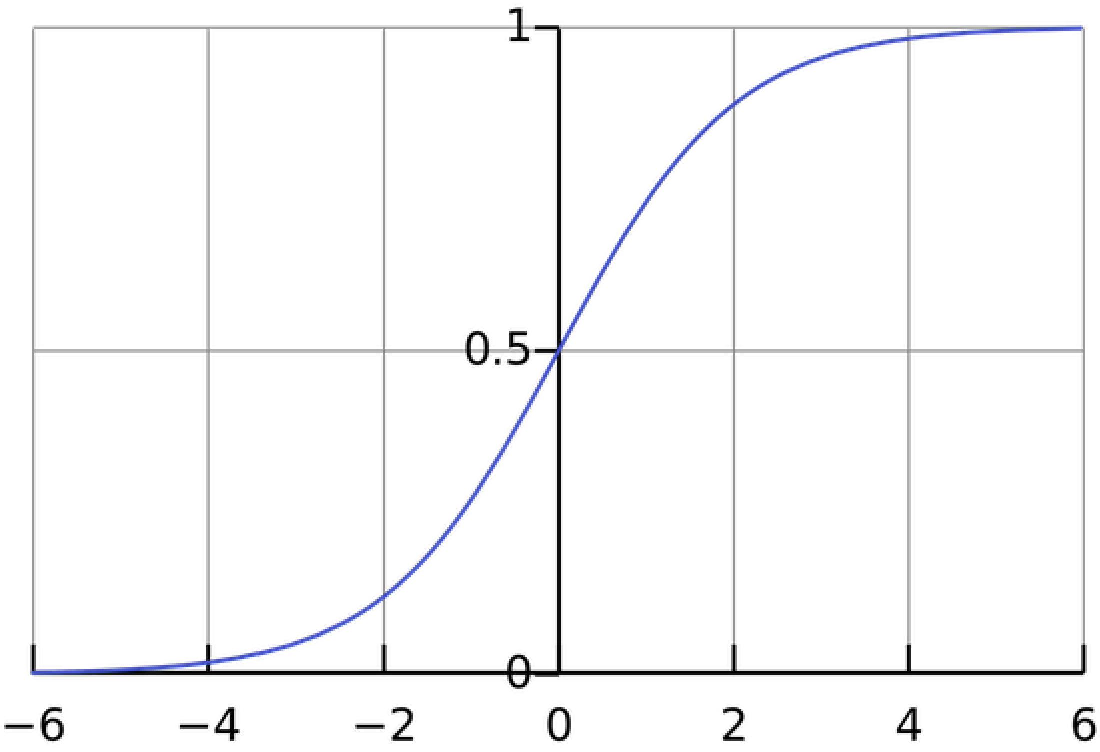

FIG 1.23 – *softmax function* [Shen et al., 2018]

OutputLayer

The output layer in a CNN as explained is a FC layer, where the input from the other layers is flattened and sent so as they transform the output into the number of classes as desired by the network. The Output layer contains the label which is in the form of one hot encoded. The output of the CNN is also a 4D array. Where batch size would be the same as input batch size but the other 3 dimensions of the image might change depending upon the values of the filter, kernel size, and padding we use.

Conclusion

In the first section, we presented an overview of biometric recognition , followed by an explanation of internal structure of a biometric system and there operating modes, and we mentioned the various fields of use for this technique, with an explanation of the difference between unimodal and multimodal and we gave a simple explanation of some biometric techniques.

THE PROPOSED FINGER VEIN RECOGNITION SYSTEM

1 INTRODUCTION

In this chapter, we discuss the state of the art of finger veins recognition in the last years. Then, we propose our finger vein recognition system and its components. A detail description of each part of our system is provided in order to give an idea about methods and techniques used in this work.

2 FINGER VEINS RECOGNITION STATE-OF-THE-ART

Using Machine learning

Some machine learning techniques have been used in the feature extraction and matching stage of biometrics. These kinds of techniques have also proved to be efficient for feature extraction, matching and enhancing the performance of the FVR method. In most FVR techniques, machine learning classifier-based methods were employed during the matching stage of FVR. However, conventional finger vein approaches employ distance-based methods during the matching stage. The accuracy rate of almost all the proposed machine learning finger vein algorithms is close to 100% , in 2011 [Wu and Liu, 2011] [1] with his personal data of 10 persons achieved 98% accuracy with processing time = 0.15s , [Wang et al., 2012][2] he also used his personal data which contain 800 pictures captured from 10 different persons they reached to index ERR=5.6 and ring ERR=6.5 with middle and little up to EER = 8.5 and 11.9 , [Khellat-Kihel et al., 2014][3] used two famous databases called PKU V2 and V4 20 people each brings high accuracy 98.75% and 95% respectively , [Zhou et al., 2015][4] and [Veluchamy and Karlmarx, 2016][5] used their personal data 105 and 100 people to lower ERR to 4.88 and 0.35 , [Veluchamy and Karlmarx, 2017][6] researchers do their work with SHIMLA -HMT 100 people only and used SIFT as Method of future ex- traction and K-SVM for classification to obtain 96% accuracy , [Khanam et al., 2019][7] used all SHIMLA -HMT database (106 people) and picked KNN for classification to reach accuracy of 92.21% , [Meng et al., 2020][8] they used two open source database

HKPU and SHIMLA-HMT they archived low rates of ERR with an average of 0.004 and 0.0266 , [Kapoor et al., 2021][9] reached accuracy equal to 98% using GWO-SVM and by using full database of HKPU which take from 156 people

Machine Learning Survey

Ref	databases	subject	Format	Test/train	Methodesfuturs extraction	Matching classification	Parameters	Performance	Year
[1]	Personal data	10	Not reported	100	PCA+ LDA	SVM	not mentioned	Accuracy = 98.00% Processing time = 0.15 s	2011
[2]	Personal data	10	Not reported	800	LBPV+ LBP	SVM Global matching method	not mentioned	Index EER = 5.6 Ring EER = 6.5 Middle EER = 8.5 Little EER = 11.9	2012
[3]	PKU(V2 and PKU(V4)	PKU(V2) = 20 PKU(V4) = 20	Not reported	PKU(V2) = 200 PKU(V4) = 160	Gabor filter	SVM	not mentioned	PKU(V2) Accuracy = 98.75% PKU(V4) Accuracy = 95%	2014
[4]	Personal data	105	BMP	1872	gradients and Gabor based features,	SVR	not mentioned	EAR = 4.88	2015
[5]	Personal data	100	BMP	1000			not mentioned	Accuracy = 96.00%	2016
[6]	SHIMLA-HMT IIT Delhi fingers knuckles	100	BMP	3816	SIFT	k-SVM	not mentioned	Accuracy = 96%.	2017
[7]	SHIMLA-HMT	106	BMP	3816	FAST	KNN	not mentioned	accuracy = 92.21%	2019
[8]	HKPU SHIMLA-HMT	HKPU=156 SDUMLA-HMT=106	Not reported	HKPU=1872 SDUMLA-HMT=3816	LBP+ LLBP+ LDC+ SIFT	SVM	not mentioned	average EER of 0.0040 and 0.0266	2020
[9]	HKPU	156	BMP	2460	Hybrid LPQ-LDP	GWO-SVM	not mentioned	Accuracy= 98%	2021

TABLE 2.1 – *Machine learning survey*

Using Deep learning

Deep learning is a form of machine learning that involves multiple layers of learning algorithms. This allows deep learning methods to learn hierarchical representations / characteristics from the data. Therefore, deep learning has replaced traditional feature extraction approaches in a variety of areas such as computer vision, speech, and natural language processing. With its powerful functional mapping capabilities, researchers have brought deep learning to the realm of biometrics. Recent studies have built multiple deep learning models based on different datasets. However, deep learning has also been successfully applied in the field of FVR. [Qin and El-Yacoubi, 2015][10] used a deep learning approach in the field of FVR to achieve an average of 88% and 72% accuracy in two databases with different image quality. Inspired by recent advances in deep learning algorithms in various research fields, [Radzi et al., 2016] [11] proposed a database for finger vein biometrics using a convolutional neural network and achieved the accuracy of 100.00%. [Qin and El-Yacoubi, 2017][12] The experimental results on two public finger-vein databases show a significant improvement in terms of finger-vein verification accuracy [Liu et al., 2017][13] experimental results are superior to traditional approaches to finger vein detection with 2970 images achieving 99.53% accuracy. In addition, [Qin and El-Yacoubi, 2017][14] The experimental results on two public finger-vein databases show that the proposed scheme accurately identifies high-and low-quality images and significantly outperforms existing approaches in terms of the impact on equal error-rate decrease, [Guo et al., 2019][15] propose a novel deep learning based image restoration method to improve the integrity of finger-vein networks, this method [Boucherit et al., 2020] [16] improves the recognition rate of the SDUMLAHMT database and THUFVFDT2, with 99.48% and 99.56% accuracy respectively, [Meng et al., 2021] [17] This work was proposed to overcome the problem of unwanted image quality and deformation. They achieved an error rate of 0.0036%. Compared to unimodal biometric systems, multimodal systems can effectively improve recognition performance in terms of accuracy and security [Li et al., 2021a]. [18] proposed an identifiable local coding-based convolutional neural network (LCCNN) for multimodal finger recognition by fusing fingerprints, finger veins, and knuckle print capabilities. Average accuracy = 98.92% , [Tao et al., 2021] [19] Uses two different databases for accurate stable and robust multimodal finger recognition performance. In addition , [Shaheed et al., 2022a][20] method proposed in this article achieved 99% accuracy with a 98% F1 score. Under THUFVFDT2 the proposed method achieved 90% accuracy with an F1 score of 88%. Table 2.2 shows a performance analysis of recent deep learning approaches in finger vein detection.

Deep learning survey :

ref	databases	subject	Format	Test/train	Method	Parameters	Performance	year
[10]	A = HKPU B = Univ Sains Malaysia	Database A = 105 Database B = 123	BMP	Database A = 2520 Database B = 5904	DNN+P-SVM	not mentioned	EER of high- and low-quality image on database A = 88.99% and 88.18% EER of same on B = 74.98% and 70.07%	2015
[11]	Personal data : VeCAD Laboratory	50	not mentioned	500	CNN	not mentioned	Accuracy = 100.00%, total processing time = 0.15 s	2016
[12]	A = HKPU B = USM	Database A = 105 Database B = 123	BMP	Database A = 2520 Database B = 5904	not mentioned fully convolutional networks (FCN)	not mentioned	HKPU EAR = 2.70 USM EAR = 1.42	2017
[13]	personal data	198	not mentioned	2970	BDAE	not mentioned	accuracy 99.53%	2017
[14]	A = Univ Sains Malaysia B = HKPU	Database a = 123 Database B = 105	BMP	Database A = 5904 Database B = 2520	DNN+P-SVM	not mentioned	High- and low-quality image accuracy on database A = 71.01%, 73.57% same on Database B = 87.08%,86.36%	2018
[15]	Personal data	585	not mentioned	5850	Fully convolutional network (FCN)	not mentioned	EER= 0.0016%	2019
[16]	SHIMLA-HMT THU-FVFDT2	SHIMLA =106 FVFDT2 =610	BMP	3816	CNN	not mentioned	Accuracy= 99.48% Accuracy= 99.56%	2020
[17]	HKPU	156	BMP	6264	CNN	Repeated 10 times 9 size of the blocks	EER=0.0036%	2021
[18]	SHIMLA-HMT	106	BMP	3816	LC-CNN and SVM classifier	batch size is 30 LC-CNN was set at 0.0001 numbers of epochs =20 Optimizer SGD Train number 32000	Average accuracy =98.92%	2021
[19]	A and B FV-USM A and B FV-SIPL	FV-SUM =123 FV-SIPL =36	not mentioned	FV-USM train =600 FV-USM test = 300 FV-SIPL train = 864 FV-SIPL test =432	CNN (VGG19) + feature concatenation CNN (ResNet50)+ feature concatenation CNN (VGG19) + feature concatenation CNN (ResNet50) + feature concatenation SVM classifier	Batch size 64 Epoch 500 Optimizer SGD Train number 32000	A and B FV-USM 98.00 time 16.88 99.67 time 38.42 A and B FV-SIPL 99.07 time 21.84 99.31 time 43.70	2021
[20]	SHIMLA-HMT THU-FVFDT2	SHIMLA =106 FVFDT2 =610	BMP	SHIMLA =3816	DS CNN	Rotation range 15 Width shift range 0.2 Shear range 0.2 Zoom range 0.2 Horizontal flip True Vertical flip False	Average accuracy =98.5% Average accuracy =90%	2022

TABLE 2.2 – *Deep learning survey*

3 PROPOSED FINGER VEIN RECOGNITION SYSTEM

The Recognition System process consists of three main steps in Training : Preprocessing, extraction of features and classifiers. and in the test : Preprocessing, extraction of features and Final DÃ©sections

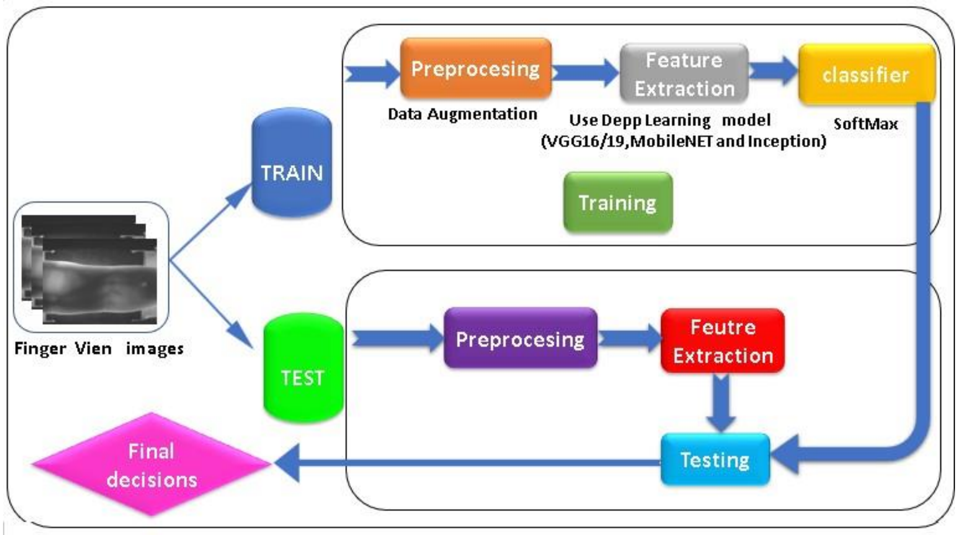

FIG 2.1 – *The proposed system framework[Shaheed et al., 2022b]*

Preprocessing

In this work, we perform data augmentation to image(a) as preprocessing in order to increase performance and results of our neural networks models by creating new and different samples image(b) to train datasets. This task returns datasets rich and sufficient for model training, which makes recognition system performs better and more accurately.

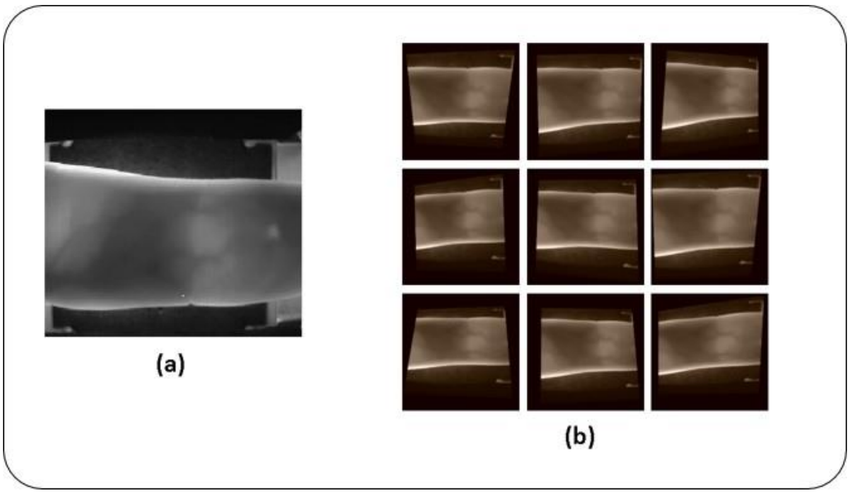

FIG 2.2 – *Examples of applying data augmentation on finger vein images.*

Feature extraction using deep learning

As far as we know, work has been done on CNN to identify the finger vein. A problem occurs when working with CNN to find the appropriate parameters that yield the highest percentage recognition rate. For this, we started a series of tests where we worked on four models of it (VGG16, VGG19, Mobile Net, Inception).

VGG16 Model

VGG16 is the CNN (Convolutional Neural Network) architecture that won the 2014 ILSVR (ImageNet) competition[Simonyan and Zisserman, 2014]. To this day, it is considered one of the outstanding vision model architectures. The most unique thing about VGG16 is that instead of using a lot of hyperparameters, they focus on convolutional layers of 3x3 filters in step 1, and always use the same padding and max pool layers of 2x2 filters in step 2. It follows this order of convolutions and max pooling layers throughout the architecture[Rezende et al., 2018]. Finally, it has 2 FCs (fully connected layers) followed by a SoftMax of the output. The 16 in VGG16 means that it has 16 layers of weights. This network is a fairly large network with about 138 million (approximately) parameters.

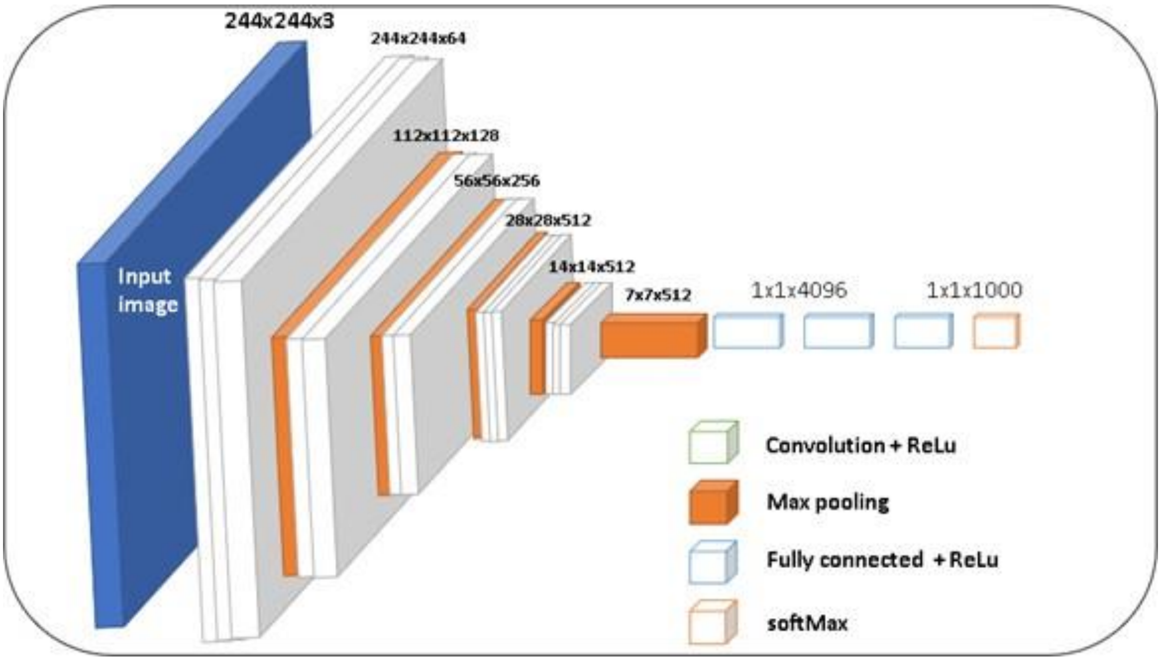

FIG 2.3 – *VGG16 architecture[Kavala and Pothuraju, 2022]*

Summary of VGG16 :

Layer (type)	Output Shape	parameter
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0

TABLE 2.3 – *VGG16 Summary*

VGG19 Model

VGG-19 is a convolutional neural network that is 19 layers deep. Trained on more than a million images from the ImageNet database. VGG19 and VGG16 are commonly called to as VGGNet, which was introduced to ILSVRC in 2014[Simonyan and Zisserman, 2014]. It is called VGG16 or VGG19 depending on the number of layers. The powerful point of these models is simplicity. They only use 3 x 3 convolutional layers and max pooling. These models are just stacked layers the far right is. We evaluate performance based on the number of these two layers role model. VGG19 has three more layers than VGG16[Lee and Lee, 2019].

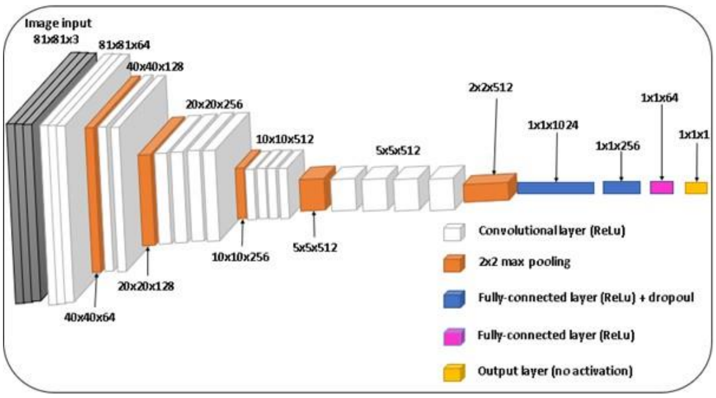

FIG 2.4 – *VGG 19 architecture[Kavala and Pothuraju, 2022]*

Summary of VGG19 :

Layer (type)	Output Shape	parameter
input_2 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv4 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv4 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv4 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0

TABLE 2.4 – *VGG19 Summary*

Inception v3 Model

Inception v3. As shown in Figure 2, Inception v3 is a deeper and broader model than VGGNet. it is. Also presented ILSVRC 2014 and won. The model consists of a base module which includes the following convolutional layers and pooling layers are parallelized. The inception module even makes the model trainable although deep and broad[Lee and Lee, 2019]. We mark the initial module as a block. Although there are wider and deeper models, it has fewer parameters than VGGNet. So, the model converges very quickly.

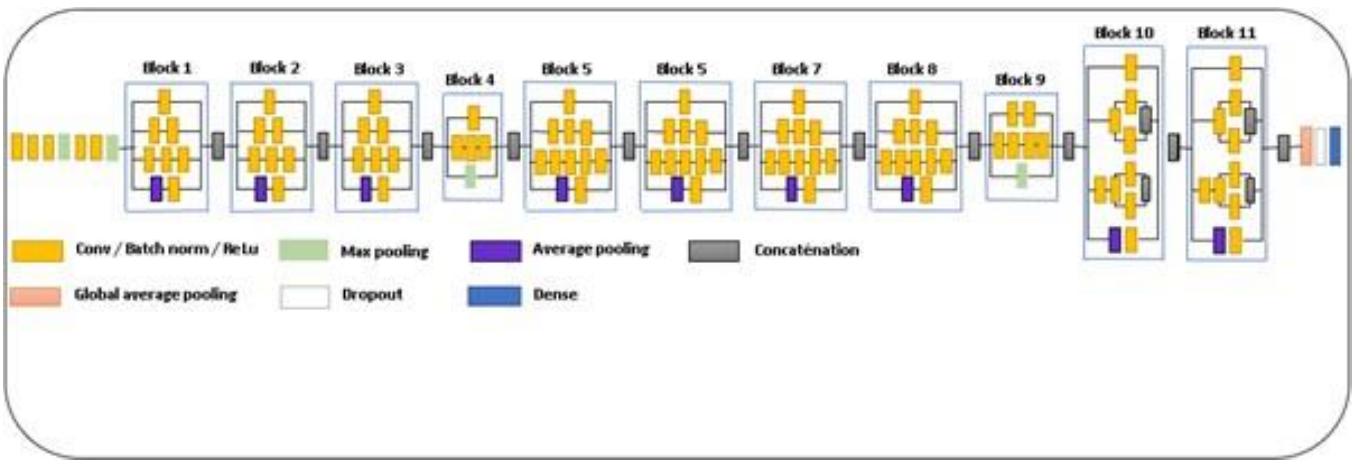

FIG 2.5 – *Inception v3 model architecture[Lee and Lee, 2019]*

Summary of inception v3 :

Layer (type)	Output Shape	Parameter	Connected to
input 4 (InputLayer)	[(None, 224, 224, 3)]	0	[]
conv2d 94 (Conv2D)	(None, 111, 111, 32)	864	['input 4[0][0]']
batch normalization 94 (BatchNormalization)	(None, 111, 111, 32)	96	['conv2d 94[0][0]']
activation 94 (Activation)	(None, 111, 111, 32)	0	['batch normalization 94[0][0]']
conv2d 95 (Conv2D)	(None, 109, 109, 32)	9216	['activation 94[0][0]']
batch normalization 95 (BatchNormalization)	(None, 109, 109, 32)	96	['conv2d 95[0][0]']

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Layer (type)	Output Shape	Parameter	Connected to
activation 179 (Activation)	(None, 5, 5, 320)	0	['batch normalization 179[0][0]']
mixed9 1 (Concatenate)	(None, 5, 5, 768)	0	['activation 181[0][0]', 'activation 182[0][0]']
concatenate 3 (Concatenate)	(None, 5, 5, 768)	0	['activation 185[0][0]', 'activation 186[0][0]']
activation 187 (Activation)	(None, 5, 5, 192)	0	['batch normalization 187[0][0]']
mixed10 (Concatenate)	(None, 5, 5, 2048)	0	['activation 179[0][0]', 'mixed9 1[0][0]', 'concatenate 3[0][0]', 'activation 187[0][0]']

TABLE 2.5 – *Inception v3 Summary*

MobileNet v2 Model

MobileNet-v2 is a convolutional neural network that is 53 layers deep. Trained on more than a million images from the ImageNet database[Akay et al., 2021]. The retrained network can classify images into 1000 object categories. A better module structure is introduced in MobileNetV2. This time, the non-linearity in the narrow slices is removed. With MobileNetV2 as the backbone for feature extraction[Sandler et al., 2018], it also achieves state-of-the-art performance in object recognition and semantic segmentation.

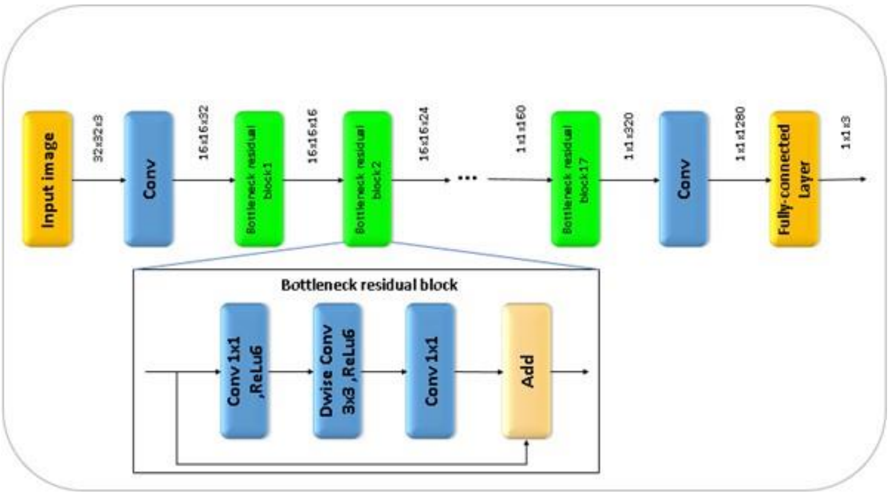


FIG 2.6 – *MobileNet V2 Architecture[Seidaliyeva et al., 2020]*

Summary of MobileNet V2 :

Layer (type)	Output Shape	Parameter	Connected to
input 3 (InputLayer)	[(None, 224, 224, 3)]	0	[]
Conv1 (Conv2D)	(None, 112, 112, 32)	864	['input 3[0][0]']
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32)	128	['Conv1[0][0]']
Conv1 relu (ReLU)	(None, 112, 112, 32)	0	['bn Conv1[0][0]']
expanded_conv_depthwise (Depth wiseConv2D)	(None, 112, 112, 32)	288	['Conv1_relu[0][0]']
	.		
	.		
	.		
	.		
	.		
block_16_depthwise relies (ReLU)	(None, 7, 7, 960)	0	['block_16_depthwise BN[0][0]']
block_16_project (Conv2D)	(None, 7, 7, 320)	307200	['block_16_depthwise relu[0][0]']
block_16_project_BN (BatchNormalization)	(None, 7, 7, 320)	1280	['block_16_project [0][0]']
Conv_1 (Conv2D)	(None, 7, 7, 1280)	409600	['block_16_project BN[0][0]']
Conv_1_bn (BatchNormalization)	(None, 7, 7, 1280)	5120	['Conv_1[0][0]']
out relu (ReLU)	(None, 7, 7, 1280)	0	['Conv 1 bn[0][0]']

TABLE 2.6 – *MobileNet V2 Summary*

Classification

The softmax function,which normalizes output real values from the last fully connected layers to label class probabilities,where each value ranges between zero and one and all values total to one , is an activation function used in the multi-classification problems.

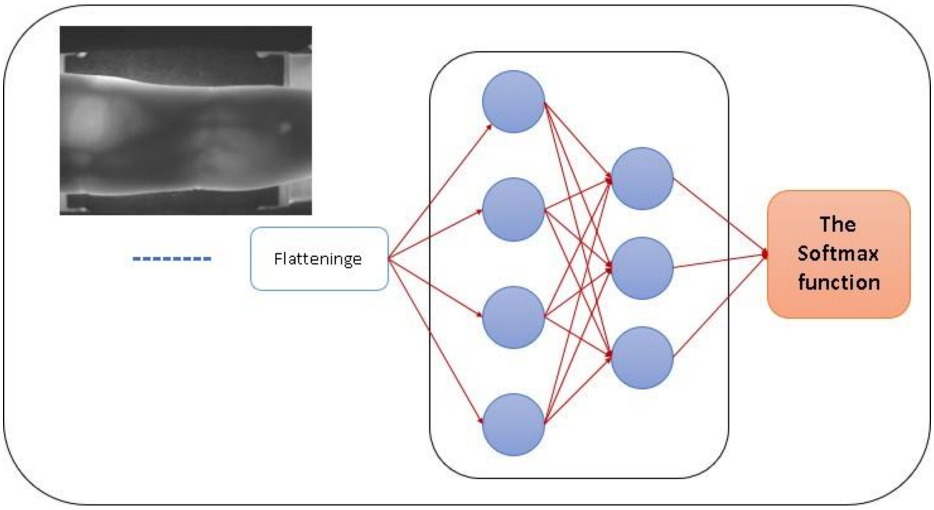


FIG 2.7 – *The proposed system framework*

CONCLUSION

We have discussed in this chapter the state of the art of finger veins recognition for machines and deep learning ,we have seen the preprossicng of our database and explained the different architecture of CNN. In the next chapter, we will report our different results with quantitative and qualitative discussions to bring out the strengths and weaknesses of our system.

RESULTS AND DISCUSSIONS

1 INTRODUCTION

In this chapter, we give a detailed description to our used database Then, we provided an explanation to the evaluation metrics that used in this work .we will report our different results with quantitative and qualitative discussions to bring out the strengths and weaknesses of our system followed by comparative study .

2 DATASET DESCRIPTION

The database used in our work is from Shandong University's group of machine learning and applications. A database called SDUMLAHMT is a homologous multimodal characteristic database that contains true multimodal data from individuals. As far as their knowledge,the SDUMLAHMT finger vein database is the first open finger vein database [Podgantwar and Raut, 2013]. The device used to capture images of finger veins was developed by Wuhan University's Joint Laboratory for Intelligent Computing and Intelligent Systems. In the capturing process, each subject was asked to provide images of the index, middle, and ring fingers of both hands, and each of the 6 fingers was collected 6 times to obtain images of the veins of 36 images. Therefore, the finger vein database consists of 3,816 images with 320-240 pixels[Podgantwar and Raut, 2013]. In BMP format. In our system, we take only 30 subjects with 5 images for each one. The first 3 images are selected for training and the rest for testing. Fig 3.1 represents some finger vein images from subjects.

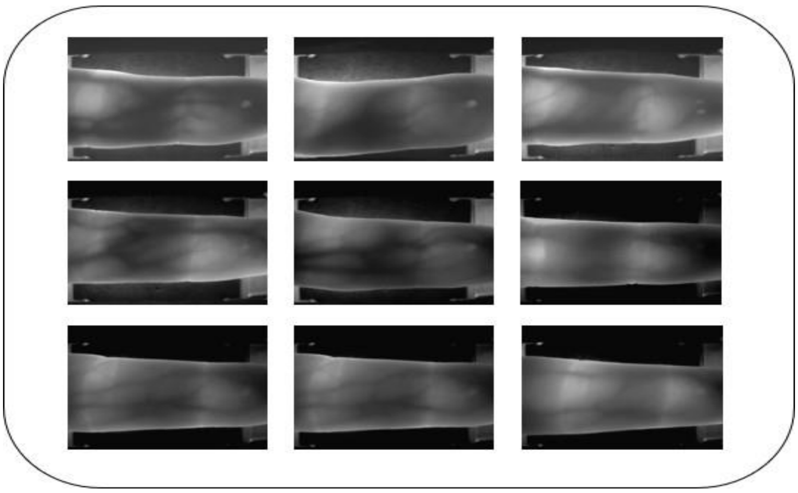


FIG 3.1 – *Some samples from the SDUMLA dataset*

3 EVALUATION METRICS

As a performance evaluation, we consider the confusion matrix to calculate our metrics such as accuracy, precision, F1score, Recall, CM, and CMC. The Confusion matrix is a power measurement technique for classification in deep learning. It is a graph that helps you determine the performance of your classification model on the test dataset so you know the true value. The term "confusion matrix" itself is quite simple, but the terms associated with it can be a bit confusing. Here are some simple explanations for this technique Negative, False Negatives, and True Negatives. The real positives : They positively predicted, and it turned out to be true.[Zhu et al., 2010]

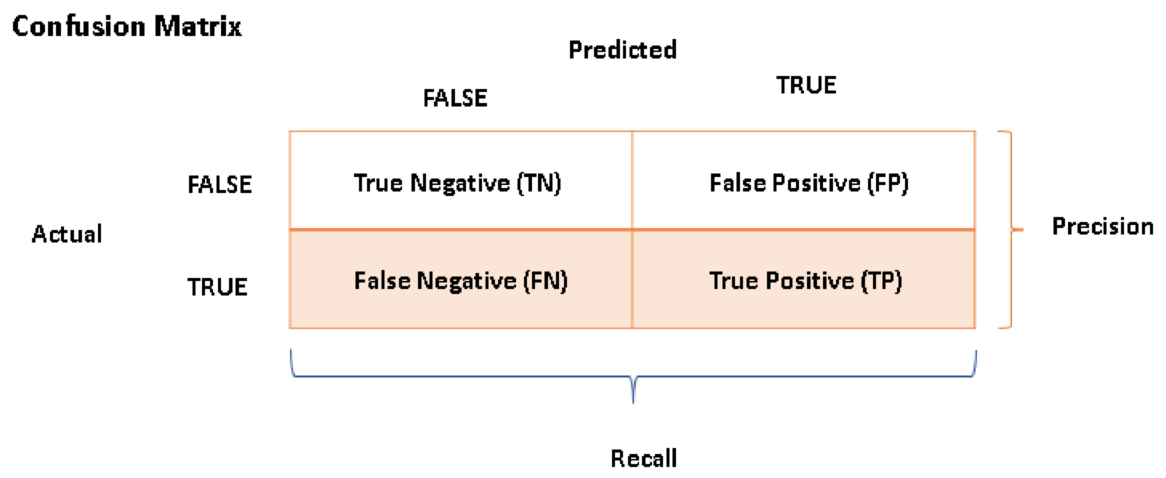


FIG 3.2 – *Confusion matrix*

[Zhu et al., 2010]

- TP : True Positive : Predicted values correctly predicted as actual positive
- FP : Predicted values incorrectly predicted an actual positive. i.e., negative values predicted as positive
- FN : False Negative : Positive values predicted as negative
- TN : True Negative : Predicted values correctly predicted as an actual negative

and we can compute the accuracy from the confusion matrix :

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

Precision

Of all the positive predictions I made, how many were actually positive ? The Number of True Positives (TP) is divided by the Total Number of True Positives (TP) and False Positives (FP).

$$Precision = \frac{TP}{TP + FP} \tag{3.2}$$

Recall

Of all the actual positive examples, I correctly predict how many of them are positive ? Number of True Positives (TP) is divided by the Total Number of True Positives (TP) and False Negatives (FN).

$$Recall = \frac{TP}{TP + FN} \tag{3.3}$$

If you compare the precision and recall formulas, you'll see that they all look similar. The only difference is the second term in the denominator, which is a false positive on precision and a false negative on recall.

F1 Score

To fully evaluate model performance, we should examine precision and recall. F1 score is a useful metric that does both. Harmonized mean of precision and recall for a more balanced summary of model performance.

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3.4}$$

[Ayan and Ünver, 2019]

4 RESULTS

VGG16 results

Influence of epoch number and batch size on the VGG16 accuracy

optimizer : Adam / Learning rate : 0.002

Number of epochs \ Batch size	16	32	64	128
10	**58 %**	**58.33 %**	**73.33 %**	**60 %**
20	**61.67 %**	**66.67 %**	**75 %**	**73.33 %**
30	**56.67 %**	**68.33 %**	**75 %**	**80 %**
40	**65 %**	**71.67 %**	**80 %**	**80 %**
50	**65 %**	**73.33 %**	**76.67 %**	**78.33 %**
60	**70 %**	**70 %**	**81.67 %**	**78.33 %**
70	**70 %**	**68.33 %**	**71.67 %**	**80 %**
80	**71.67 %**	**66.67 %**	**76.67 %**	**80 %**
90	**68.33 %**	**68.33 %**	**81.67 %**	**80 %**
100	**70 %**	**70 %**	**78.33 %**	**80 %**

TABLE 3.1 – *Influence of epoch number and batch size on the VGG16* accuracy

In this experiment, we fixed the learning rate and the optimizer, and we augmented the number of epochs and varied the batch size. As we illustrated in the previous table, the number of epochs is between 10 and 100 epochs , the values of batch size are : 16, 32, 64, and 128. The influence of batch size on the number of epochs is explained in the following paragraph :

considering our results, the worst Accuracy 58% was on 10 epochs and 16 batch size, and the medium accuracy 70% was on 60 and 100 epoch , 16 and 32 batch size. the best that we found in this model was on 60 and 90 epochs and 64 batch size with an accuracy of 81.67%

Influence of optimizer and learning rate on the VGG16 accuracy

Number of epochs : 60 / batch sizes : 64

optimizer \ learning rate	0.1	0.01	0.001	0.002	0.004	0.0001	0.0002	0.0004
Adam	**3.33 %**	**3.33 %**	**76.67%**	**65 %**	**35 %**	**66.67%**	**81.67%**	**81.67 %**
RMSprop	**3.33 %**	**3.33 %**	**6.67 %**	**3.33%**	**3.33%**	**78.33%**	**75%**	**40 %**
SGD	**6.67%**	**3.33%**	**6.67%**	**5%**	**6.67%**	**3.33%**	**3.33%**	**6.67%**

TABLE 3.2 – *Infiuence of optimizer and learning rate on the VGG16 accuracy*

In this experiment, we fixed the Number of epochs and the batch size, and we augmented the learning rates and varied the types of optimizers. As we illustrated in the previous table, the optimizers are : Adam, RMSprop and SGD and the values of learning rates are : 0.1, 0.01, 0.001, 0.002, 0.004, 0.0001, 0.0002 and 0.0004. The influence of the learning rate on the optimizers is explained in the following paragraph :

— The best learning rate in optimizer Adam is 0.0004, 0.0002 because it gave us higher Accuracy 81.67%

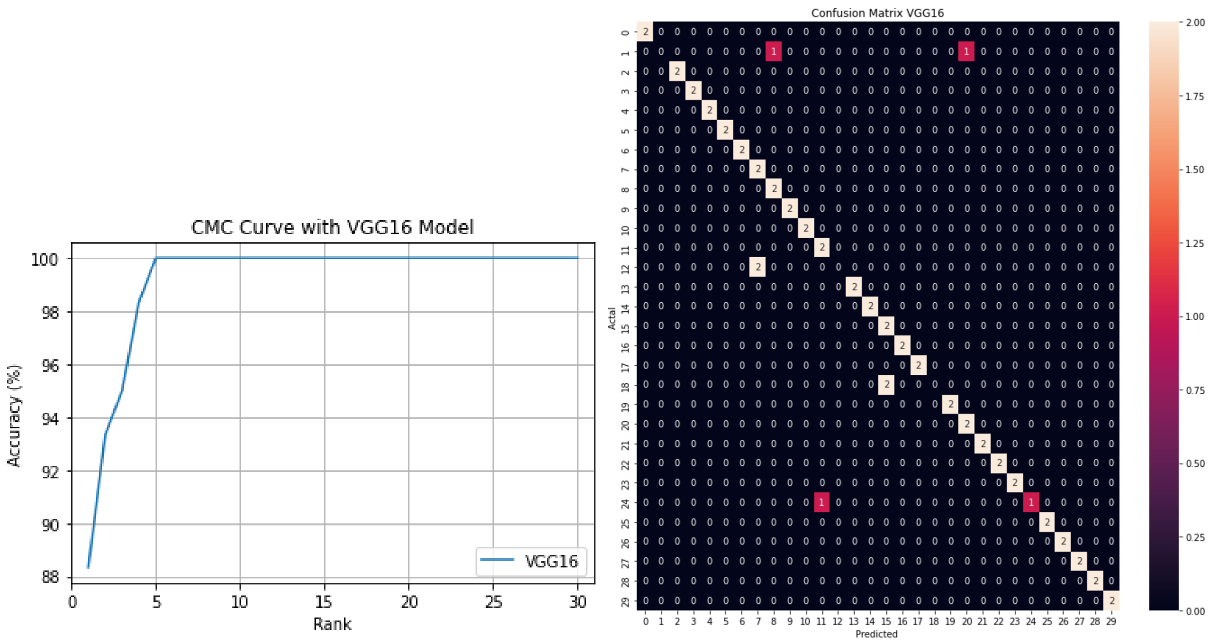
— The best learning rate in optimizer RMSprop is 0.0001 because it gave us higher Accuracy 78.33%

— in optimizer SGD is giving us worst Accuracy in this modal it is 6.67%

Metrics \ Parameter	BS : 64 Opt : Adam NE : 60 Lr : 0.002	BS : 16 Opt : Adam NE : 20 Lr : 0.002	BS : 64 Opt : Adam NE : 60 Lr : 0.01	BS : 64 Opt : RMSprop NE : 60 Lr : 0.0005
Accuracy	**88%**	**87%**	**93%**	**87%**
F1 Score	**85%**	**83%**	**92%**	**83%**
Precision	**83%**	**83%**	**93%**	**83%**
Recall	**88%**	**87%**	**93%**	**87%**

TABLE 3.3 – *Summary Accuracy of VGG16 Model*

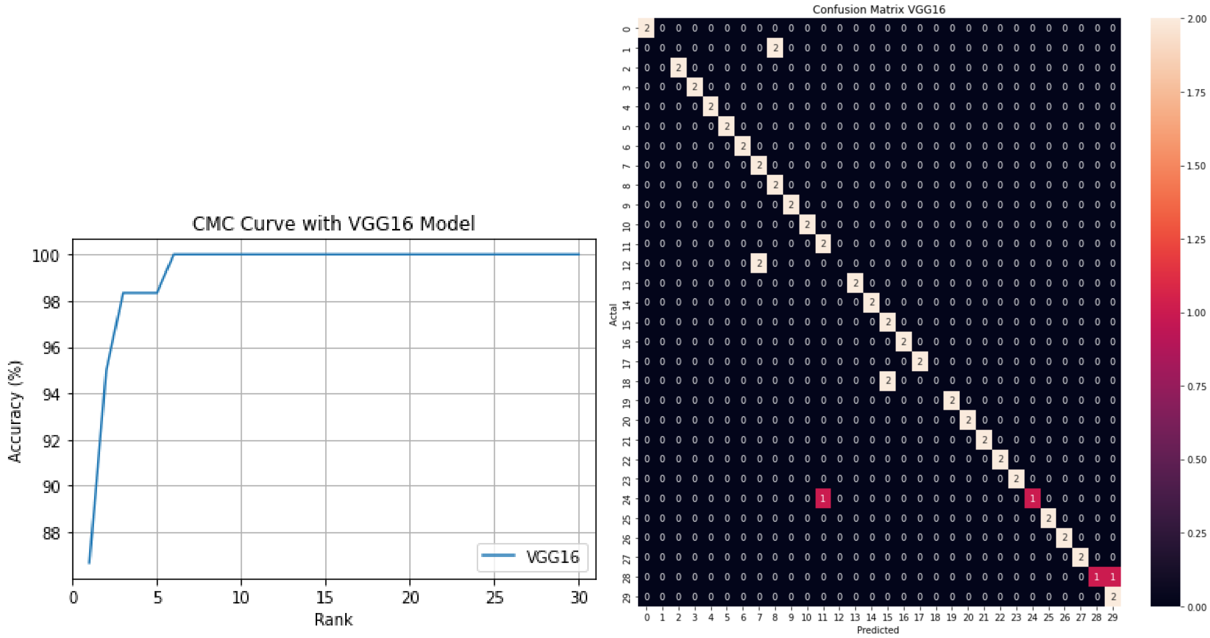
In this table, we use the 4 parameters essential for testing our model : the batch size, the learning rate, and the type of optimizer. Firstly, we choose the best parameters from the previous table. After that, we calculate the F1score, the precision, the recall, the confusion matrix, and the cumulative match characteristic. Finally, we save the best results, as we show in the table and the figures.



(a) CMC *(b) CM*

FIG 3.3 – *CM and CMC with accuracy 88%*

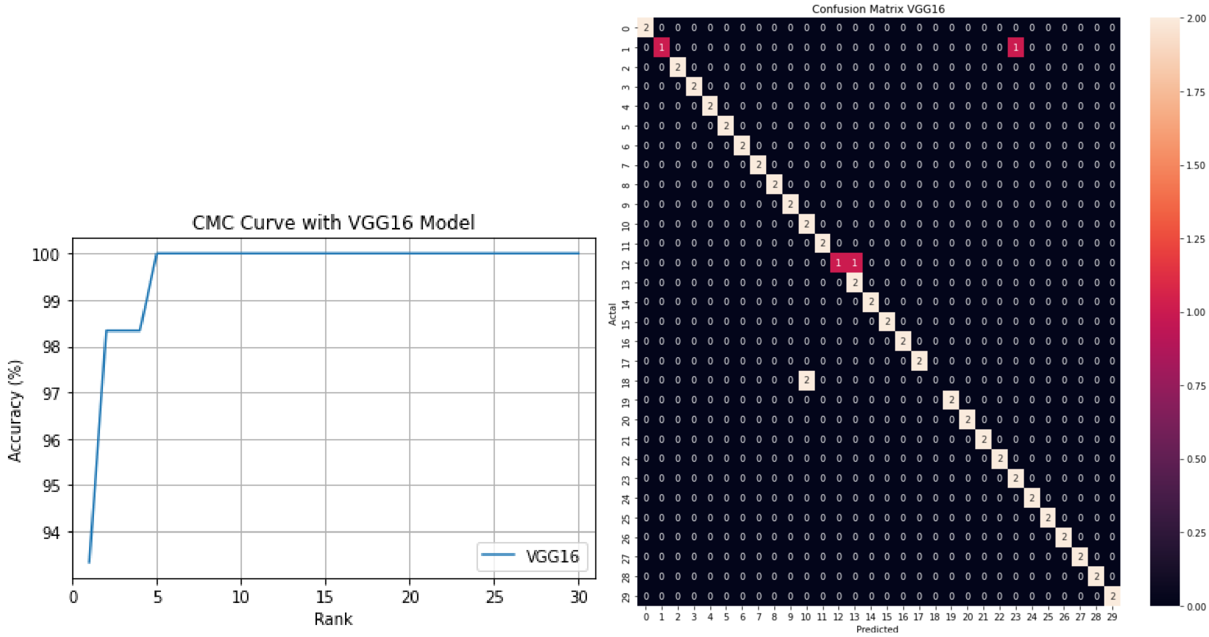
In fig 3.3 : There have been 25 correct class identifications and 5 incorrect class identifications. such as subject number 12 being classified in class number 7. and for the CMC we can see in this fig The recognition accuracy at Rank-1 is 88.50% and from Rank 5 to Rank 30 it is 100%.



(a) CMC *(b) CM*

FIG 3.4 – *CM and CMC with accuracy 87%*

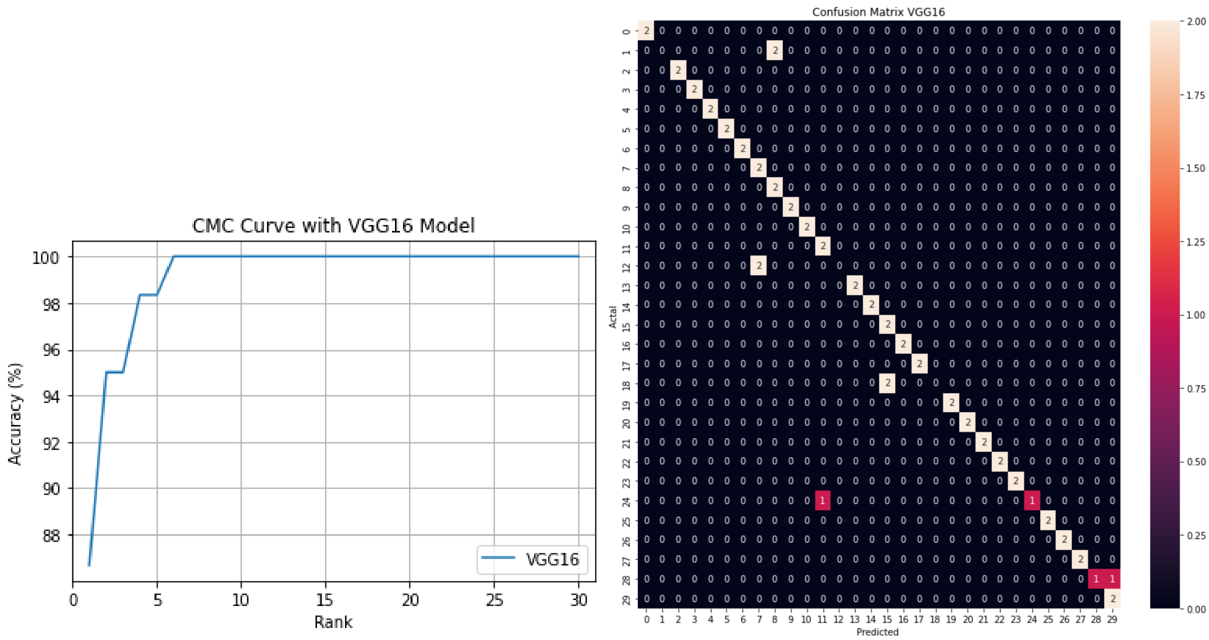
In fig 3.4 : There have been 25 correct class identifications and 5 incorrect class identifications. such as subject number 01 being classified in class number 8. and for the CMC we can see in this fig The recognition accuracy at Rank-1 is 88.50% and from Rank 3 to Rank 5 it is 98.20% and from rank 5 to rank 6 it is 99% and from rank 6 to rank 30 it is 100%.



(a) CMC *(b) CM*

FIG 3.5 – *CM and CMC with accuracy 93%*

In fig 3.5 : There have been 27 correct class identifications and 3 incorrect class identifications. such as subject number 18 being classified in class number 10. and for the CMC we can see in this fig The recognition accuracy at Rank 01 is 93.20% and from Rank 02 to Rank 04 it is 98.20% and from rank 04 to rank 05 it is 99% and from rank 05 to rank 30 it is 100%.



(a) CMC *(b) CM*

FIG 3.6 – *CM and CMC with accuracy 87%*

In fig 3.6 : There have been 25 correct class identifications and 05 incorrect class identifications. such as subject number 12 being classified in class number 07. and for the CMC we can see in this fig The recognition accuracy at Rank 01 is 87.20% and from Rank 02 to Rank 03 it is 95% and from rank 03 to rank 04 it is 97.50% and from rank 04 to rank 05 it is 98.20% and from rank 05 to rank 6 it is 99% and from rank 06 to rank 30 it is 100%.

VGG19 results

Influence of epoch number and batch size on the VGG19 accuracy

optimizer : Adam / Learning rate : 0.002

Batch size / Number of epochs	16	32	64	128
10	55%	66.67%	56.67%	\\\\\\\\\\\\\\\\\\
20	60%	75%	71.67%	\\\\\\\\\\\\\\\\\\
30	66.67%	78.33%	73.33%	\\\\\\\\\\\\\\\\\\
40	66.67%	68.33%	71.67%	\\\\\\\\\\\\\\\\\\
50	70%	70%	75%	\\\\\\\\\\\\\\\\\\
60	65%	71.67%	75%	\\\\\\\\\\\\\\\\\\
70	68.33%	76.67%	71.67%	\\\\\\\\\\\\\\\\\\
80	68.33%	76.67%	68.33%	\\\\\\\\\\\\\\\\\\
90	71.67%	73.33%	70%	\\\\\\\\\\\\\\\\\\
100	73.33%	71.67%	76.67%	\\\\\\\\\\\\\\\\\\

TABLE 3.4 – *Infiuence of epoch number and batch size on the VGG19 accuracy*

In this experiment, we fixed the learning rate and the optimizer, and we augmented the number of epochs and varied the batch size. As we illustrated in the previous table, the number of epochs is between 10 and 100 epochs , the values of batch size are : 16, 32, 64 and 128. The influence of batch size on the number of epochs is explained in the following paragraph :

considering our results, the worst Accuracy 55% was on 10 epoch and 16 batch size, and the medium accuracy 65% was on 60 epoch and 16 batch size. the best that we found in this model was on 30 epoch and 32 batch size with accuracy of 78.33%

Influence of optimizer and learning rate on the VGG19 accuracy

Number of epochs : 30 / batch sizes : 32

learning rate / optimizer	0.1	0.01	0.001	0.002	0.004	0.0001	0.0002	0.0004
Adam	3.33%	3.33%	83.33%	75%	36.67%	63.33%	83.33%	83.33%
RMSprop	3.33%	3.33%	6.67%	3.33%	3.33%	80%	90%	46.67%
SGD	16.67%	6.67%	3.33%	3.33%	3.33%	3.33%	3.33%	3.33%

TABLE 3.5 – *Infiuence of optimizer and learning rate on the VGG19 accuracy*

In this experiment, we fixed the Nâ€™epoch and the batch size, and we augmented the number of learning rate and varied the optimizer. As we illustrated in the previous table, the optimizers are between Adam, RMSprop and SGD and the values of learning rates are : 0.1, 0.01, 0.001, 0.002, 0.004, 0.0001, 0.0002 and 0.0004. The influence of learning rate on the optimizers is explained in the following paragraph :

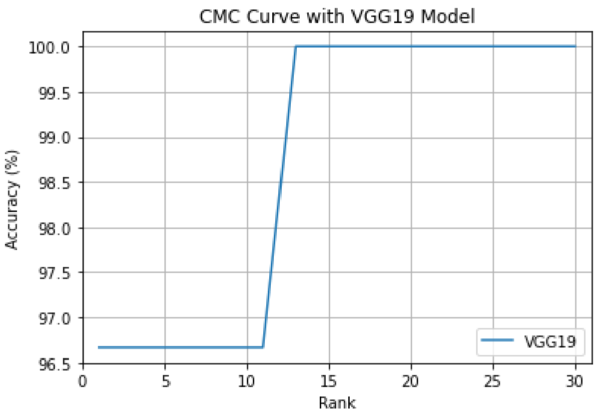
— The best learning rate in optimizer Adam is 0.001/0.0002/0.0004 because it gave us higher Accuracy = 83.33%

— The best learning rate in optimizer RMSprop is 0.0002 because it gave us higher Accuracy = 90%

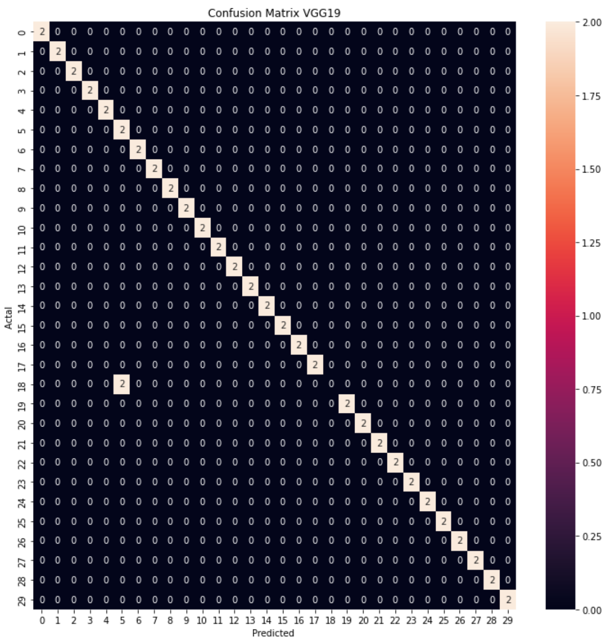
— in optimizer SGD is giving us worst Accuracy in this modal it is = 16.67%

Parameter / Metrics	BS :32	BS :16	BS :32	BS :32
	Opt :Adam	Opt :Adam	Opt :RMS	Opt :Adam
	NE :30	NE :10	NE :30	NE :30
	Lr :0.002	Lr :0.002	Lr :0.0005	Lr :0.01
Accuracy	97%	93.33%	97%	95%
F1 Score	96%	92%	95%	94%
Precision	95%	93%	94%	94%
Recall	97%	93%	97%	95%

TABLE 3.6 – *Summary Accuracy of VGG19 Model*



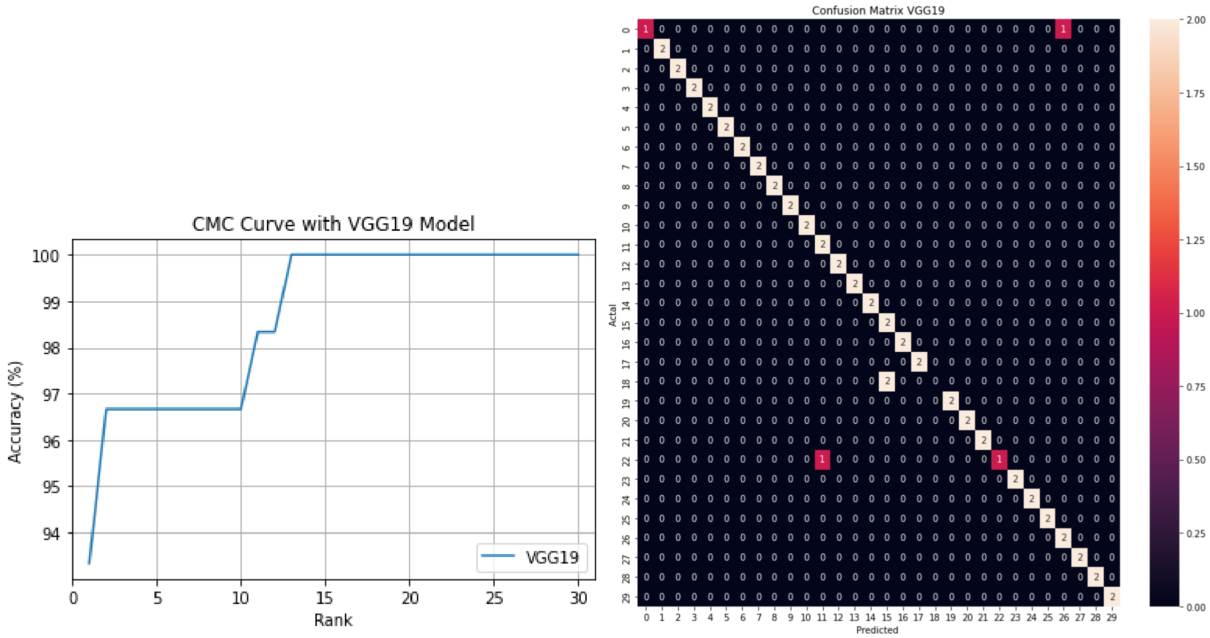
(a) CMC



(b) CM

FIG 3.7 – *CM and CMC withe accuracy 97%*

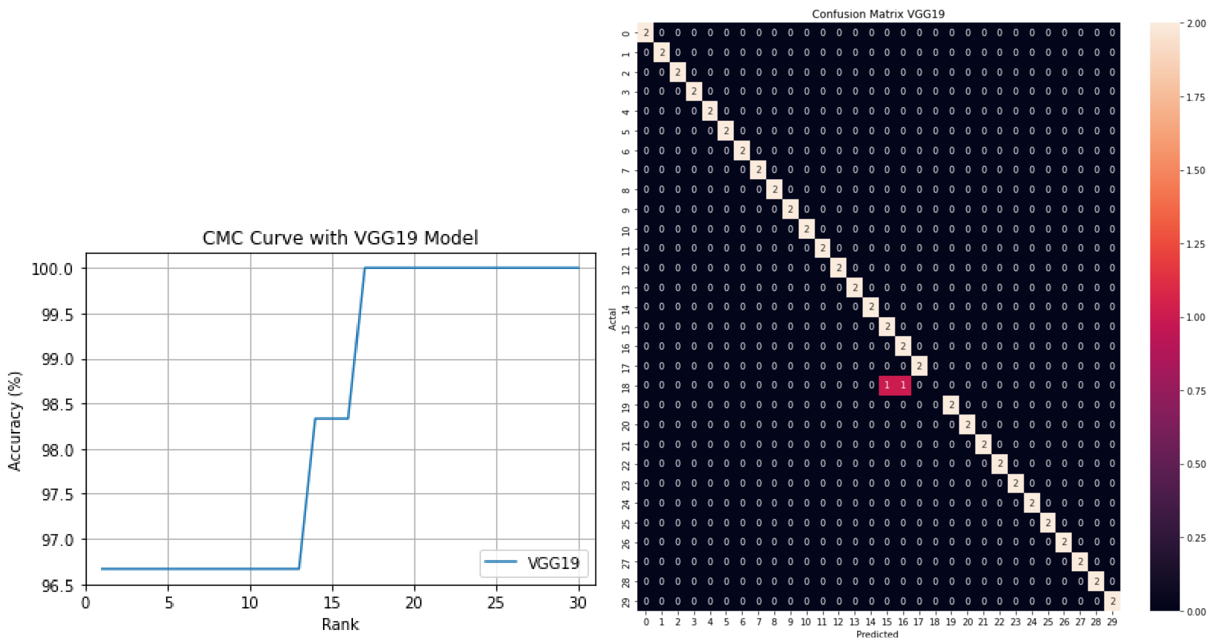
There were 29 correct class identifications and 01 incorrect class identifications in fig. As an example, subject number 18 is assigned to class number 05. The recognition accuracy at Rank-1 is 96.70 %, and from Rank 10 to Rank 13 it is 99.5 %,and from Rank 13 to Rank 30 it is 100 %, as seen in this graph.



(a) CMC *(b) CM*

FIG 3.8 – *CM and CMC with accuracy 93.33%*

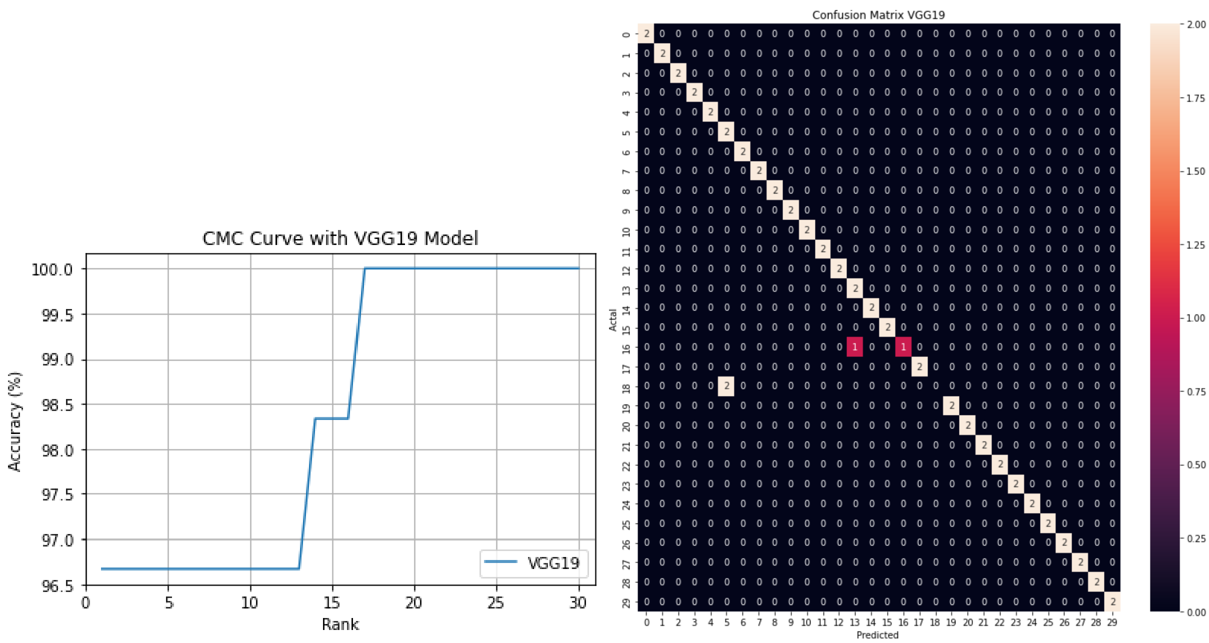
There were 27 correct class identifications and 03 incorrect class identifications in fig. As an example, subject number 18 is assigned to class number 15. The recognition accuracy at Rank-1 is 93.20 %, and from Rank 02 to Rank 10 it is 96.6%, and from Rank 10 to Rank 11 it is 97.50%, and from Rank 11 to Rank 12 it is 98.20%, and from Rank 12 to Rank 13 it is 99.50%, and from Rank 13 to Rank 30 it is 100%, as seen in this graph.



(a) CMC *(b) CM*

FIG 3.9 – *CM and CMC with accuracy 97%*

There were 25 correct class identifications and 5 incorrect class identifications in fig. As an example, subject number 12 is assigned to class number 7. The recognition accuracy at Rank-1 is 88.50 percent, and from Rank 5 to Rank 30 it is 100 percent, as seen in this graph.



(a) CMC *(b) CM*

FIG 3.10 – *CMC and CMC with accuracy 95%*

There were 28 correct class identifications and 02 incorrect class identifications in fig. As an example, subject number 18 is assigned to class number 05. The recognition accuracy at Rank-1 is 96.60%, and from Rank 13 to Rank 14 it is 98%,and from Rank 14 to Rank 16 it is 98.40%,and from Rank 16 to Rank 17 it is 99.5%,and from Rank 17 to Rank 30 it is 100%, as seen in this graph.

Inception V3 results

Influence of epoch number and batch size on the Inception V3 accuracy

optimizer : Adam / Learning rate : 0.002

Batch size / Number of epochs	16	32	64	128
10	**75%**	**38.33%**	**20%**	**15%**
20	**90%**	**86.67%**	**61.67%**	**43.33%**
30	**91.67%**	**85%**	**88.33%**	**46.67%**
40	**90%**	**86.67%**	**85%**	**65%**
50	**90%**	**88.33%**	**91.67%**	**80%**
60	**90%**	**88.33%**	**91.67%**	**86.67%**
70	**88.33%**	**88.33%**	**90%**	**86.67%**
80	**91.67%**	**86.67%**	**90%**	**85%**
90	**93.33%**	**88.33%**	**90%**	**88.33%**
100	**90%**	**83.33%**	**91.67%**	**88.33%**

TABLE 3.7 – *Influence of epoch number and batch size on the Inception V3 accuracy*

In this experiment, we fixed the learning rate and the optimizer, and we augmented the number of epochs and varied the batch size. As we illustrated in the previous table, the number of epochs is between 10 and 100 epochs , the values of batch size are : 16,32,64 and 128. The influence of batch size on the number of epochs is explained in the following paragraph : considering our results, the worst Accuracy 15% was on 10 epoch and 128 batch size, and the medium accuracy 65% was on 40 epoch , 16 and 64 batch size. the best that we found in this model was on 90 epoch and 16 batch size with accuracy of 93.33%

Influence of optimizer and learning rate on the Inception V3 accuracy

Number of epochs : 90 / batch sizes : 16

learning rate / optimizer	0.1	0.01	0.001	0.002	0.004	0.0001	0.0002	0.0004	0.0006
Adam	**3.33%**	**61.67%**	**83.33%**	**86.67%**	**85%**	**88.33%**	**90%**	**91.67%**	**95%**
RMSprop	**6.67%**	**65%**	**90%**	**85%**	**81.67%**	**93.33%**	**88.33%**	**88.33%**	**91.67%**
SGD	**86.67%**	**91.67%**	**43.33%**	**66.67%**	**83.33%**	**1.67%**	**5%**	**8.33%**	**15%**

TABLE 3.8 – *Infiuence of optimizer and learning rate on the Inception V3 accuracy*

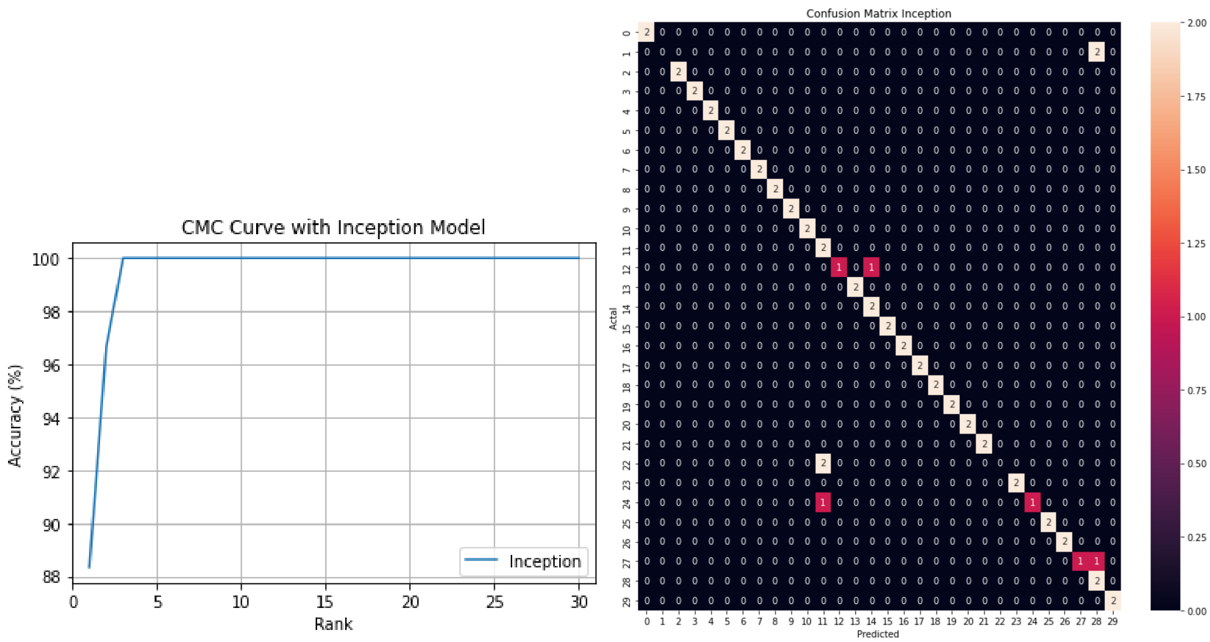
In this experiment, we fixed the Number of epochs and the batch size, and we augmented the number of learning rate and varied the optimizer. As we illustrated in the previous table, the optimizers are between Adam, RMSprop and SGD and the values of learning rates are : 0.1, 0.01, 0.001, 0.002, 0.004, 0.0001, 0.0002 , 0.0004 and 0.0006. The influence of learning rate on the optimizers is explained in the following paragraph :

— The best learning rate in optimizer Adam is 0.0006 because it gave us higher Accuracy 95%

— The best learning rate in optimizer RMSprop is 0.0001 because it gave us higher Accuracy 93.33%

— The best learning rate in optimizer SGD is 0.01 because it gave us higher Accuracy 91.67%

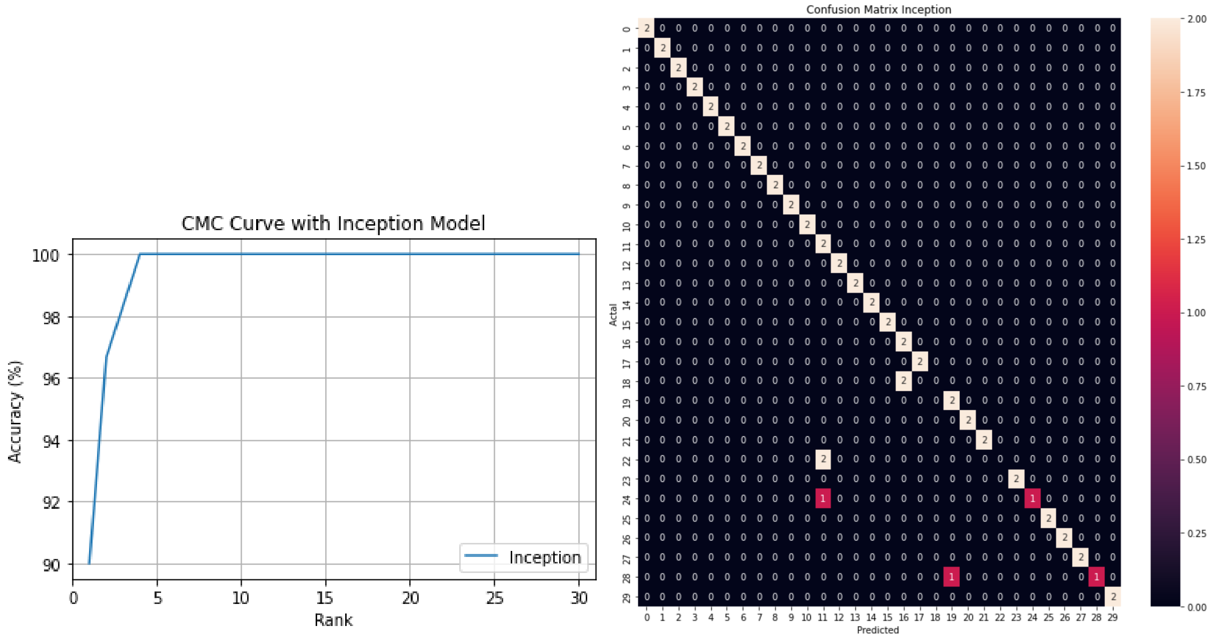
Parameter / Metrics	BS :16 Opt :Adam NE :90 Lr :0.002	BS :32 Opt :Adam NE :50 Lr :0.002	BS :32 Opt :Adam NE :50 Lr :0.01	BS :16 Opt :RMS NE :90 Lr :0.0001
Accuracy	**88%**	**90%**	**80%**	**90%**
F1 Score	**86%**	**88%**	**75%**	**88%**
Precision	**88%**	**89%**	**74%**	**89%**
Recall	**88%**	**90%**	**80%**	**90%**



(a) CMC *(b) CM*

FIG 3.11 – *CM and CMC with accuracy 88%*

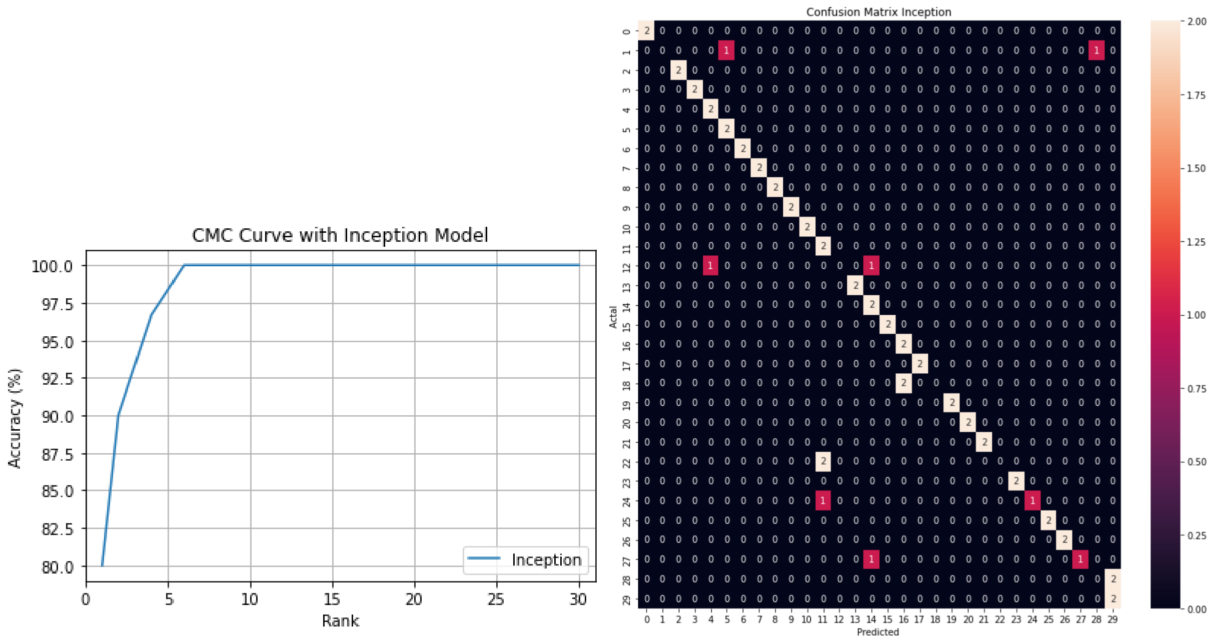
In fig. 3.11, there were 25 valid class identifications and 05 incorrect class identifications. Subject number 22 is allocated to class number 11, for example. As seen in this graph, the recognition accuracy at Rank-1 is 89%, and from Rank 01 to Rank 03 it is 98.50%, and from Rank 03 to Rank 30 it is 100%.



(a) CMC *(b) CM*

FIG 3.12 – *CM and CMC with accuracy 90%*

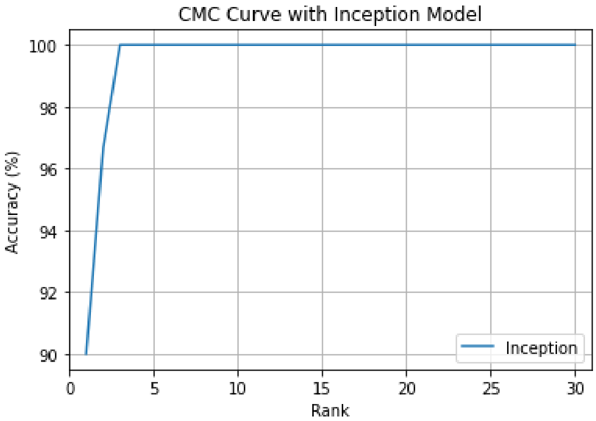
In fig. 3.12, there were 26 valid class identifications and 04 incorrect class identifications. Subject number 18 is allocated to class number 16, for example. As seen in this graph, the recognition accuracy at Rank-1 is 09%, and from Rank 02 to Rank 04 it is 98.50%, and from Rank 04 to Rank 30 it is 100%.



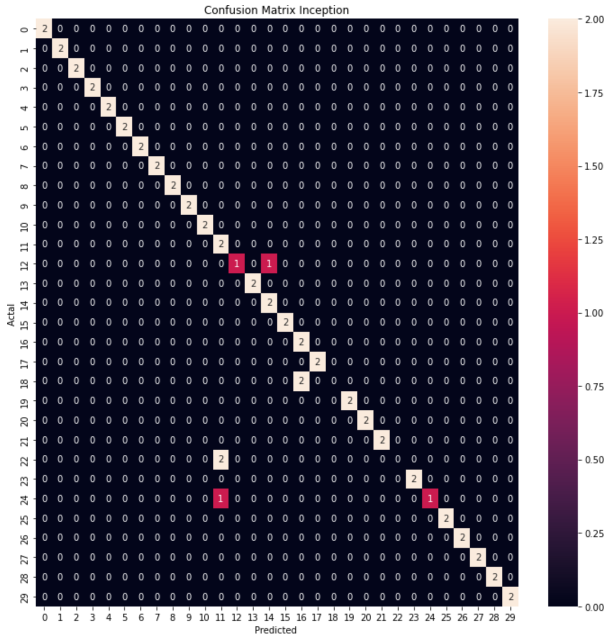
(a) CMC *(b) CM*

FIG 3.13 – *CM and CMC with accuracy 80%*

In fig. 3.13, there were 23 valid class identifications and 07 incorrect class identifications. Subject number 22 is allocated to class number 11, for example. As seen in this graph, the recognition accuracy at Rank-1 is 80%, and from Rank 02 to Rank 06 it is 98.50%, and from Rank 06 to Rank 30 it is 100%.



(a) CMC



(b) CM

FIG 3.14 – *CM and CMC withe accuracy 90%*

In fig. 3.14, there were 26 valid class identifications and 04 incorrect class identifications. Subject number 18 is allocated to class number 16, for example. As seen in this graph, the recognition accuracy at Rank-1 is 90%, and from Rank 02 to Rank 03 it is 98.50%, and from Rank 03 to Rank 30 it is 100%.

MobileNet results

Influence of epoch number and batch size on the MobileNet accuracy

optimizer : Adam / Learning rate : 0.002

Batch size / Number of epochs	16	32	64	128
10	**46.67%**	**35%**	**21.67%**	**10%**
20	**71.67%**	**66.67%**	**75%**	**13.67%**
30	**76.67%**	**71.67%**	**86.67%**	**51.67%**
40	**76.67%**	**73.33%**	**93.33%**	**80%**
50	**78.33%**	**75%**	**96.67%**	**88.33%**
60	**80%**	**71.67%**	**95%**	**90%**
70	**75%**	**71.67%**	**95%**	**93.33%**
80	**81.67%**	**85%**	**95%**	**91.67%**
90	**83.33%**	**86.67%**	**95%**	**91.67%**
100	**85%**	**85%**	**95%**	**91.67%**

TABLE 3.9 – *Infiuence of epoch number and batch size on the MobileNet accuracy*

In this experiment, we fixed the learning rate and the optimizer, and we augmented the number of epochs and varied the batch size. As we illustrated in the previous table, the number of epochs is between 10 and 100 epochs , the values of batch size are : 16,32,64 and 128. The influence of batch size on the number of epochs is explained in the following paragraph :

considering our results, the worst Accuracy 10% was on 10 epoch and 128 batch size, and the medium accuracy 78.33% was on 50 epoch and 16 batch size. the best that we found in this model was between 60 and 100 epoch , 64 batch size with accuracy of 95%

Influence of optimizer and learning rate on the MobileNet accuracy

Number of epochs : 50 / batch sizes : 64

learning rate / optimizer	0.1	0.01	0.001	0.002	0.004	0.0001	0.0002	0.0004
Adam	**3.33%**	**3.33%**	**96.67%**	**93.33%**	**13.33%**	**81.67%**	**96.67%**	**96.67%**
RMSprop	**3.33%**	**3.33%**	**3.33%**	**3.33%**	**3.33%**	**95%**	**90%**	**40%**
SGD	**13.33%**	**8.33%**	**8.33%**	**3.33%**	**3.33%**	**3.33%**	**5%**	**3.33%**

TABLE 3.10 – *Infiuence of optimizer and learning rate on the MobileNet accuracy*

In this experiment, we fixed the Number of epochs and the batch size, and we augmented the number of learning rate and varied the optimizer. As we illustrated in the previous table, the optimizers are between Adam, RMSprop and SGD and the values of learning rates are : 0.1, 0.01, 0.001, 0.002, 0.004, 0.0001, 0.0002 and 0.0004. The influence of learning rate on the optimizers is explained in the following paragraph :

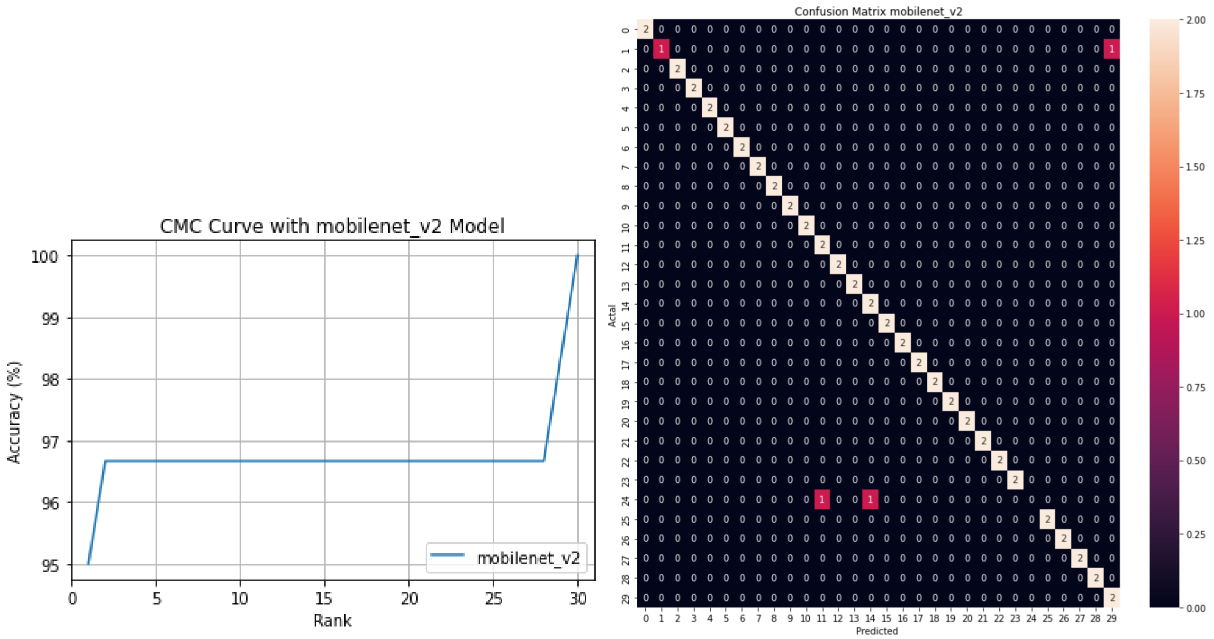
— The best learning rate in optimizer Adam is 0.001/0.0002/0.0004 because it gave us higher Accuracy 96.67%

— The best learning rate in optimizer RMSprop is 0.0001 because it gave us higher Accuracy 95%

— in optimizer SGD is giving us worst Accuracy in this modal it is 13.33 :%

Parameter / Metrics	BS :64	BS :32	BS :64	BS :64
	Opt :Adam	Opt :Adam	Opt :RMS	Opt :Adam
	NE :50	NE :25	NE :50	NE :50
	Lr :0.001	Lr :0.001	Lr :0.0002	Lr :0.0004
Accuracy	**95%**	**80%**	**93%**	**95%**
F1 Score	**94%**	**74%**	**91%**	**95%**
Precision	**93%**	**73%**	**89%**	**97%**
Recall	**95%**	**80%**	**93%**	**95%**

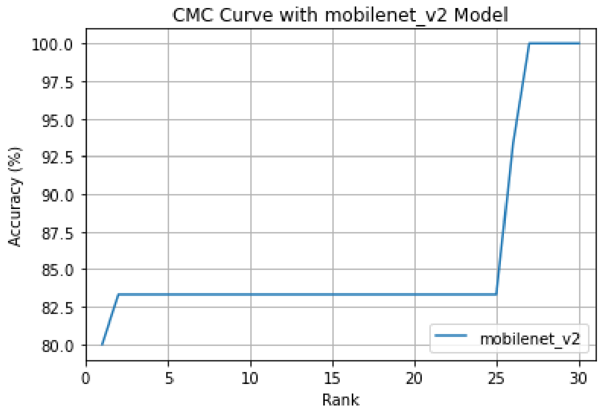
TABLE 3.11 – *Summary Accuracy of MobileNet Model*



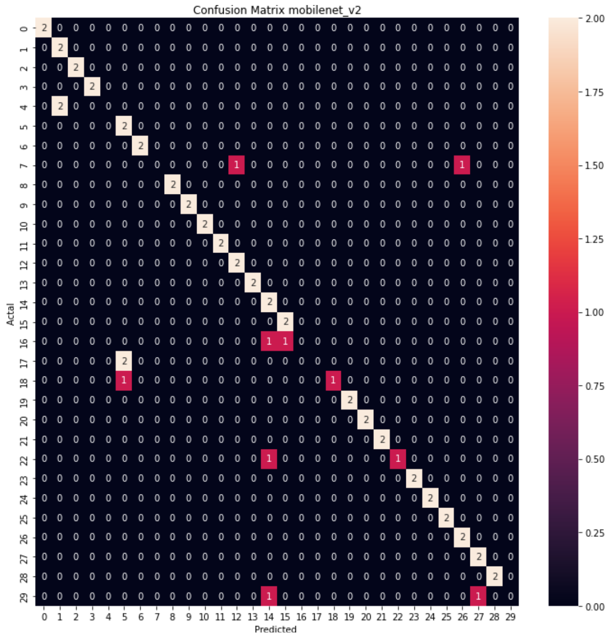
(a) CMC *(b) CM*

FIG 3.15 – *CM and CMC with accuracy 95%*

There were 28 correct class identifications and 04 incorrect class identifications in fig. For example, subject number 24 is assigned to class number 11 and 14. As seen in this graph, recognition accuracy is 95% at Rank-1, 96.50% from Rank 02 to Rank 28,and 100% from Rank 28 to Rank 30.



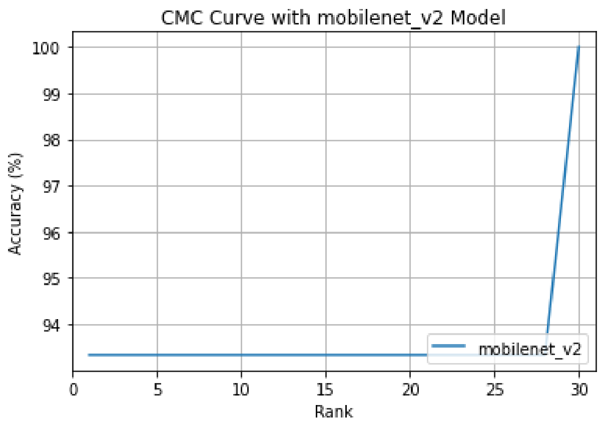
(a) CMC



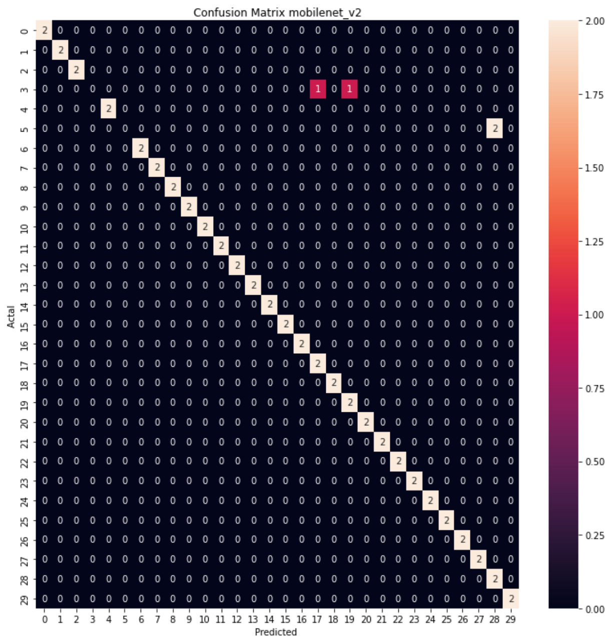
(b) CM

FIG 3.16 – *CM and CMC with accuracy 80%*

There were 23 correct class identifications and 07 incorrect class identifications in fig. For example, subject number 17 is assigned to class number 05. As seen in this graph, recognition accuracy is 80% at Rank-1, 83% from Rank 02 to Rank 25, and 98% from Rank 25 to Rank 27,and 100% from Rank 27 to Rank 28.



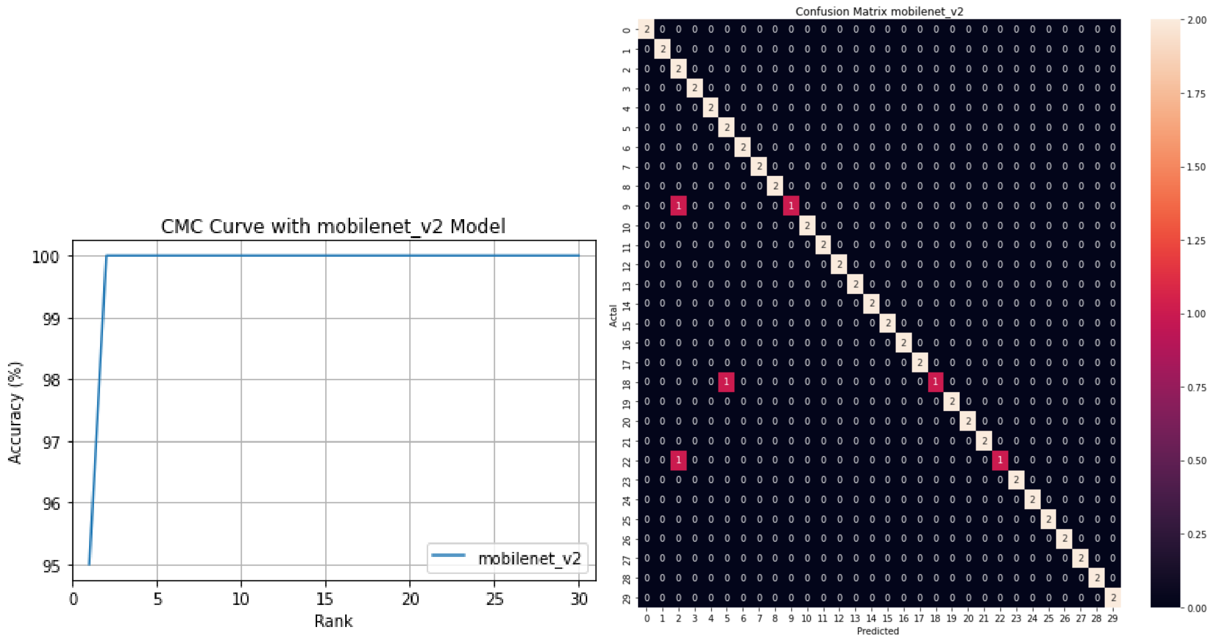
(a) CMC



(b) CM

FIG 3.17 – *CM and CMC with accuracy 93%*

There were 28 correct class identifications and 02 incorrect class identifications in fig. For example, subject number 05 is assigned to class number 28. As seen in this graph, recognition accuracy is 93.20% at Rank-1,and 100% from Rank 28 to Rank 30.



(a) CMC *(b) CM*

FIG 3.18 – *CM and CMC with accuracy 95%*

There were 27 correct class identifications and 03 incorrect class identifications in fig. For example, subject number 22 is assigned to class number 02. As seen in thisgraph, recognition accuracy is 95% at Rank-1,and 100% from Rank 02 to Rank 30.

5 COMPARATIVE STUDY

In this section, we make a meaningful comparison with works that used the same dataset for finger veins recognition .Table 3.12 reports the comparison statistics.

Paper	Published Year	Feature Extraction Method	database	Journal or Publisher	Accuracy %
Kumar et al.	2011	Gabor filter with morphological processing	HKPU (105 categories)	IEEE Transactions on image processing	90.08
Yu L., et al.	2013	Polydirectional Local Line Binary Pattern	SDUMLA-HMT	2013 International conference on ICT Convergence (ICTC) IEEE	99.21
Xie SJ., etal.	2014	Block-based average absolute deviation (ADD)features	SDUMLA-HMT	Cognitive Computation	97.76
Hoang TV., et al.	2015	MFRAT & GridPCA	SDUMLA-HMT	2015 Seventh International Conference on Knowledge and Systems Engineering (KSE)	95.67
Li Z Z., et al.	2016	SPCF	SDUMLA-HMT	IEEE International Joint Conference on Biometrics	92.71
Qiu S., et al.	2016	Dula-sliding window + location + Pseudo-elliptical transformer + 2D-PCA	SDUMLA-HMT	Expert Systems with Applications	97.61
Wen JL., et al	2017	CNN (based on AlexNet)	SDUMLA-HMT	IEEE Conference on Industrial Electronics and applications	99.53
Banerjee A.,et al.	2018	CLAHE + directional dilation	SDUMLA-HMT	Multimedia Tools and Applications	90.72
Rig D., et al.	2019	CNN (Proposed CNN)	SDUMLA-HMT	IEEE Transactions on Information Forensics and Security	98.90
In this paper	2022	CNN (Based on vgg16-vgg19-mobilenet-inception)	SDUMLA-HMT / OWN(FV-SIPL)		99.25 / 99.08

From Table 3.12, we notice that our system performs very well with VGG 19 model compared to other methods. Despite a number of subjects is different, but our proposed system presents a high accuracy in terms of accuracy 97%.

CONCLUSION

We have discussed in this chapter our used database ,and seen the criteria that evaluate our work . In this chapter, we presented some tests carried out on the different parameters used in our finger vein pattern recognition system with 4 different modalities vgg16 and vgg19 and inception and Mobilnet using softmax as classifier and compared our work with some papers published in the domain

General Conclusion and Perspectives

The work carried out within the framework of this graduation thesis aims to study one of the biometric systems allowing to identify and classifying the individuals according to the vein of their finger ,using the modern technique deep learning for Deep feature extraction and classification , the precision of the recognition plays an important role, this biometric technology is considered to be very strong in terms of security,Because of its biometric characteristics which are unique to the individual, with almost zero possibility that other individuals may have the same characteristics. Even for the case of identical twins We worked on how to raise the accuracy of identifying and classifying individuals in the biometric system (finger veins) using the methods : We chose the following four methods : MobileNet, Inception V3, VGG19 and 16 with various types of optimizers Adam and RMSprop and SGD Thanks to these methods, we have reached an ideal accuracy rate , which is very interesting because it makes our system more reliable and allows us to achieve the goal we had set ourselves at the start : to extract finger vein features and classify theme

Bibliography

[Akay et al., 2021] Akay, M., Du, Y., Sershen, C. L., Wu, M., Chen, T. Y., Assassi, S., Mohan, C., and Akay, Y. M. (2021). Deep learning classification of systemic sclerosis skin using the mobilenetv2 model. *IEEE Open Journal of Engineering in Medicine and Biology*, 2 :104–110.

[Ayan and Ünver, 2019] Ayan, E. and Ünver, H. M. (2019). Diagnosis of pneumonia from chest x-ray images using deep learning. In *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, pages 1–5. Ieee.

[Bakshi and Bakshi, 2018] Bakshi, K. and Bakshi, K. (2018). Considerations for artificial intelligence and machine learning : Approaches and use cases. In *2018 IEEE Aerospace Conference*, pages 1–9. IEEE.

[BENAGGA and TELIB, 2016] BENAGGA, L. T. A. and TELIB, L. (2016). Reconnaissance des personnes basée sur l'empreinte de l'articulation de doigt. *Master académique, UniversitéUKM Ouargla*.

[Boucherit et al., 2020] Boucherit, I., Zmirli, M. O., Hentabli, H., and Rosdi, B. A. (2020). Finger vein identification using deeply-fused convolutional neural network. *Journal of King Saud University-Computer and Information Sciences*.

[Bouchrika, 2018] Bouchrika, I. (2018). A survey of using biometrics for smart visual surveillance : Gait recognition. In *Surveillance in Action*, pages 3–23. Springer.

[Byrd et al., 2009] Byrd, K. A., Szu, H., and Chouikha, M. F. (2009). Implications of the advanced mini-max (amm) classifier on non-cooperative standoff biometrics. In *Independent Component Analyses, Wavelets, Neural Networks, Biosystems, and Nanoengineering VII*, volume 7343, page 734315. International Society for Optics and Photonics.

[Chaari, 2009] Chaari, A. (2009). *Nouvelle approche d'identification dans les bases de données biométriques basée sur une classification non supervisée*. PhD thesis, Université d'Evry-Val d'Essonne.

[Dargan and Kumar, 2020] Dargan, S. and Kumar, M. (2020). A comprehensive survey on the biometric recognition systems based on physiological and behavioral modalities. *Expert Systems with Applications*, 143 :113114.

[Dumoulin and Visin, 2016] Dumoulin, V. and Visin, F. (2016). A guide to convolution arithmetic for deep learning. *arXiv preprint arXiv :1603.07285*.

[El-Abed, 2011] El-Abed, M. (2011). *Évaluation de système biométrique*. PhD thesis, Université de Caen.

[Gaur et al., 2012] Gaur, S., Shah, V., and Thakker, M. (2012). Biometric recognition techniques : a review. *International journal of advanced research in electrical, electronics and instrumentation engineering*, 1(4) :282–290.

[Goodfellow et al., 2016] Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep learning*. MIT press.

[Guo et al., 2019] Guo, X.-j., Li, D., Zhang, H.-g., and Yang, J.-f. (2019). Image restoration of finger-vein networks based on encoder-decoder model. *Optoelectronics Letters*, 15(6) :463–467.

[Jain et al., 2007] Jain, A. K., Flynn, P., and Ross, A. A. (2007). *Handbook of biometrics*. Springer Science & Business Media.

[Jain et al., 2004] Jain, A. K., Ross, A., and Prabhakar, S. (2004). An introduction to biometric recognition. *IEEE Transactions on circuits and systems for video technology*, 14(1) :4–20.

[Kapoor et al., 2021] Kapoor, K., Rani, S., Kumar, M., Chopra, V., and Brar, G. S. (2021). Hybrid local phase quantization and grey wolf optimization based svm for finger vein recognition. *Multimedia Tools and Applications*, 80(10) :15233–15271.

[Kavala and Pothuraju, 2022] Kavala, S. A. P. N. and Pothuraju, R. (2022). Detection of grape leaf disease using transfer learning methods : Vgg16 & vgg19. In *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, pages 1205–1208. IEEE.

[Khanam et al., 2019] Khanam, R., Khan, R., and Ranjan, R. (2019). Analysis of finger vein feature extraction and recognition using da and knn methods. In *2019 Amity international conference on artificial intelligence (AICAI)*, pages 477–483. IEEE.

[Khellat-Kihel et al., 2014] Khellat-Kihel, S., Cardoso, N., Monteiro, J., Benyettou, M., et al. (2014). Finger vein recognition using gabor filter and support vector machine. In *International image processing, applications and systems conference*, pages 1–6. IEEE.

[Kost, 2018] Kost, A. (2018). Applying neural networks for tire pressure monitoring systems.

[Kumar et al., 2020] Kumar, A., Sarkar, S., and Pradhan, C. (2020). Malaria disease detection using cnn technique with sgd, rmsprop and adam optimizers. In *Deep Learning Techniques for Biomedical and Health Informatics*, pages 211–230. Springer.

[Kumar and Imran, 2010] Kumar, G. H. and Imran, M. (2010). Research avenues in multimodal biometrics. *IJCA Special Issue on "Recent Trends in Image Processing and Pattern Recognition", RTIPPR*, 3 :1–8.

[Laith et al., 2021] Laith, A., Jinglan, Z., Humaidi, A. J., Ayad, A.-D., Ye, D., Al-Shamma, O., Santamaria, J., Fadhel, M. A., Muthana, A.-A., and Laith, F. (2021). Review of deep learning : concepts, cnn architectures, challenges, applications, future directions. *Journal of Big Data*, 8(1).

[Lee and Lee, 2019] Lee, J.-H. and Lee, J.-H. (2019). A reliable defect detection method for patterned wafer image using convolutional neural networks with the transfer learning. In *IOP Conference Series : Materials Science and Engineering*, volume 647, page 012010. IOP Publishing.

[Li et al., 2021a] Li, S., Zhang, B., Zhao, S., and Yang, J. (2021a). Local discriminant coding based convolutional feature representation for multimodal finger recognition. *Information Sciences*, 547 :1170–1181.

[Li et al., 2021b] Li, Z., Liu, F., Yang, W., Peng, S., and Zhou, J. (2021b). A survey of convolutional neural networks : analysis, applications, and prospects. *IEEE Transactions on Neural Networks and Learning Systems*.

[Liu et al., 2017] Liu, W., Li, W., Sun, L., Zhang, L., and Chen, P. (2017). Finger vein recognition based on deep learning. In *2017 12th IEEE conference on industrial electronics and applications (ICIEA)*, pages 205–210. IEEE.

[Makinde et al., 2014] Makinde, A. S., Nkansah-Gyekye, Y., and Laizer, L. S. (2014). Enhancing the accuracy of biometric feature extraction fusion using gabor filter and mahalanobis distance algorithm. *arXiv preprint arXiv :1407.6748*.

[Meng et al., 2020] Meng, X., Xi, X., Li, Z., and Zhang, Q. (2020). Finger vein recognition based on fusion of deformation information. *Ieee Access*, 8 :50519–50530.

[Meng et al., 2021] Meng, X., Zheng, J., Xi, X., Zhang, Q., and Yin, Y. (2021). Finger vein recognition based on zone-based minutia matching. *Neurocomputing*, 423 :110–123.

[Morizet, 2009] Morizet, N. (2009). *Reconnaissance biométrique par fusion multimodale du visage et de l'iris*. PhD thesis, Télécom ParisTech.

[Najm et al., 2019] Najm, H., Ansaf, H., and Hassen, O. A. (2019). An effective implementation of face recognition using deep convolutional network. *Journal of Southwest Jiaotong University*, 54(5).

[Podgantwar and Raut, 2013] Podgantwar, U. D. and Raut, U. (2013). Extraction of finger vein patterns using gabor filter in finger vein image profiles. *International Journal of Engineering Research and Technology*, 2(6) :3294–3298.

[Qin and El-Yacoubi, 2015] Qin, H. and El-Yacoubi, M. A. (2015). Finger-vein quality assessment by representation learning from binary images. In *International Conference on Neural Information Processing*, pages 421–431. Springer.

[Qin and El-Yacoubi, 2017] Qin, H. and El-Yacoubi, M. A. (2017). Deep representation-based feature extraction and recovering for finger-vein verification. *IEEE Transactions on Information Forensics and Security*, 12(8) :1816–1829.

[Radzi et al., 2016] Radzi, S. A., Hani, M. K., and Bakhteri, R. (2016). Finger-vein biometric identification using convolutional neural network. *Turkish Journal of Electrical Engineering & Computer Sciences*, 24(3) :1863–1878.

[Rezende et al., 2018] Rezende, E., Ruppert, G., Carvalho, T., Theophilo, A., Ramos, F., and Geus, P. d. (2018). Malicious software classification using vgg16 deep neural network's bottleneck features. In *Information Technology-New Generations*, pages 51–59. Springer.

[Ross and Jain, 2003] Ross, A. and Jain, A. (2003). Information fusion in biometrics. *Pattern recognition letters*, 24(13) :2115–2125.

[Sabhanayagam et al., 2018] Sabhanayagam, T., Venkatesan, V. P., and Senthamaraikannan, K. (2018). A comprehensive survey on various biometric systems. *International Journal of Applied Engineering Research*, 13(5) :2276–2297.

[Sandler et al., 2018] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., and Chen, L.-C. (2018). Mobilenetv2 : Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4510–4520.

[Sanjekar and Patil, 2013] Sanjekar, P. and Patil, J. (2013). An overview of multimodal biometrics. *Signal & Image Processing*, 4(1) :57.

[Seidaliyeva et al., 2020] Seidaliyeva, U., Akhmetov, D., Ilipbayeva, L., and Matson, E. T. (2020). Real-time and accurate drone detection in a video with a static background. *Sensors*, 20(14) :3856.

[Shaheed et al., 2022a] Shaheed, K., Mao, A., Qureshi, I., Kumar, M., Hussain, S., Ullah, I., and Zhang, X. (2022a). Ds-cnn : A pre-trained xception model based on depth-wise separable convolutional neural network for finger vein recognition. *Expert Systems with Applications*, 191 :116288.

[Shaheed et al., 2022b] Shaheed, K., Mao, A., Qureshi, I., Kumar, M., Hussain, S., and Zhang, X. (2022b). Recent advancements in finger vein recognition technology : Methodology, challenges and opportunities. *Information Fusion*, 79 :84–109.

[Shen et al., 2018] Shen, L., Zhang, Q., Cao, G., and Xu, H. (2018). Fall detection system based on deep learning and image processing in cloud environment. In *Conference on Complex, Intelligent, and Software Intensive Systems*, pages 590–598. Springer.

[Simonyan and Zisserman, 2014] Simonyan, K. and Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv :1409.1556*.

[Sultan et al., 2019] Sultan, H. H., Salem, N. M., and Al-Atabany, W. (2019). Multi-classification of brain tumor images using deep neural network. *IEEE Access*, 7 :69215–69225.

[Tao et al., 2021] Tao, Z., Zhou, X., Xu, Z., Lin, S., Hu, Y., and Wei, T. (2021). Finger-vein recognition using bidirectional feature extraction and transfer learning. *Mathematical Problems in Engineering*, 2021.

[Toufik, 2016] Toufik, H. (2016). *Reconnaissance Biométrique Multimodale basée sur la fusion en score de deux modalités biométriques : l'empreinte digitale et la signature manuscrite cursive en ligne*. PhD thesis, Ph. D. thesis, Universite Badji Mokhtar-Annaba.

[Vazhenina and Markov, 2020] Vazhenina, D. and Markov, K. (2020). End-to-end noisy speech recognition using fourier and hilbert spectrum features. *Electronics*, 9(7) :1157.

[Veluchamy and Karlmarx, 2016] Veluchamy, S. and Karlmarx, L. (2016). System for multimodal biometric recognition based on finger knuckle and finger vein using feature-level fusion and k-support vector machine classifier. *IET Biometrics*, 6(3) :232–242.

[Veluchamy and Karlmarx, 2017] Veluchamy, S. and Karlmarx, L. (2017). System for multimodal biometric recognition based on finger knuckle and finger vein using feature-level fusion and k-support vector machine classifier. *IET Biometrics*, 6(3) :232–242.

[Wang et al., 2012] Wang, K.-Q., Khisa, A. S., Wu, X.-Q., and Zhao, Q.-S. (2012). Finger vein recognition using lbp variance with global matching. In *2012 international conference on wavelet analysis and pattern recognition*, pages 196–201. IEEE.

[Wu and Liu, 2011] Wu, J.-D. and Liu, C.-T. (2011). Finger-vein pattern identification using svm and neural network technique. *Expert Systems with Applications*, 38(11) :14284–14289.

[Yuan and Mu, 2014] Yuan, L. and Mu, Z. (2014). Ear recognition based on gabor features and kfda. *The Scientific World Journal*, 2014.

[Zhou et al., 2015] Zhou, L., Yang, G., Yang, L., Yin, Y., and Li, Y. (2015). Finger vein image quality evaluation based on support vector regression. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, 8(8) :211–222.

[Zhu et al., 2010] Zhu, W., Zeng, N., Wang, N., et al. (2010). Sensitivity, specificity, accuracy, associated confidence interval and roc analysis with practical sas implementations. *NESUG proceedings : health care and life sciences, Baltimore, Maryland*, 19 :67.

Abstract

Cross-sectoral insecurity increased crime, and piracy is all major topics these days. Furthermore, people's movement, financial transactions, and access to services necessitate an urgent need to guarantee their identity. Traditional security solutions rely on previously learned information (PIN codes, passwords) or access tokens (keys, identifiers, badges). However, in many situations, these technologies are less reliable because they are unable to discern between legitimate persons and scammers. In this master’s thesis, we chose a deep learning finger vein recognition system. This system is difficult to Falsification. There are numerous benefits, including ease of use and inexpensive cost. Our work can be divided into two stages. To start, data augmentation utilizing various geometrical techniques is used to compensate for the paucity of training samples required for the deep learning model's training. Second, the four CNN algorithms are used to execute feature extraction and classification tasks in order to validate the person's identity. The suggested model's performance is tested and evaluated using the SDUMLA dataset. With Vgg16 and 97.22 percent with Vgg19, 90 percent with the inception model, and 95 percent with MobilenetV2, our suggested technique for the SDUMLA database achieved an accuracy of 93 percent with Vgg16 and 97.22 percent with Vgg19, 90 percent with the inception model, and 95 percent with MobilenetV2. The proposed work achieves good performance when compared to existing methods, according to the findings of the experiments.

Keywords: Finger vein, recognition, classification, CNN, deep learning, data augmentation, feature extraction.

Résumé

L’insécurité intersectorielle a augmenté la criminalité, et la piraterie est aujourd’hui un sujet majeur. En outre, le mouvement des personnes, les transactions financières et l’accès aux services nécessitent un besoin urgent de garantir leur identité. Les solutions de sécurité traditionnelles reposent sur des informations déjà apprises (codes PIN, mots de passe) ou des jetons d’accès (clés, identifiants, badges). Cependant, dans de nombreuses situations, ces technologies sont moins fiables parce qu’elles sont incapables de discerner entre les personnes légitimes et les fraudeurs. Dans ce mémoire de maîtrise, nous avons choisi un système de reconnaissance profonde des veines des doigts. Ce système est difficile à falsifier. Il y a de nombreux avantages, y compris la facilité d’utilisation et le coût peu coûteux. Notre travail peut être divisé en deux étapes. Pour commencer, l’augmentation des données à l’aide de diverses techniques géométriques est utilisée pour compenser la rareté des échantillons de formation requis pour la formation du modèle d’apprentissage profond. Deuxièmement, les quatre algorithmes CNN sont utilisés pour exécuter des tâches d’extraction et de classification des caractéristiques afin de valider l’identité de la personne. La performance du modèle suggéré est testée et évaluée à l’aide de l’ensemble de données SDUMLA. Avec Vgg16 et 97,22 pour cent avec Vgg19, 90 pour cent avec le modèle initial et 95 pour cent avec MobilenetV2, notre technique suggérée pour la base de données SDUMLA a atteint une précision de 93 pour cent avec Vgg16 et 97,22 pour cent avec Vgg19, 90 pour cent avec le modèle initial, et 95 % avec MobilenetV2. Les travaux proposés donnent de bons résultats par rapport aux méthodes existantes, selon les résultats des expériences.

Mots clés : Veine du doigt Reconnaissance, Classification, CNN, deep learning, l'augmentation de données, l'extraction de caracteristiques .

الملخص

إن انعدام الأمن عبر القطاعات ، وزيادة الجريمة ، والقرصنة كلها مواضيع رئيسية هذه الأيام. علاوة على ذلك ، فإن حركة الناس والمعاملات المالية والوصول إلى الخدمات تتطلب حاجة ملحة لضمان هويتهم. تعتمد حلول الأمان التقليدية على المعلومات التي تم تعلمها مسبقًا (رموز PIN وكلمات المرور (أو رموز الوصول)المفاتيح والمعرفات والشارات(. ومع ذلك ، في كثير من الحالات ، تكون هذه التقنيات أقل موثوقية لأنها غير قادرة على التمييز بين الأشخاص الشرعيين والمحتالين. في هذا المثال ، اخترنا نظام التعرف على وريد الإصبع التعلم العميق. هذا النظام يصعب تزويره. هناك فوائد عديدة منها سهولة الاستخدام والتكلفة غير المكلفة ويمكن تقسيم عملنا إلى مرحلتين. للبدء ، يتم استخدام زيادة البيانات باستخدام تقنيات هندسية مختلفة للتعويض عن ندرة عينات التدريب المطلوبة لتدريب نموذج التعلم العميق. ثانيًا ، تُستخدم خوارزميات CNN الأربعة لتنفيذ مهام استخراج الميزات والتصنيف من أجل التحقق من هوية الشخص. يتم اختبار أداء النموذج المقترح وتقييمه باستخدام مجموعة بيانات

SDUMLA. باستخدام Vgg16 و 97.22 بالمائة معVgg19 ، و 90 بالمائة مع نموذج البداية ، و 95 بالمائة معMobilenetV2 ، حققت تقنيتنا المقترحة لقاعدة بيانات SDUMLA دقة بنسبة 93 بالمائة مع Vgg16 و 97.22 بالمائة معVgg19 ، و 90 بالمائة مع نموذج البداية ، و 95٪ مع MobilenetV2. ويحقق العمل المقترح أداءً جيداً عند مقارنته بالأساليب الحالية حسب نتائج التجارب.

كلمات مفتاحية : ،وريد الصبع , التعرف , التصنيف CNN الكلمات المفتاحية التعلم العميق ، زيادة البيانات ، استخراج الميزات