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Speciality of Embedded Systems Electronics (ESEM)

a Master’s Thesis Titled:

A Feature Extraction Method for Iris Recognition System Based on CNN(Transfer Learning)

Presented and Supported by:

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A thesis submitted in fulfilment of the requirements

to obtain the degree of Master in: Electronics

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Academic Year: 2022/2023

Dedication

⌈ I dedicate this Thesis:

to my family and many friends.

A special feeling of gratitude to my loving parents,

whose words of encouragement and push for tenacity

ring in my ears.

To all the professors and teachers,

I have had during All my school curriculum and

which allowed me to succeed in my studies.

My Brother and Sisters have never left my side and

are very special.

I also dedicate this Thesis to my many friends who

have supported me throughout the process. I will

always appreciate all they have done. ⌋

∼ *Aymen*

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always appreciate all they have done. ⌋

∼ *Salim*

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Abstract

Iris recognition refers to the automated process of recognising individuals based on their iris patterns. The seemingly stochastic nature of the iris stroma makes it a distinctive cue for biometric recognition. This textural descriptor has been observed to be a robust feature descriptor with very low false match rates and low computational complexity. However, recent advancements in deep learning and computer vision indicate that generic descriptors extracted using Convolutional Neural Networks (CNNs) are able to represent complex image characteristics. Deep CNN is a powerful visual model of machine learning. We tend to present robustness and an effective structure for the iris recognition system. The image first pass through these stages: enhancing the image quality, determining the iris and pupil centre and radius for iris segmentation, and converting the image from the Cartesian coordinates to the polar coordinates to reduce the time of processing. The proposed system is named IRISNet which extracts the feature and classifies them automatically without any domain knowledge. The architecture of IRISNet consists of CNN layers to extract features and a softmax layer to classify them into N classes for training CNN, the back-propagation algorithm and Adam optimisation method are used for updating the weights and the learning rate, respectively. The performance of the proposed system was evaluated using the Sdumla iris database. The results obtained from the proposed system outperform the supervised classification model (VGG16, MobileNet, Inception, and Xception). The identification rate is 97.32% and 96.43% for original and normalised images, respectively. The recognition time per person is less than 1s. Experimental results conclude that the proposed work obtained good performance compared to existing methods.

Keywords: Iris, CNN, Training, Convolution, Deep Learning, Image Recognition, Testing, Feature Extraction.

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List of Abbreviations

ACC	**A**ccuracy
AE	**A**utoencode
AP	**A**verage **P**recision
AI	**A**rtificial **I**ntelligence
CASIA	**C**hinese **A**cademy of **S**ciences **I**nstitute of **A**utomation
CMC	**C**umulative **C**atch **C**haracteristics
CNN	**C**onvolutional **N**eural **N**etworks
DL	**D**eep **L**earning
DNN	**D**eep **N**eural **N**etworks
FN	**F**alse **N**egative
FP	**F**alse **P**ositive
ML	**M**achine **L**earning
RNN	**R**ecurrent **N**eural **N**etworks
TN	**T**rue **N**egative
TP	**T**rue **P**ositive
SL	**S**upervised **L**earning
UL	**U**nsupervised **L**earning
VGG	**V**isual **G**eometry **G**roup

General Introduction

Biometrics is the automated recognition of individuals based on their behavioural and biological characteristics. Biometric authentication is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance. Biometric identifiers are the distinctive, measurable characteristics used to label and describe individuals. Biometric identifiers are often categorised as physiological characteristics which are related to the shape of the body. Examples include, but are not limited to fingerprint, palm veins, face, and iris recognition. Behavioural characteristics are related to the behaviour of a person, including typing rhythm, gait, and voice. Biometric data can be used to access information on a device like a smartphone, but there are also other ways biometrics can be used. Biometric authentication is based upon biometric recognition, which is an advanced method of recognising biological and behavioural characteristics of an individual. Overall, biometrics is a promising technology that has the potential to improve security and identification in various settings, from healthcare to military applications.

In our work, we chose iris recognition as the method for acquiring biometric data needed for issuing unique IDs. Iris recognition is widely considered to be the most accurate modality of biometric identification. The technology uses mathematical pattern-recognition techniques on video images of one or both of the irises of an individual's eyes, whose complex patterns are unique, stable, and can be seen from some distance. The iris of the eye has been described as the ideal part of the human body for biometric identification for several reasons, including its stability, uniqueness, and high entropy of iris templates.

Our work is divided into three chapters, and the overall dissertation document is presented as follows:

After introducing both the topic and the problem statement. The first chapter, *"Biometrics and Artificial Intelligence"*, will present an overview about biometrics and how its works, and talk about biometrics systems, advantages and disadvantages, characteristics, applications of Biometrics and multimodale and also focus on machine and deep learning with description of Convolutional Neural Network (CNN).

Moreover, the second chapter, *"Proposed Iris Recognition"*, will mainly discusses the most popular approaches and techniques for deep learning and machine learning-based Iris recognition, which are based on various databases.

Likewise, the third chapter, *"Results and Discussions"*, will provide a description of the database used, training and testing dataset SDUMLA with four models (VGG16, MOBILENETV2, InceptionV3, XCEPTION) and a comparative analysis. Then, concluding with the research results and a conclusion.

Chapter One:

Biometrics and Artificial Intelligence

Introduction

Iris recognition is the automated process of identifying people based on their iris patterns. It is one of the most promising biometric identification techniques now in use and is frequently used in a variety of industries.

Large databases, Algorithms for iris recognition have a high matching efficiency according to benefits like autonomous learning, high accuracy, and strong generalisation capacity.

Recently, several deep learning algorithms have been used in biometric recognition [1, 2].

1.1 Biometric

Biometric data is linked to unique human characteristics. The most promising methods for user authentication are biometric systems. Biometric authentication may be preferred over many traditional strategies such as smart cards and passwords because it is difficult to steal information using biometrics.

The biometric recognition device allows you to recognise a person under surveillance and access control. Physiological and behavioural characteristics are generally classified into biometric identifiers.

Physiological features refer to physical features of the body, such as fingerprints, palm veins, DNA, facial recognition, iris ... etc [3].

1.1.1 Biometric System

A generic biometric system has 4 important modules: the sensor module which captures the trait in the form of raw biometric data; the feature extraction module which processes the data to extract a feature set that is a compact representation of the trait; the matching module which employs a classifier to compare the extracted feature set with the templates residing in the database to generate matching scores; the decision module which uses the matching scores to either determine the identity or validate a claimed identity.

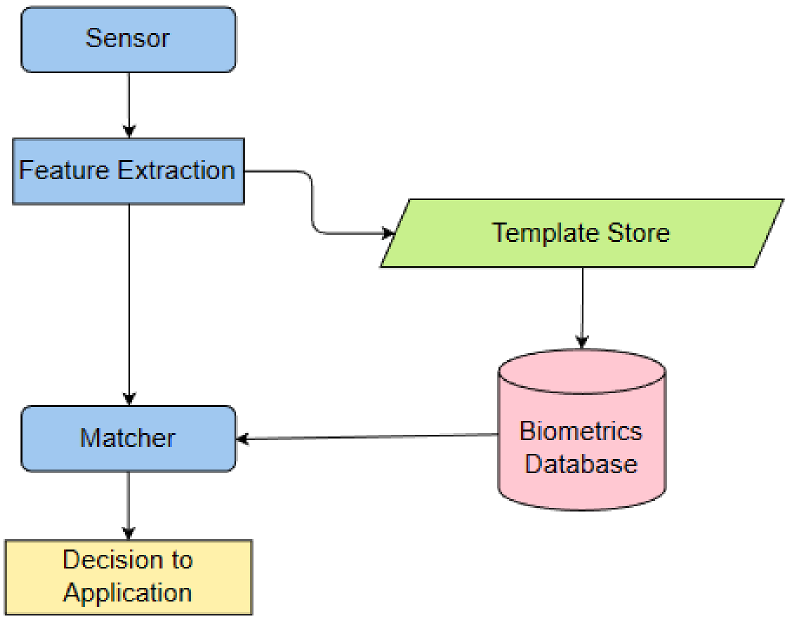


FIGURE 1.1: General block diagram of a traditional biometric system.

1.1.1.1 Sensor Module / Image Acquisition

To collect raw biometric information about a person, such as audio, video, and image data or other signals.

1.1.1.2 Feature Extraction Module

The process of using computer vision, machine learning, and pattern recognition tools to extract specific biometric traits and build templates.

1.1.1.3 Database Module

Captured biometric data from users and saved several user templates.

1.1.1.4 Matching Module

To detect similarities between two biometrics samples, the currently retrieved features are compared to saved templates to get a match score or value.

1.1.1.5 Decision-making Module

Compare results to a specific threshold to decide whether accepted or rejected.

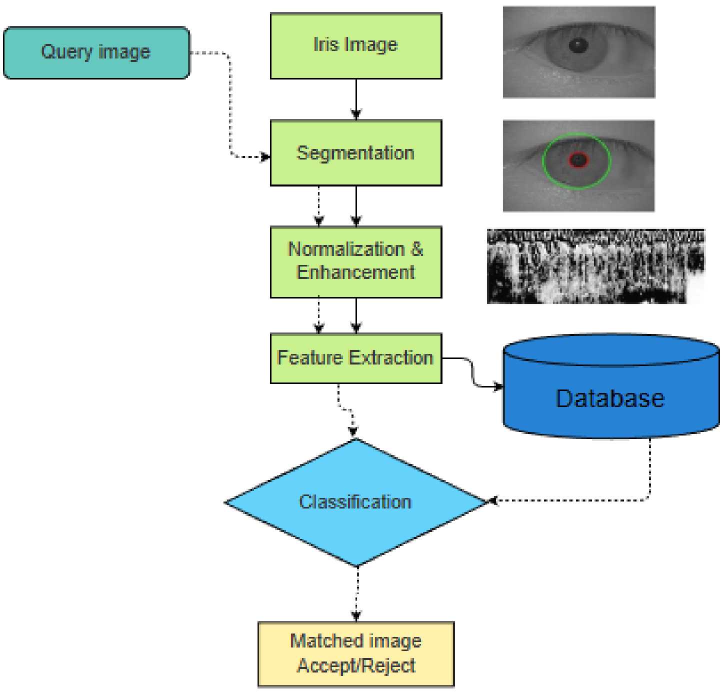


FIGURE 1.2: Working flow of iris recognition system.

1.1.2 Advantages and Disadvantages of Biometrics

Advantages	Disadvantages
Increase security	False positives
Can not be copied	Adaptability to rate of change
Can not be shared	Scalability
Convenience	Difficult to control sensor
Auditable trial	Complex Processor
Accuracy	Expensive
Can not be lost	Financial cost
Minimise paperwork	Privacy issues

TABLE 1.1: Advantages and Disadvantages of Biometrics [4].

1.1.3 Applications of Biometrics

1.1.3.1 Access Control

Access to physical locations like buildings, rooms, and vehicles can be restricted using biometrics.

1.1.3.2 Identification and Verification

A person's identity can be verified using biometrics for a variety of reasons, including voting, banking, and receiving security clearance.

1.1.3.3 Marketing

Marketing may customise goods and services depending on client preferences by using biometrics.

1.1.3.4 Healthcare

Medical errors can be decreased and patient identification can be improved.

1.1.4 Biometric Characteristics

Several biometric traits are used in a variety of applications. Each biometric has advantages and disadvantages, As a result, in addition to its performance, a biometric trait's selection for a certain application depends on a number of other factors. have outlined seven factors that influence whether a physical trait or behavioural trait can be used in a biometric application [5].

- **Universality:** Every person who uses the application should have this quality.
- **Uniqueness:** The population's members should sufficiently differ in terms of the provided trait.
- **Permanence:** The biometric characteristic of a person should be sufficiently stable over time with regard to the matching algorithm. A feature that drastically fluctuates over time is not a good option for a biometric.
- **Measurability:** The biometric attribute should be able to be collected and digitally stored using appropriate tools without the person experiencing undue hardship. Additionally, processing of the acquired raw data should be possible in order to extract representative feature sets.
- **Performance:** The application's limits should be met by the recognition accuracy and the resources needed to reach that accuracy.
- **Acceptability:** The intended target users of the program must be willing to provide the system access to their biometric trait.
- **Circumvention:** This relates to how easily a person's trait can be mimicked, either through mimicry for behavioural traits or artefacts (such as fake fingers) in the case of physical qualities.

1.1.5 Unimodal and Multimodal Biometrics System

Individuals are verified and identified using their physiological or behavioral characteristics utilizing biometric technology. These characteristics fall into two categories: unimodal and multimodal systems, while the former suffer from a number of flaws that lower the system's accuracy such as: noisy data, inter-class similarity, intra-class variation, spoofing, and non-universality. Yet, systems for multimodal biometric sensing and processing, which utilize the recognition and processing of two or more physiological or behavioral features, Have shown that they considerably increase the success rate of identification and verification.

1.1.5.1 Unimodal Biometric System

A system that utilizes a single biometric feature is known as a unimodal (or single) biometric system. According to reports, the accuracy and dependability of unimodal systems have constantly increased. However, as was previously mentioned, they frequently experience difficulties throughout the registration process as a result of:

- non-universality;
- Susceptibility To Circumvention;
- Lack of Individuality;
- noisy data.

In real-world applications, unimodal biometric systems perform less as expected. Consequently, using a multimodal biometric authentication system is a way to address these problems.

1.1.5.2 Multimodal Biometrics System

A very wide variety of civilian applications have the potential to embrace multimodal biometric systems in a significant way. E.g. banking security such as ATM security, check cashing and credit card transactions. Either a "genuine individual" type of decision or an "imposter" type of decision is made by a multimodal biometric system. The enrolment phase and the authentication phase are the two stages that multimodal biometrics typically operates in [6].

1.1.5.3 Modules of Multimodal Biometrics

- **Sensor module:-** Biometric modalities are recorded at the sensor module and provided as inputs for the feature extraction module.
- **Feature extraction module:** After preprocessing, features are extracted from several modalities at the feature extraction module. These features produce a condensed representation of these qualities or modalities, and the matching module is then given these features for comparison.
- **Matching module:** The retrieved features from the matching module are compared to the template(s) that are recorded in the database.
- **Decision-making module:** Based on the matching in the matching module, the user is either accepted or rejected in this module.

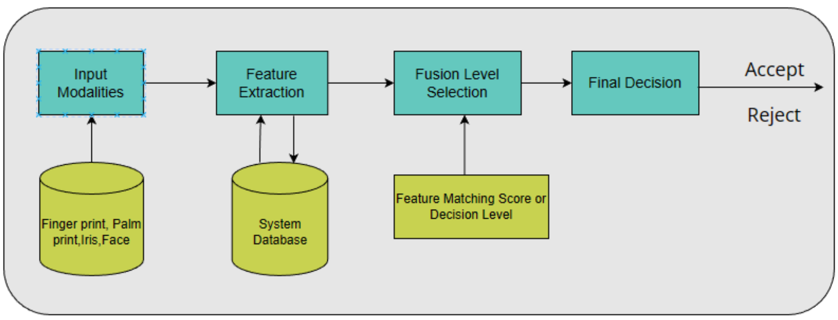


FIGURE 1.3: Block Diagram of Multimodal Systems.

1.1.6 Biometrics Modalities

According to the kind of human attribute it accepts as input, a biometric modality is nothing more than a category of a biometric system.

Most of the biometrics is statistical. The chance that the system is unique and trustworthy increases with the amount of sample data available. It may be used to measure a person's body and features using a variety of modalities, and behavioural patterns. The biological characteristics of the person are used to categorise the modalities [7].

1.1.6.1 Types of Biometric Modalities

The measuring of an individual's traits for the purpose of unique identification and verification is referred to as a biometric trait. These unique characteristics serve as the foundation for the development of the biometric recognition system. biometric traits are of two types, called physiological and behavioural traits.

Physiological traits are an individual's physical characteristics, such as fingerprint, hand and palm geometry, ear, deoxyribonucleic acid (DNA), palm vein and finger vein authentication, voice/speech, and Iris. Because of qualities like collectability, uniqueness, durability, and affordability for attaining verification and identification, these properties are widely recognised.

A person's walk, keystroke, signature, handwriting, and speech are examples of behavioural features, which are characteristics that describe their personality and behaviour [8].

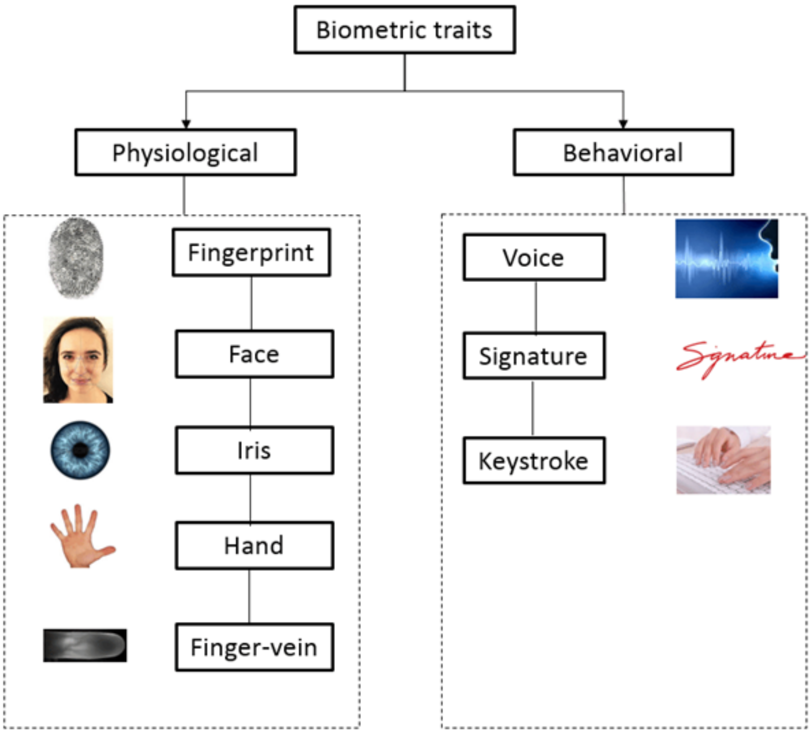


FIGURE 1.4: Classification of biometric traits [9].

1.1.6.2 Physiological Modality

This modality pertains to the shape and size of the body. E.g.

- Fingerprint Recognition;
- Hand Geometry Recognition System;
- Facial Recognition System;
- Iris Recognition System;
- Hand Geometry Recognition System;
- Retinal Scanning System;
- DNA Recognition System.

1.1.6.3 Behavioural Modality

This modality is related to changes in human behaviour over time. E.g.

- Gait (the way one walks);
- Rhythm of typing keys;
- Signature.

1.1.6.4 Combination of Both Modalities

This modality includes both traits, where the traits are depending upon physical as well as behavioural changes. E.g.

- **Voice Recognition:** It depends on the health, size, and shape of the vocal cord, nasal cavities, mouth cavity, shape of lips, etc., and the emotional status, age, and illness (behaviour) of a person.

1.1.6.5 Iris Recognition

Iris recognition is a new biometric identification method, making it crucial to conduct further study in this area. Iris localization, normalization, and feature extraction algorithms have made significant strides in recent years, making it possible to reliably recognize the iris and efficiently encode its patterns. However, storing and retrieving iris code for a sizable database is difficult. As the collection of iris templates grows, the iris matching time significantly increases. Because of this, the overall system performance could suffer [10].

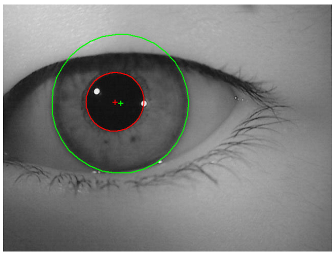


FIGURE 1.5: Iris Recognition

1.1.6.6 Fingerprint Recognition

On the surface of the fingertips, fingerprints are pictorial patterns of ridges and valleys. Minuae refers to the ridge's termination and ridge bifurcation. Everybody has a fingerprint that sets them apart from each other. The two fundamental presumptions that underlie fingerprint identification are invariance and singularity. When a fingerprint is invariant, it means that its properties remain constant over time. Singularity: The concept that no two people have the exact same fingerprint pattern [11].

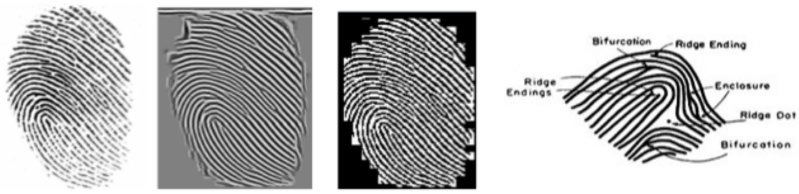


FIGURE 1.6: Fingerprint Recognition.

1.1.6.7 Face Recognition

Over the past few years, face recognition has emerged as the most crucial biometric authentication technique. Because there are so many possible uses, it has recently become a new important research topic. These applications cover a variety of topics, including personal identification, security access control, and computer-human interaction. Numerous face recognition techniques have been put forth. These techniques can be categorised into two categories: constituent-based and face-based. The link between human facial characteristics such as the eye(s), mouth, nose, profile silhouettes, and face border provides the basis for recognition in the constituent-based method [12].

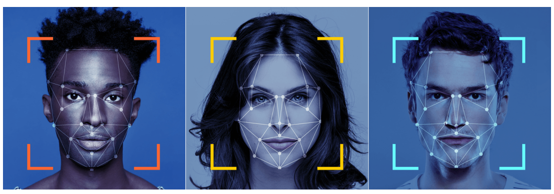


FIGURE 1.7: Face Recognition.

1.1.6.8 Ear Recognition

Ear Geometry Recognition uses the ear's shape to carry out identification. It is advised that human ears have specific properties and shapes in general. Infrared light and the capacity to distinguish at a distance can be utilised to eliminate hair [13].

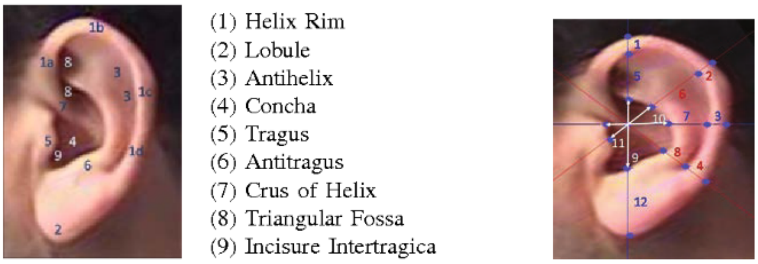


FIGURE 1.8: Ear Recognition [14, 15].

1.1.6.9 Voice Recognition:

Due to each person's unique pitch period, voice can also be used to identify them. It falls under the behavioural category because it depends on how one speaks. The vocal tract, mouth, nasal activities, and lip movements utilised in sound synthesis determine a person's voice [16].

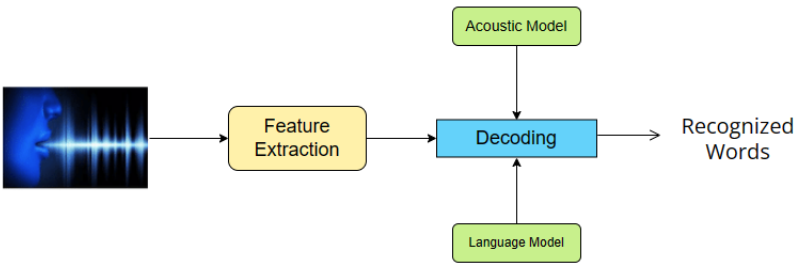


FIGURE 1.9: Voice Recognition

1.1.6.10 Handwritten Signature

A behavioural biometric called signature biometrics uses the pattern of a person's signature to identify them. Both static and dynamic signature recognition are used to operate it [13]. Below are the signature biometrics:

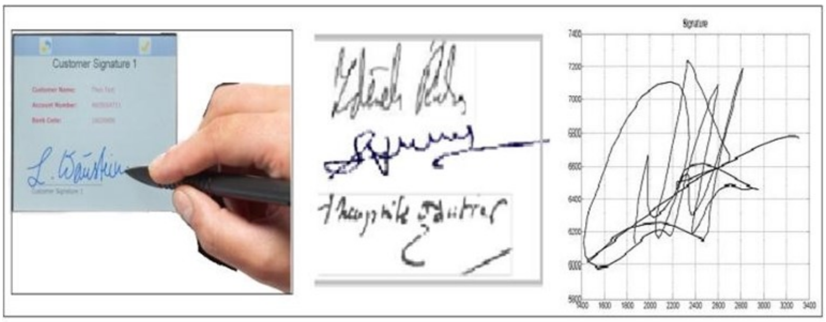


FIGURE 1.10: Handwritten signature

1.2 Deep Learning and Maching Learning

Making intelligent machines with AI is a scientific and engineering effort. especially complex computer programs. It has something to do with the related task of employing computers to analyse human intelligence [17, 18].

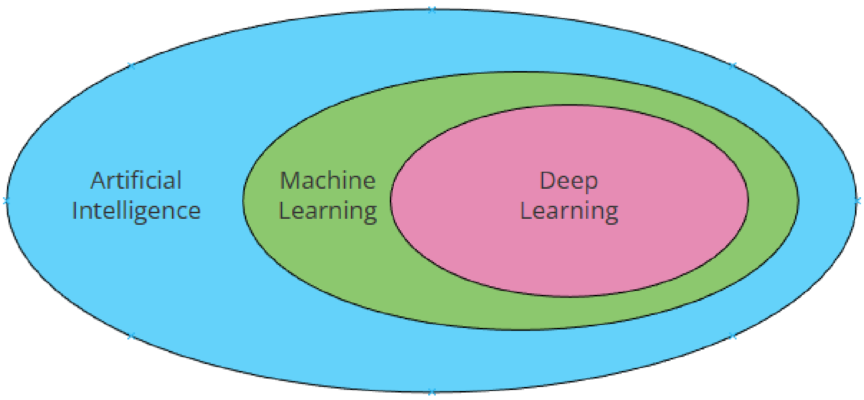


FIGURE 1.11: Deep learning Overview.

1.2.1 Machine Learning (ML)

Machine Learning is a subset of artificial intelligence that helps you build AI-driven applications [18].

It is used to train machines to handle data more effectively. Sometimes, even after viewing the data, we are unable to evaluate or apply the information. We then use machine learning in that situation [19].

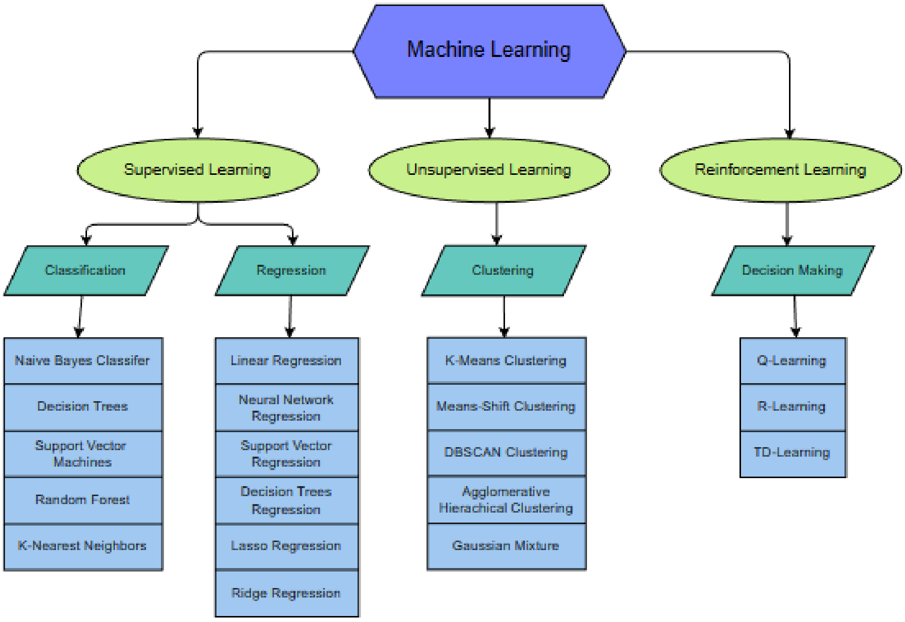


FIGURE 1.12: Types of Machine Learning [20].

1.2.2 Deep Learning (DL)

Deep Learning is a subset of machine learning that uses vast volumes of data and complex algorithms to train a model [18].

The biological sciences are increasingly using an effective type of machine learning that helps computers to resolve perceptual difficulties like picture and speech recognition [21].

- **Deep Autoencoder:** Utilise a built-in statistical structure, these networks convert input patterns to a compressed hidden representation [22].

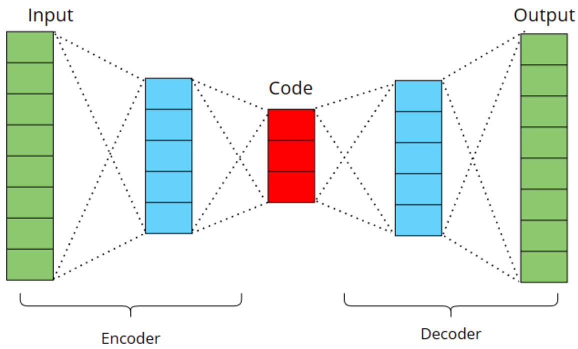


FIGURE 1.13: Structure of a basic AE.

- **Deep Recurrent Neural Network (RNN):** A type of artificial neural network known as an RNN adds loops to the feedforward neural network to increase its functionality.By having a recurrent hidden state whose activation at each step depends on that of the previous step, an RNN is able to process multiple inputs [23].

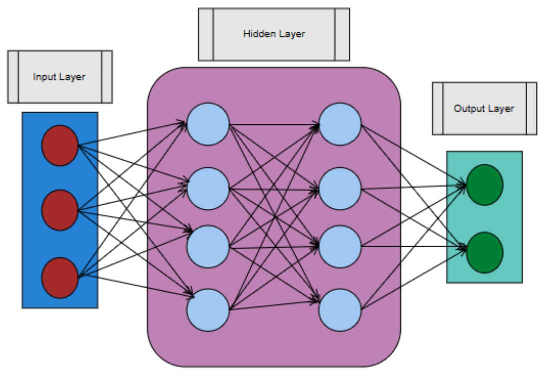


FIGURE 1.14: Architecture of Deep Recurrent Neural Network.

- **Deep Convolutional Neural Network (CNN):** CNN Model, which combines discrete convolution and NN, provides the deep layers' unquestionable benefits in image recognition. The convolution kernel in the network allows CNN to automatically extract features from row images, avoiding the challenging feature extraction and data reconstruction processes. using the symbols of natural signals as a guide [24].

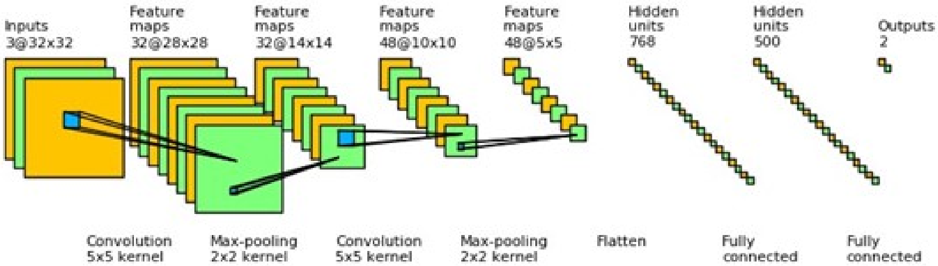


FIGURE 1.15: Convolutional Neural Network Architecture [24].

– **Filter Convolution** Convolution of a filter over an image depends on a number of factors, which are discussed here. Choosing the right values for the filter size, stride, and zero padding parameters, To determine whether the convolution will function with the feature map dimensions, some elementary mathematics must be performed. Figure 1.16 demonstrates how a convolution is computed with a filter across the top three filter positions in an image [25].

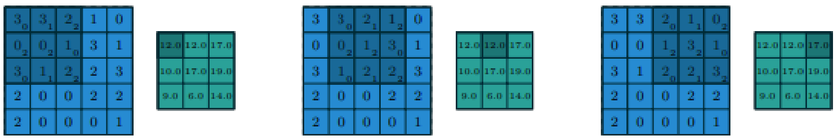


FIGURE 1.16: Computing the output values of a discrete convolution. For the subplots, dark blue squares indicate neurons in the filter region. Dark green squares indicate the output neuron for which the total input activation is computed [25].

– **Filter Size** In the literature, square filters are almost typical. the filter's size in relation to the image's size (or activation layer's), defines which traits the filters are capable of detecting. In AlexNet, for example, the input layer has 11×11 filters, applied to images which are 224×224 pixels. Each filter length, on side, comprises only 4.3% of the (square) image side length. These filters in the first layers cannot extract features which span more than 0.24% of the input image area [25].

– **Padding** A space of zero values is used as padding around the image. The output from the current convolutional layer can have its padding depth adjusted so that, after convolution, the output doesn't decrease in size [25]. Figure 1.17 below shows this effect:

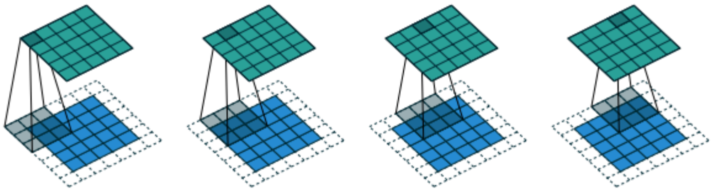


FIGURE 1.17: With zero padding, the effect of output size reduction is counteracted to maintain the input size at the output [25].

– **Stride** The parameter known as S specifies how many pixels a filter will be shifted horizontally. Stride is sometimes used in place of max pooling in network architectures to reduce layer size [25].

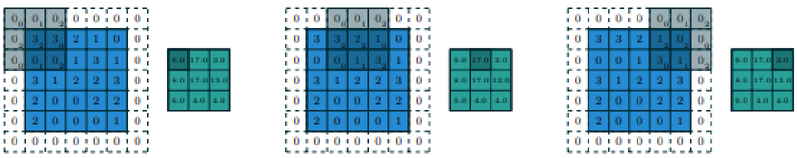


FIGURE 1.18: Convolution with zero padding and stride > 1. Only the 1st three subplots are shown here. Padding is of depth 1, stride is 2, and filter size is 3×3 [25].

Conclusion

In this chapter, we talked about biometrics and biometric systems, including their applications and modalities, we also discussed the use of machine learning and deep learning methods in biometrics, including their applications and techniques.

Chapter Two:

Proposed Iris Recognition

Introduction

In this chapter, we will provide an introduction to iris recognition. We will begin by discussing the current state of the art in iris recognition over the past few years. We will then introduce our iris recognition system and its various components. A detailed description of each part of our system will be provided to give readers an idea of the methods and techniques used in this work. By the end of this chapter, readers will have a good understanding of the basics of iris recognition and the specific approach taken in our system.

2.1 Iris Recognition State-of-the-Art

2.1.1 Using Machine Learning

The step of biometrics' feature extraction and matching has utilised some machine learning methods. These methods have additionally shown to be effective for feature extraction, matching and improving the Iris Recognition method's performance. During the matching stage of Iris Recognition, machine learning classifier-based methods were used in the majority of Iris Recognition methods. Nearly all of the suggested machine learning Iris algorithms have accuracy rates of greater than 100%.

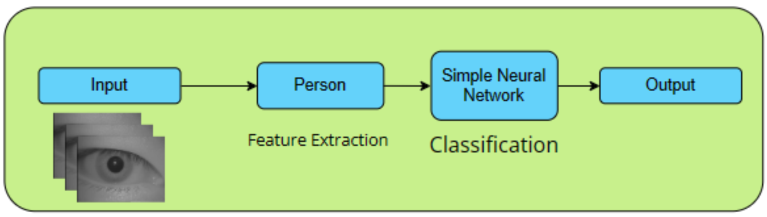


FIGURE 2.1: Iris recognition using machine learning

In table 2.1, we compare different machine learning methods for iris recognition with different datasets from previous years.

Authors. Year	Dataset	Features	$A(\%)$
[26] Chowhan et al. '11	CASIA-IrisV1	SVD	95.68
[27] Saminathan et al. '15	CASIA-IrisV3In	Intensity Image	98.50
[28] Chen et al. '23	CASIA-IrisV4, UBIRIS.v2	Iris-based Human Identity Recognition	99.50
[29] Al-Allaf et al. '13	CASIA-IrisV1In	Partitioned Intensity Image	98.90
[30] Rai et al. '14	CASIA-IrisV1	HAAR Wavelet Decomposition, 1D Log Gabor Wavelet	99.88
[31] Srivastava et al. '14	CASIA-Iris	Evolutionary Fuzzy Clustering	99.99
[32] Adamović et al. '19 (This contribution)	CASIA-IrisV4	Stylometric Features	98.12
[33] Khedkar et al. '13	CASIA-IrisV1	2D Walsh-hadamard Transform	95.00
[34] Pillai et al. '13	Notre Dame	Daugman's Iris Code	87.82
[2] Nguyen et al. '17	ND-CrossSensor-'13, CASIA-IrisTh	Of-the-Shelf CNN Features	98.90

TABLE 2.1: Survey of Machine Learning Methods, $A = Accuracy$.

2.1.2 Using Deep Learning

In many fields, including computer vision, voice, and natural language processing, deep learning has taken the place of conventional feature extraction techniques. Deep learning has been introduced to the field of biometrics by researchers thanks to its effective functional connecting capabilities. Recent studies have built multiple deep learning models based on different datasets. Based on several deep learning models, recent studies have been constructed. However, deep learning has also been successfully applied in the field of Iris Recognition.

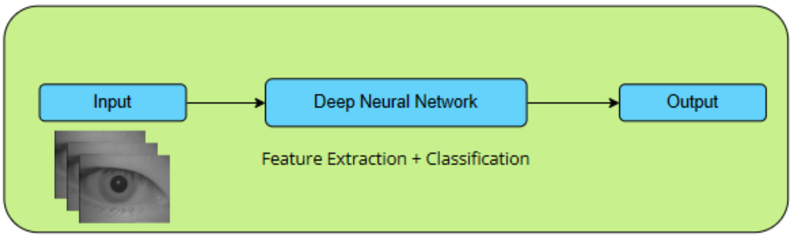


FIGURE 2.2: Iris recognition using deep learning

In table 2.2, we compare different deep learning methods for iris recognition with different datasets from previous years.

Authors, Year	Dataset	Features	$A(\%)$
[35] Zhao et al. '19	ND-IRIS-0405	Spatially Corresponding Feature	98.9
[36] Sallam et al. '21	CASIA-Iris	ResNet	98.00
[37] Albadarneh et al. '15	UBIRIS.V1	(HOG), Combined Gabor + DCT, (GLCM).n	92.00
[38] Minaee et al. '16	IIT Delhi Iris Database	Pre-trained VGG-Net	99.00
[39] Alaslani et al. '18	CASIA-IrisV1	Pre-trained Alex-Net	98.30
[40] Wang et al. '18	UBIRIS.V2	MiCoRe-Net	96.12
[41] Tobji et al. '19	CASIA-IrisTh	FCN + MCNN	95.63
[42] Proença et al. '19	CASIA-IrisV4	VGG-19 based CNN	99.58
[43] Boyd et al. '19	CASIA-IrisV4	Pre-trained Finetuned CNN ResNet-50 + SVM	99.03

TABLE 2.2: Survey of Deep Learning Methods, $A = Accuracy$.

2.2 Proposed Iris Recognition System

The recognition system depends on two basic stages (Training and Testing). During training, the system uses preprocessing, feature extraction, and classifiers. The system does preprocessing, features extraction, and provides final conclusions during testing.

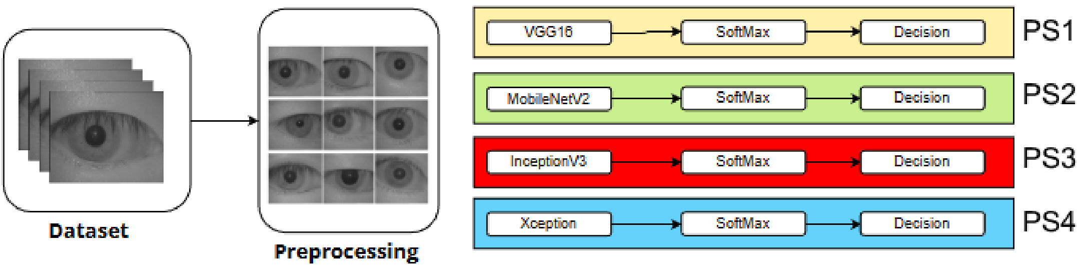


FIGURE 2.3: The proposed system framework,
PS = proposed system.

2.2.1 Preprocessing

Preprocessing is an essential step in iris recognition systems, and it determines the accuracy of matching [44].

The aim of image preprocessing is to improve the quality of iris images and to remove noise and other artefacts that may affect the accuracy of the recognition system [45, 46].

Preprocessing techniques such as segmentation, normalisation, and enhancement are employed to improve the accuracy of iris recognition systems [47].

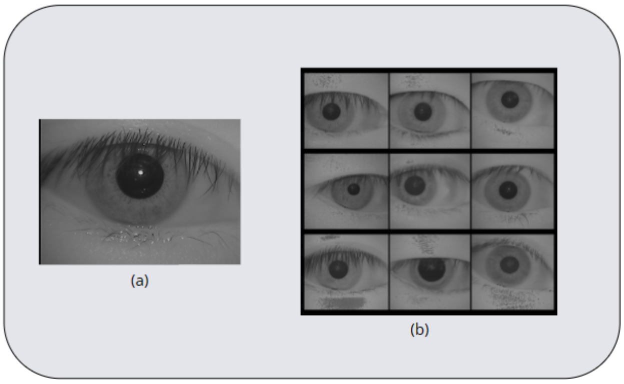


FIGURE 2.4: Applying data augmentation on an iris image

2.2.2 Feature Extraction Stage

Work has been done on Convolutional Neural Networks to identify the finger vein, but a problem occurs when working with CNN to find the appropriate parameters that yield the highest percentage recognition rate.

To address this issue, a series of tests were started on four models of it (**VGG16**, **MobileNet**, **Inception** and **Xception**).

2.2.2.1 VGG16 Model

VGG16 is a model for a 16-layer CNN model. It is still considered one of today's best and most effective models. Instead of having numerous parameters, the VGG16 model architecture focuses on ConvNet layers with a 3×3 kernel size. The significance of this model lies in the fact that its values are freely available online and may be downloaded for use in one's systems and applications. When compared to other developed comprehensive, it is noted for its simplicity. This model's minimum expected input image size is 224×224 pixels with three channels. In neural networks, optimisation algorithms are used to evaluate whether a neuron must be engaged or not, by determining the weighted sum of input. The need for kernel function arises from inducing non-linearity into the output neuron. A neural network's neurons function together with weight, bias, and the related training procedure. The neurons' link weights are adjusted based on output inaccuracy. The input layer and the activation function add non-linearity to artificial neural [48].

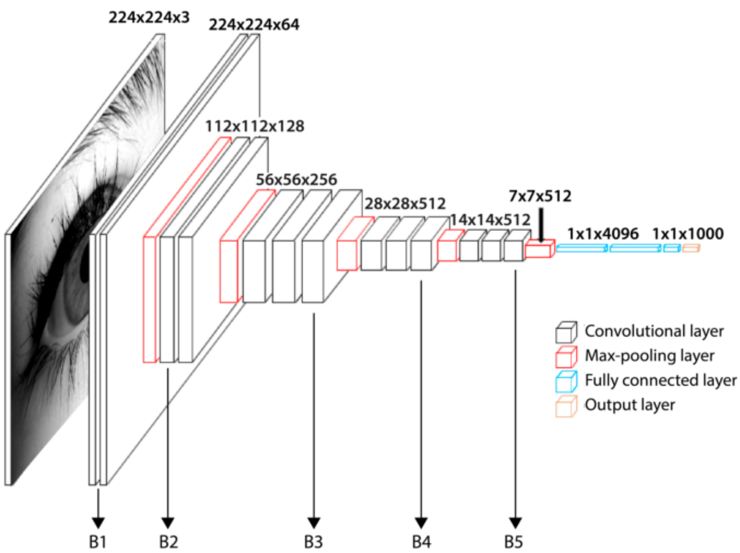


FIGURE 2.5: Architecture of VGG16 Model.

Layer(type)	Output Shape	Param
conv2d_1 (conv2d)	(N, 224, 224, 64)	1792
conv2d_2 (conv2d)	(N, 224, 224, 64)	36928
max_pooling2d_1 (MaxPooling2)	(N, 112, 112, 64)	0
conv2d_3 (conv2d)	(N, 112, 112, 128)	73856
conv2d_4 (conv2d)	(N, 112, 112, 128)	147584
max_pooling2d_2 (MaxPooling2)	(N, 56, 56, 128)	0
conv2d_5 (conv2d)	(N, 56, 56, 256)	295168
conv2d_6 (conv2d)	(N, 56, 56, 256)	590080
conv2d_7 (conv2d)	(N, 56, 56, 256)	590080
max_pooling2d_3 (MaxPooling2)	(N, 28, 28, 256)	0
conv2d_8 (conv2d)	(N, 28, 28, 512)	1180160
conv2d_9 (conv2d)	(N, 28, 28, 512)	2359808
conv2d_10 (conv2d)	(N, 28, 28, 512)	2359808
max_pooling2d_4 (MaxPooling2)	(N, 14, 14, 512)	0
conv2d_11 (conv2d)	(N, 14, 14, 512)	2359808
conv2d_12 (conv2d)	(N, 14, 14, 512)	2359808
conv2d_13 (conv2d)	(N, 14, 14, 512)	2359808
max_pooling2d_5 (MaxPooling2)	(N, 7, 7, 512)	0

TABLE 2.3: Summary of VGG16 Model, N=None.

2.2.2.2 MobileNetV2 Model

MobileNet is a light CNN model which was developed especially for embedded vision applications. It has 28 layers [49].

The great idea behind MobileNet models is to replace expensive convolutional layers with depthwise separable convolutional blocks where each block consists of a 3x3 depthwise convolutional layer that filters the input, followed by a 1x1 pointwise convolutional layer that combines these filtered values to create new features.

It is much faster than the regular convolution with approximately the same result [50].

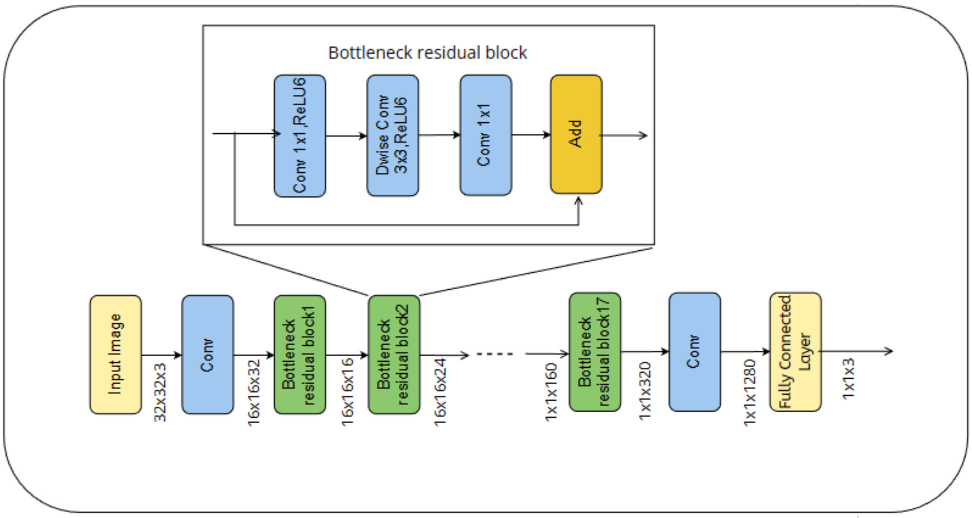


FIGURE 2.6: Architecture of MobileNetV2 Model.

Type / Stride	Filter Shape	Input Size
Conv/s2	3×3×3×32	224×224×3
Conv dw/s1	3×3×32dw	112×112×32
Conv/s1	1×1×32×64	112×112×32
Conv dw/s2	3×3×64dw	112×112×64
Conv/s1	1×1×64×128	56×56×64
Conv dw/s1	3×3×128dw	56×56×128
Conv/s1	1×1×128×128	56×56×128
Conv dw/s2	3×3×128dw	56×56×128
Conv/s1	1×1×128×256	28×28×128
Conv dw/s1	3×3×256dw	28×28×256
Conv/s1	1×1×256×256	28×28×256
Conv dw/s2	3×3×256dw	28×28×256
Conv/s1	1×1×256×512	14×14×256

TABLE 2.4: Summary of MobileNetV2 Model.

2.2.2.3 InceptionV3 Model

One major change made to the naive Inception layer is that a 1x1 convolution layer was added before the 3x3 and 5x5 convolution layer and after the max pooling layer. This change was implemented in the architecture of the Inception neural network to limit the number of inputs which in turn reduces the computational cost and was named GoogleNet. Given below is the inception layer after implementing the changes stated above [51].

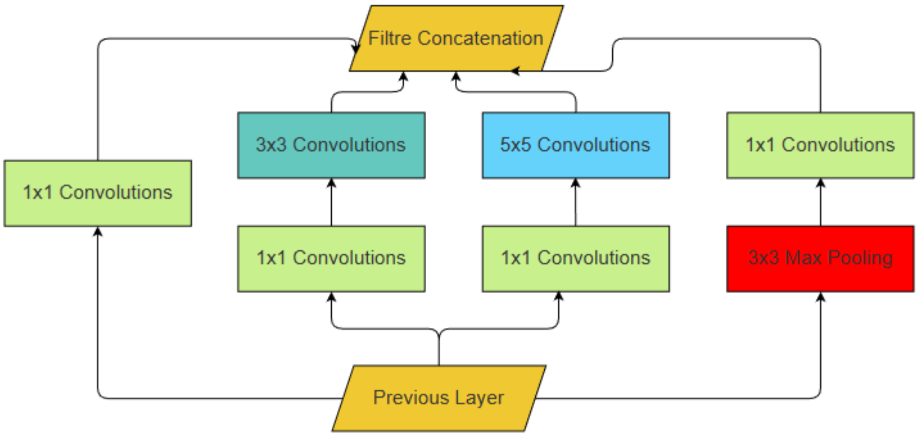


FIGURE 2.7: Architecture of Inception Model.

Layer (type)	Output Shape	Param	Connected to
input_1(InputLayer)	(N, 299, 299, 3)	0	-
block1_conv1	(N, 149, 149, 32)	864	input_1[0][0]
block1_conv1_bn	(N, 149, 149, 32)	128	block1_conv1[0][0]
block1_conv1_act	(N, 149, 149, 32)	0	block1_conv1_bn[0][0]
block1_conv2	(N, 147, 147, 64)	18432	block1_conv1_act[0][0]
block1_conv2_bn	(N, 147, 147, 64)	256	block1_conv2[0][0]
block1_conv2_act	(N, 147, 147, 64)	0	block1_conv2_bn[0][0]
block2_sepconv1	(N, 147, 147, 128)	8768	block1_conv2_act[0][0]
block2_sepconv1_bn	(N, 147, 147, 128)	512	block2_sepconv1[0][0]
block2_sepconv2_act	(N, 147, 147, 128)	0	block2_sepconv1_bn[0][0]
block2_sepconv2	(N, 147, 147, 128)	17536	block2_sepconv2_act[0][0]
block2_sepconv2_bn	(N, 147, 147, 128)	512	block2_sepconv2[0][0]
conv2d	(N, 74, 74, 128)	8192	block1_conv2_act[0][0]

TABLE 2.5: Summary of Inception Model, N=None,
_conv(Conv2D), _bn(BatchNormaliza), _act(Activation), _sepconv(SeparableConv2)

2.2.2.4 Xception Model

Xception is an extreme Inception architecture that makes use of the concept of depthwise separable convolution. To control computational complexity, Xception made the original inception block bigger and replaced the multiple spatial dimensions (1x1, 5x5, 3x3) with a single dimension (3x3) followed by a 1x1 convolution. By separating spatial and feature-map (channel) correlation, Xception makes the network more computationally efficient [51].

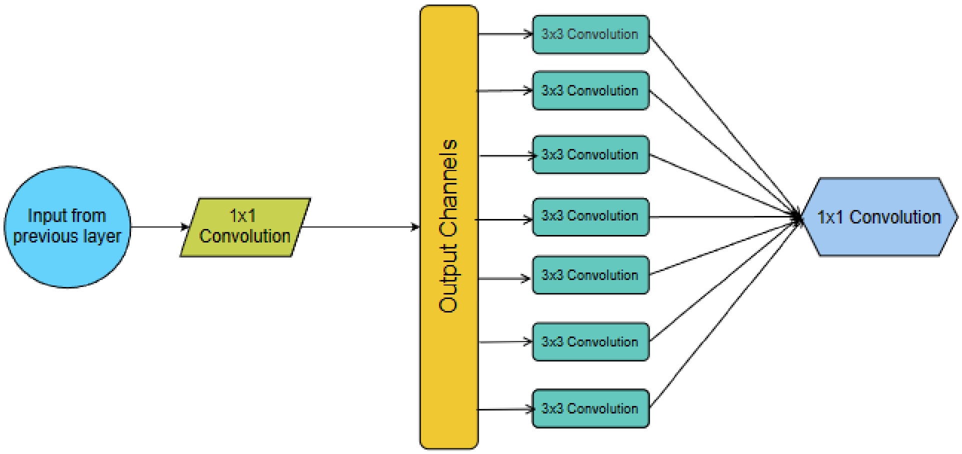


FIGURE 2.8: Architecture of Xception Model

Xception simplifies computation by individually convolving each feature-map across spatial axes, then performing crosschannel correlation via point-wise convolution (1x1 convolutions). Xception's transformation technique does not lower the amount of parameters, but it does make learning more efficient and leads to better performance. Xception's transformation technique does not lower the amount of parameters, but it does make learning more efficient and leads to better performance.

2.2.3 Classification Stage

In Deep Neural Network, the softmax layer is the network's last layer [52].

The softmax function is an activation function used in multi-classification problems. It normalizes the output real values from the last fully connected layers to label class probabilities. Each value ranges between zero and one, and the sum of all values is equal to one [53].

The softmax operation can be calculated:

$$f_{x_i} = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} (i = 1, 2, ..., N) \tag{2.1}$$

Conclusion

This chapter delves into the current state of iris recognition for machines and deep learning. We explore the preprocessing of our database and the various CNN architectures. In the upcoming chapter, we will present our results with both quantitative and qualitative discussions to highlight the strengths and weaknesses of our system.

Chapter Three:

Results and Discussions

Introduction

In this chapter, we provide a detailed description of the database used in our work. We also explain the evaluation metrics used and report our results with both quantitative and qualitative discussions to highlight the strengths and weaknesses of our system. Additionally, we conduct a comparative study to further analyse the performance of our system.

3.1 Dataset Description

The intelligent iris capture system of the University of Science and Technology of China [1] was employed to collect iris data from 106 individuals for the SDUMLA-HMT iris dataset, utilising near-infrared lighting. For each patient, ten iris pictures were obtained, resulting in a total of 1060 images in the iris database. The iris images are recorded in the ".bmp" format, with 256 grey levels and a resolution of 768×576 pixels.

In our study, we specifically utilised the left iris images from each subject, amounting to a total of 530 images from the 106 subjects.

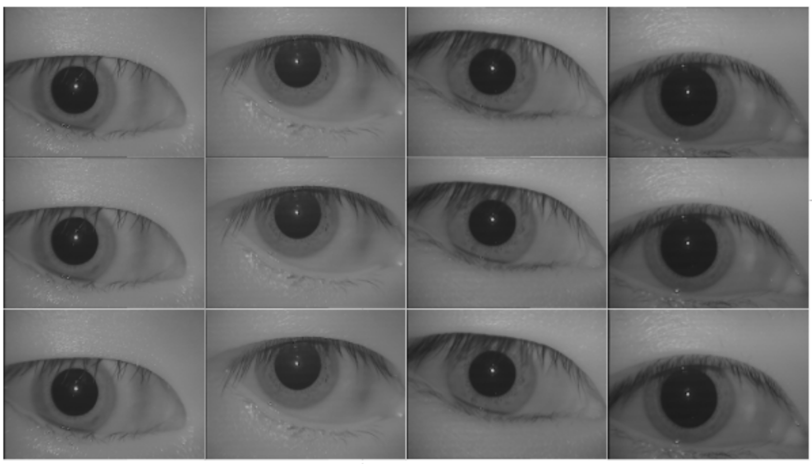


FIGURE 3.1: Some samples from the SDUMLA dataset.

3.2 Evaluation Metrics

When it comes to performance assessment early researches used to use the term *Accuracy*, which can be usually calculated by comparing the ground-truth to the prediction of the model. In the case of Object Detection, ground-truth is the corresponding bounding box and the class in the box of each object in the image. In other words, a high degree of accuracy means that the model regulates a ground-truth-like bounding box and classifies the object well.

Additionally, we present the Cumulative Match Characteristics (CMC) curves to show each model's performance across different ranks.

As a performance assessment, we consider the confusion matrix for computing our metrics such as Accuracy, Precision, Recall, F1-Score,...etc.

The Confusion matrix is a very usual metric used to solve classification problems, it can be utilised for binary classification and multi-class classification problems.

	Classified as Positive	**Classified as Negative**
Really is Positive	True Positive (TP)	False Negative (FN)
Really is Negative	False Positive (FP)	True Negative (TN)

TABLE 3.1: Confusion Matrix.

Accuracy

Accuracy is the amount of correct classifications over all of the classifications made.

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

Precision

Precision is used to show how accurate the predicted result is.

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

Recall

Recall is used to indicate how well a positive is given as an input.

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

F1-Score

$F1 - Score$ is the harmonic mean between precision and recall.

$$F1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{3.4}$$

3.3 Results and Discussion

To get successful results, We used many techniques to test our model. We fixed the learning rate and the kind of optimiser in our first test. On the other hand, we changed the number of epochs from 10 to 70 epochs, 8, 16, 32, and 64 are the values of the batch size that we employed in our research. In the second phase, we fixed the batch size and the number of epochs while varying the learning rate and the kind of optimiser in accordance with the same parameters as the first test. The tables below provide examples of these techniques.

3.3.1 VGG16 Results

3.3.1.1 Influence of Epoch Number and Batch Size on Performance

We used the optimiser RMSprop and a learning rate of 0.004.

Epochs	BS. 8	BS. 16	BS. 32	BS. 64
10	93.87%	94.34%	92.92%	88.21%
20	94.34%	96.70%	94.81%	95.28%
30	95.75%	97.17%	95.75%	95.28%
40	96.23%	94.34%	95.75%	95.28%
50	96.23%	94.81%	96.23%	95.28%
60	95.28%	95.75%	95.28%	96.28%
70	95.28%	96.70%	97.64%	95.75%
80	95.75%	97.17%	96.23%	94.81%
90	96.23%	95.28%	98.11%	95.75%
100	97.64%	97.64%	94.81%	95.28%

TABLE 3.2: Summary of VGG16 Model, BS=Batch Size.

In Table 3.2, we set the learning rate and the Optimiser in advance and start changing the number of epochs and batch size, and At epochs 90 and batch size 32 we achieve the best-estimated value accuracy of 98.11%.

3.3.1.2 Influence of Optimiser and Learning Rate on Performance

We choose Numbers epochs=90 and batch size=32.

Learning Rate	O. Adam	O. RMSprop
0.1	92.92%	91.51%
0.01	88.21%	91.51%
0.001	95.28%	97.17%
0.0001	94.81%	94.34%
0.0004	94.81%	98.11%

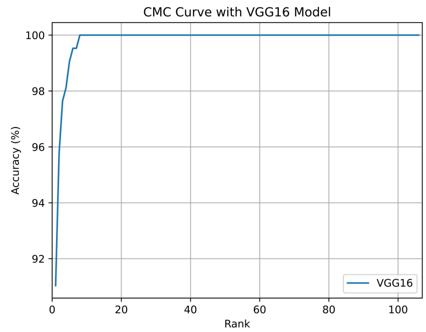
TABLE 3.3: Summary of VGG16 Model, O=Optimiser

In table 3.3, we fixed the number of epochs and the batch size based on the best value from the previous table, and begin modifying the learning rate and the optimiser until we achieve the highest level of estimated value accuracy of 98.11% by Optimiser RMSprop and Learning Rate 0.0004.

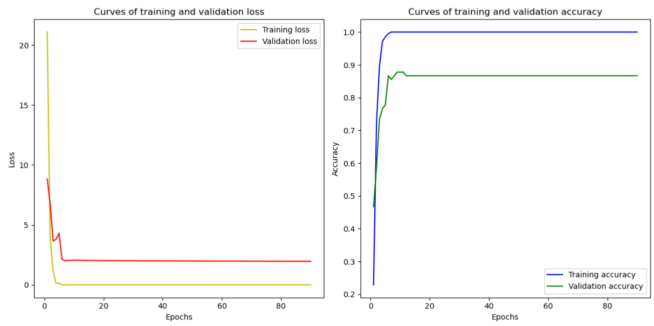
Metrics	**Parameters**		
	$BS = 32$ $O = Adam$ $EN = 90$ $LR = 0.01$	$BS = 8$ $O = RMSprop$ $EN = 10$ $LR = 0.0004$	$BS = 32$ $O = RMSprop$ $EN = 90$ $LR = 0.0004$
$Accuracy$	88.21%	93.87%	98.11%
$F1 - Score$	87.00%	92.00%	98.00%
$Precision$	88.00%	92.00%	99.00%
$Recall$	88.00%	94.00%	98.00%

TABLE 3.4: Summary of VGG16 Model. $BS = Batch\ Size$, $O = Optimiser$, $EN = Epoch\ Number$, $LR = Learning\ Rate$.

In Table 3.4, we use the four necessary parameters for evaluating our model. We selected 3 values: *Worst*, *Good*, and *Best* based on the previous table to calculate $F1 - Score$, $Precision$, $Recall$, and CMC. Results shown in below figures.



(A) CMC.



(B) Loss/Acc.

FIGURE 3.2: CMC and Loss/Acc with accuracy 88.21%.

In Figure 3.2, we can see in the *CMS curve* (A) at RANK 1 that the accuracy is 90.00%, and at RANK 5 it is 98.40%. Also, we can see in the *Loss curve* (B) that this parameter has a very high learning rate, but it has a pattern of conduct, and there is some underfitting in this parameter's *Accuracy curve* (B).

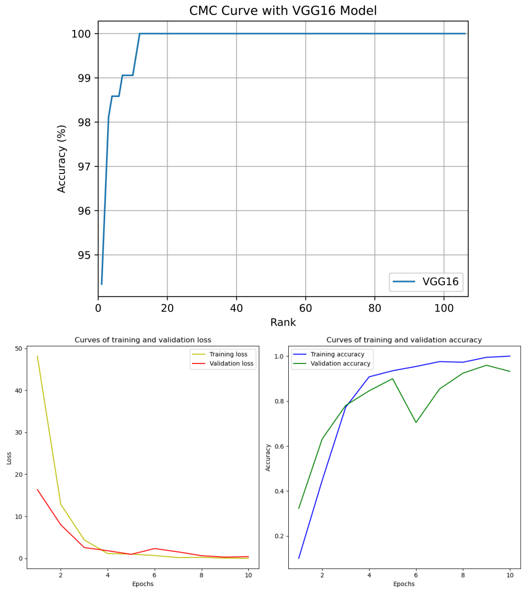


FIGURE 3.3: CMC and Loss/Acc with accuracy 93.87%.

In Figure 3.3, at RANK 1 the accuracy is 94.32%, and at RANK 5 it is 98.57%. *Loss curve* indicate that this parameter has an excellent learning rate and its *Accuracy curve* is underfitting.

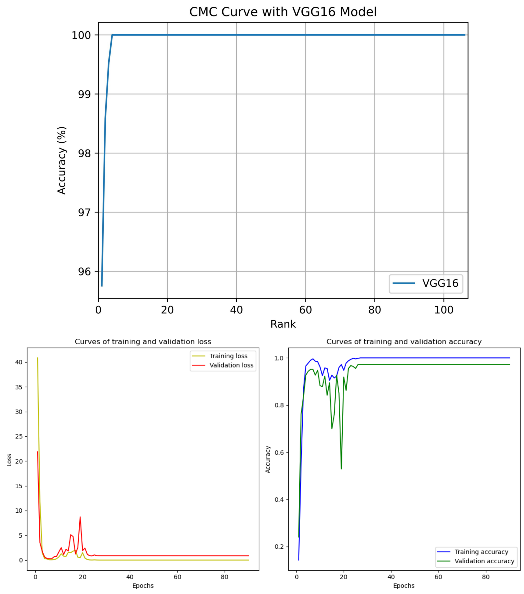


FIGURE 3.4: CMC and Loss/Acc with accuracy 98.11%.

In Figure 3.4, at RANK 1 the accuracy is 95.61%, and at RANK 5 it is 100%. *Loss curve* indicate that this parameter has a very high learning rate and its *Accuracy curve* has an ideal fit.

3.3.2 MobileNet Results

3.3.2.1 Influence of Epoch Number and Batch Size on Performance

We used the optimiser RMSprop and a learning rate of 0.004.

Epochs	BS. 8	BS. 16	BS. 32	BS. 64
10	95.75%	97.64%	98.58%	83.96%
20	98.58%	99.53%	99.53%	97.64%
30	99.06%	99.06%	99.06%	98.58%
40	99.06%	98.58%	99.06%	99.06%
50	99.06%	99.53%	99.06%	99.06%
60	99.53%	99.06%	99.06%	99.06%
70	99.06%	99.53%	99.53%	99.53%

TABLE 3.5: Summary of MobileNet Model, BS=Batch Size.

In Table 3.5, we set the learning rate and the optimiser in advance and start changing the number of epochs and batch size, and at 20 epochs and batch size 16 we achieve the best-estimated value accuracy of 99.53%.

3.3.2.2 Influence of Optimiser and Learning Rate on Performance

We choose Numbers epochs=20 and batch size=32.

Learning Rate	O. Adam	O. RMSprop
0.1	87.74%	85.85%
0.01	99.06%	96.70%
0.001	98.58%	98.58%
0.0001	88.21%	92.45%
0.0004	98.11%	99.53%

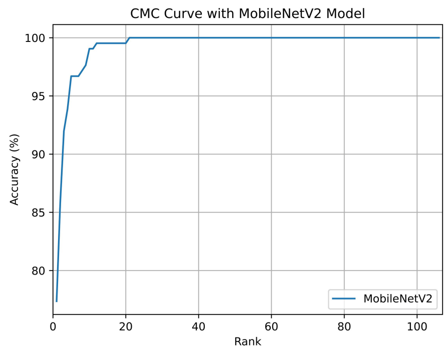
TABLE 3.6: Summary of MobileNetV2 Model, O=Optimiser

In Table 3.6, we fixed the number of epochs and batch size based on the best value from the previous table and began changing the learning rate and the optimiser until we achieved the highest level of estimated value accuracy of 99.53% by optimiser RMSprop and learning rate 0.0004.

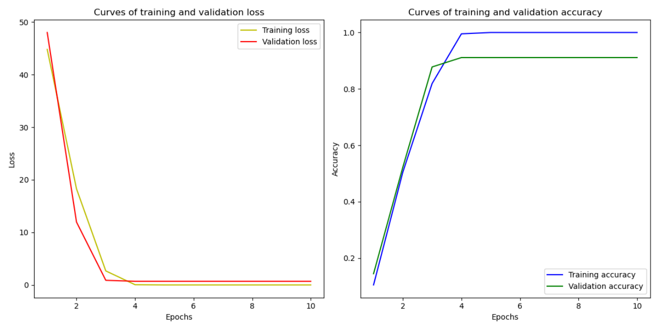
Metrics	**Parameters**		
	$BS = 64$ $O = rms$ $EN = 10$ $LR = 0.0004$	$BS = 32$ $O = adam$ $EN = 20$ $LR = 0.0001$	$BS = 32$ $O = RMSprop$ $EN = 20$ $LR = 0.0004$
$Accuracy$	83.96%	88.21%	99.53%
$F1 - Score$	82%	86%	99%
$Precision$	85%	87%	100%
$Recall$	84%	88%	100%

TABLE 3.7: Summary of MobileNetV2 Model. $BS = Batch\ Size$, $O = Optimiser$, $EN = Epoch\ Number$, $LR = Learning\ Rate$.

In Table 3.7, we use the four necessary parameters for evaluating our model. We selected 3 values: *Worst*, *Good*, and *Best* based on the previous table to calculate $F1 - Score$, $Precision$, $Recall$, and CMC. Results shown in below figures.



(A) CMC.



(B) Loss/Acc.

FIGURE 3.5: CMC and Loss/Acc with accuracy 83.96%.

In Figure 3.5, we can see in the *CMS curve* (A) at RANK 1 that the accuracy is 77.47%, and at RANK 5 it is 95.23%. Also, we can see in the *Loss curve* (B) that this parameter has a low learning rate, and this parameter's *Accuracy curve* (B) is underfitting.

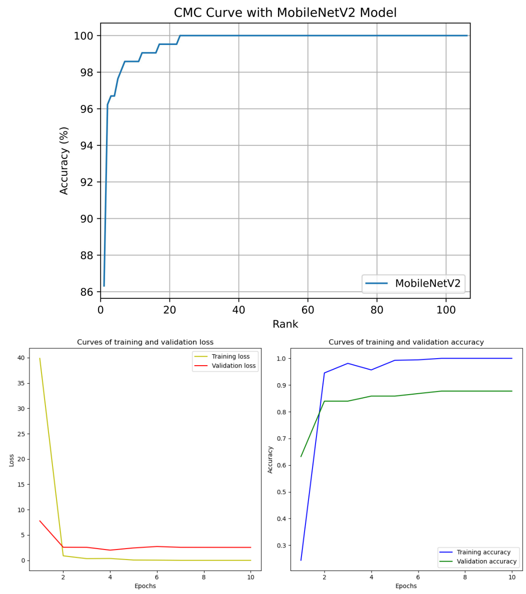


FIGURE 3.6: CMC and Loss/Acc with accuracy 88.21%.

In Figure 3.6, at RANK 1 the accuracy is 86.24%, and at RANK 5 it is 97.34%. *Loss curve* indicate that this parameter has a high learning rate and its *Accuracy curve* has a significant underfitting.

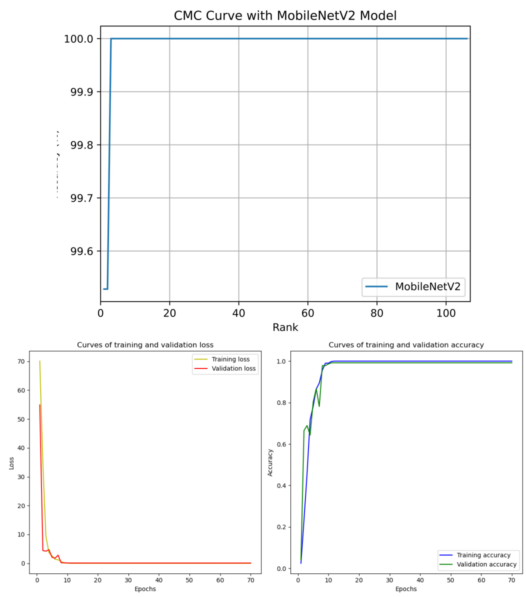


FIGURE 3.7: CMC and Loss/Acc with accuracy 99.53%.

In Figure 3.7, at RANK 1 the accuracy is 99.53%, and at RANK 5 it is 100%. *Loss curve* indicate that this parameter has a very high learning rate and its *Accuracy curve* fits the data exactly.

3.3.3 InceptionV3 Results

3.3.3.1 Influence of Epoch Number and Batch Size on Performance

We used the Optimiser RMS and a Learning Rate of 0.004.

Epochs	BS. 8	BS. 16	BS. 32	BS. 64
10	83.02%	85.85%	85.85%	58.96%
20	92.92%	91.98%	91.98%	93.40%
30	96.70%	93.87%	92.92%	93.40%
40	95.75%	95.28%	93.87%	93.40%
50	96.23%	96.23%	92.92%	93.87%
60	96.23%	96.70%	94.34%	93.40%
70	96.70%	97.64%	94.81%	94.34%

TABLE 3.8: Summary of Inception Model, BS=Batch Size.

In Table 3.8 we set the learning rate and the Optimiser in advance and start changing the number of epochs and batch size, and at epoch 70 and batch size 16 we achieve the best-estimated value accuracy of 97.64%.

3.3.3.2 Influence of Optimiser and Learning Rate on Performance

We choose Numbers epochs=70 and batch size=16.

Learning Rate	O. Adam	O. RMSprop
0.1	77.36%	72.64%
0.01	83.96%	87.74%
0.001	95.28%	95.28%
0.0001	91.04%	91.98%
0.0004	94.81%	97.64%

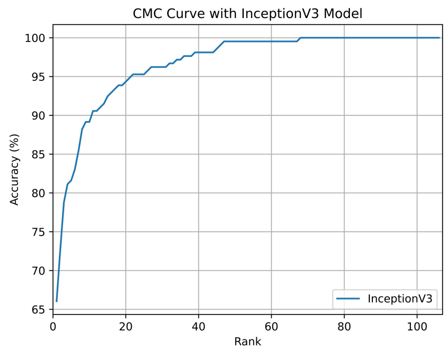
TABLE 3.9: Summary of Inception Model, O=Optimiser

In Table 3.9 we fixed to number of epochs and batch size based on the best value from previous table, and begin modifying the learning rate and Optimiser until we achieve the highest level of estimated value accuracy of 97.64% by Optimiser Rmsprop and Learning rate 0.0004.

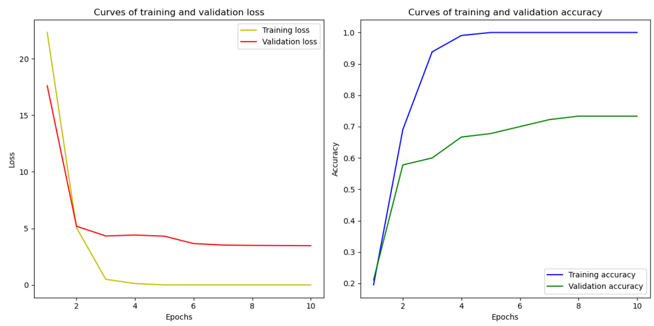
Metrics	**Parameters** $BS = 64$ $O = rms$ $EN = 10$ $LR = 0.0004$	$BS = 16$ $O = adam$ $EN = 70$ $LR = 0.01$	$BS = 16$ $O = RMSprop$ $EN = 70$ $LR = 0.0004$
$Accuracy$	58.96%	83.96%	97.64%
$F1 - Score$	55%	82%	97%
$Precision$	58%	86%	98%
$Recall$	59%	84%	98%

TABLE 3.10: Summary of InceptionV3 Model. $BS = Batch\ Size$, $O = Optimiser$, $EN = Epoch\ Number$, $LR = Learning\ Rate$.

In Table 3.10, we use the 4 necessary parameters for evaluating our model. We selected 3 values: *Worst*, *Good*, and *Best* based on the previous table to calculate $F1 - Score$, $Precision$, $Recall$, and CMC. Results shown in below figures.



(A) CMC.



(B) Loss/Acc.

FIGURE 3.8: CMC and Loss/Acc with accuracy 58.96%.

In Figure 3.8, we can see in the *CMS curve* (A) at RANK 1 that the accuracy is 66.25%, and at RANK 5 it is 83.41%. Also, we can see in the *Loss curve* (B) that this parameter has a high learning rate, and this parameter's *Accuracy curve* (B) has a significant underfitting.

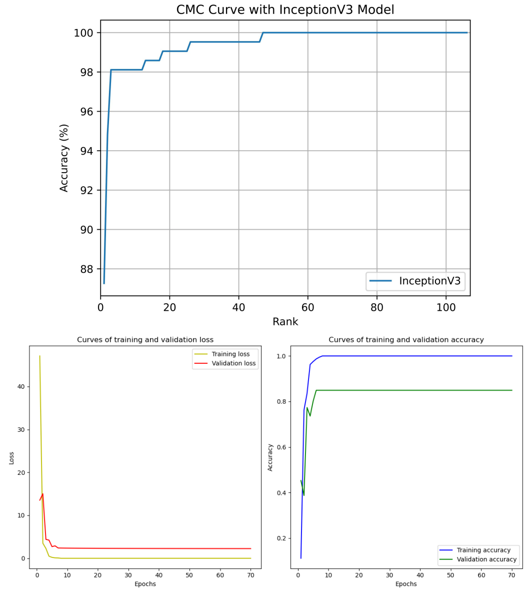


FIGURE 3.9: CMC and Loss/Acc with accuracy 83.96%.

In Figure 3.9, at RANK 1 the accuracy is 87.1%, and at RANK 5 it is 98.08%. *Loss curve* indicate that this parameter has a good learning rate, however, it has a pattern of behaviour, therefore, its *Accuracy curve* is marginally underfitting.

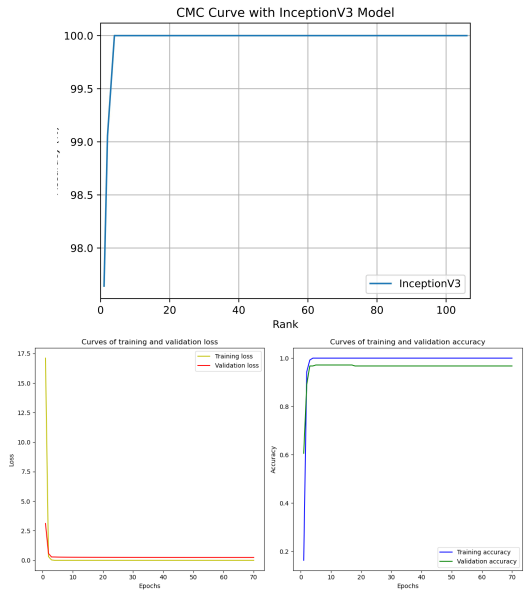


FIGURE 3.10: CMC and Loss/Acc with accuracy 97.64%.

In Figure 3.10, at RANK 1 the accuracy is 97.36%, and at RANK 5 it is 100%. *Loss curve* indicate that this parameter has a very high learning rate and its *Accuracy curve* fits the data exactly.

3.3.4 Xception Results

3.3.4.1 Influence of Epoch Number and Batch Size on performance

We used the Optimiser RMS and a learning rate of 0.004.

Epochs	BS. 8	BS. 16	BS. 32	BS. 64
10	83.02%	83.02%	83.96%	68.87%
20	91.04%	91.98%	88.68%	90.57%
30	93.87%	93.40%	93.87%	91.04%
40	97.64%	94.81%	95.75%	93.40%
50	96.70%	96.70%	95.28%	94.81%
60	97.64%	96.23%	97.17%	95.28%
70	98.58%	97.64%	97.17%	95.75%

TABLE 3.11: Summary of Xception Model, BS=Batch Size.

In Table 3.11, we set the learning rate and the Optimiser in advance and start changing the number of epochs and batch size, and at epoch 70 and batch size 8 we achieve the best-estimated value accuracy of 98.58%.

3.3.4.2 Influence of Optimiser and Learning Rate on Performance

We choose Numbers epochs=70 and batch size=8.

Learning Rate	O. Adam	O. RMSprop
0.1	74.53%	85.38%
0.01	84.43%	88.68%
0.001	97.17%	97.17%
0.0001	91.04%	91.98%
0.0004	96.23%	98.58%

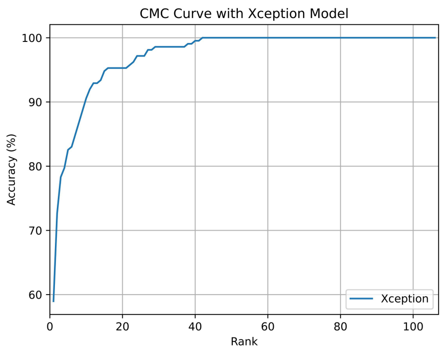
TABLE 3.12: Summary of Xception Model, $O = Optimiser$

In Table 3.12, we fixed to the number of epochs and batch size based on the best value from the previous table, and begin changing the learning rate and Optimiser until we achieve the highest level of estimated value accuracy of 98.58% by Optimiser Rmsprop and Learning rate 0.0004.

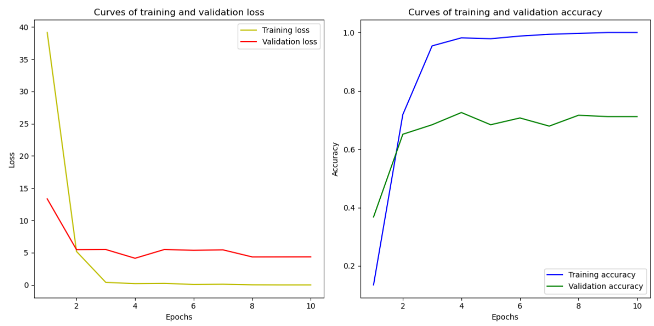
Metrics	**Parameters**		
	$BS = 64$ $O = rms$ $EN = 10$ $LR = 0.0004$	$BS = 8$ $O = adam$ $EN = 70$ $LR = 0.0001$	$BS = 8$ $O = RMSprop$ $EN = 70$ $LR = 0.0004$
$Accuracy$	68.87%	91.04%	98.58%
$F1 - Score$	65%	90%	98%
$Precision$	70%	92%	99%
$Recall$	69%	91%	99%

TABLE 3.13: Summary of Xception Model. $BS = Batch\ Size$, $O = Optimiser$, $EN = Epoch\ Number$, $LR = Learning\ Rate$.

In Table 3.13, we use the 4 necessary parameters for evaluating our model. We selected 3 values: *Worst*, *Good*, and *Best* based on the previous table to calculate $F1 - Score$, $Precision$, $Recall$, and CMC. Results shown in below figures.



(A) CMC.



(B) Loss/Acc.

FIGURE 3.11: CMC and Loss/Acc with accuracy 68.87%.

In Figure 3.11, we can see in the *CMS curve* (A) at RANK 1 that the accuracy is 58.89%, and at RANK 5 it is 81.78%. Also, we can see in the *Loss curve* (B) that this parameter has a high learning rate, and this parameter's *Accuracy curve* (B) is much underfitted.

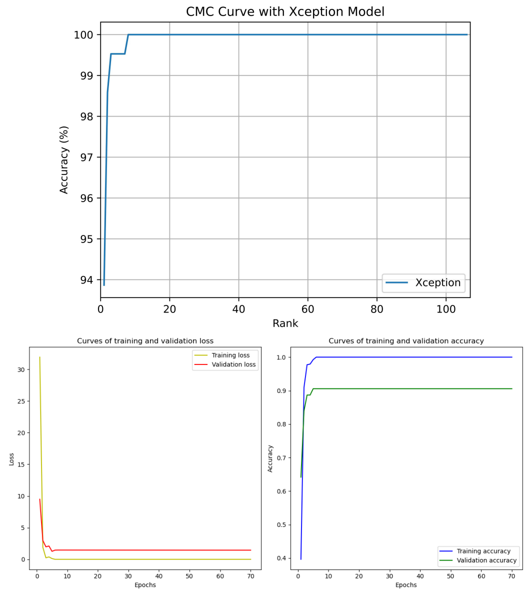


FIGURE 3.12: CMC and Loss/Acc with accuracy 91.04%.

In Figure 3.12, at RANK 1 the accuracy is 93.26%, and at RANK 5 it is 99.50%. *Loss curve* indicate that this parameter has a low learning rate and its *Accuracy curve* exhibits some underfitting.

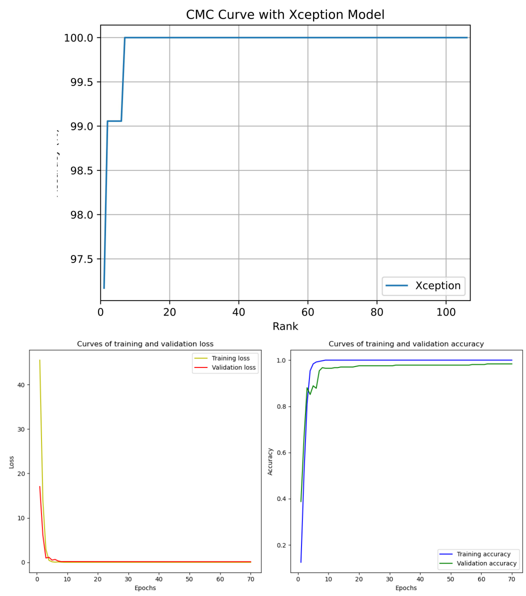


FIGURE 3.13: CMC and Loss/Acc with accuracy 98.58%.

In Figure 3.13, at RANK 1 the accuracy is 97.24%, and at RANK 5 it is 99.39%. *Loss curve* indicate that this parameter has a high learning rate and its *Accuracy curve* has an optimal Fit.

3.4 Comparative Study

In this section, we make a meaningful comparison, as shown in Table 3.14, with other works that used the same dataset for Iris recognition.

Ref	**Year**	**Features**	**Accuracy (%)**
Nassar [54]	2018	CNN (IrisConvNet)	96.99
Gad et al. [55]	2018	CHT + Rubber Sheet Model	95.75
Morampudi et al. [56]	2021	PNN	98.68
Malgheet et al. [46]	2021	IrisConvNet	100
Our Works	2023	CNN (Mobile-NetV2)	99.53

TABLE 3.14: Comparative Study

Conclusion

In this chapter, we talked about the database we use and the parameters by which our work is evaluated. Following practice and evaluation using four different models in this chapter. In comparison to other models, MobileNetv2 achieved the best accuracy.

General Conclusion

Iris recognition is a biometric technology that uses mathematical pattern-recognition techniques on video images of one or both of the irises of an individual's eyes,whose complex patterns are unique, stable, and can be seen from some distancet offers a viable method to increase the security of sensitive information.Iris recognition uses photographs of your eyes and a map of your individual iris pattern to authenticate your identity, and it is commonly regarded as the quickest and most accurate biometric identification method.
The research conducted as part of this graduation thesis aims to analyse one of the biometric systems that allows people to be identified and categorised based on the iris recognition.

Using the modern technique Deep feature extraction and classification using deep learning, The accuracy of the recognition plays a major role, and this biometric technology is thought to be quite secure. Because of its biometric characteristics which are unique to the individual.

We chose the following four methods: *VGG16, MobileNetV2, InceptionV3, Xception* with various types of optimises: *Adam and RMSprop*, We got good results, especially in **MobileNetV2** compared to other methods.

This system has a high level of accuracy performance.

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Summaries

Summary

Cross-sectoral insecurity, rising crime, and piracy are topics that are discussed more and more today. Moreover, the requirement to guarantee people's identities is urgently needed due to people's mobility, financial services transactions, and access to services. Traditional security measures rely on previously learned information (passwords, PIN codes), or token-based access (keys, badges, and identifiers). However, because they frequently cannot tell the difference between legitimately authorised individuals and fraudsters, these systems are less reliable in many contexts. In this particular case, we chose one of these systems a deep learning Iris recognition system, to be more precise to analyse. a system that uses the human iris as a biometric. This system is difficult to duplicate. There are numerous benefits, such as low cost and ease of use. There are two stages to our work. First, to make up for the lack of training samples needed to train the deep learning model, data augmentation utilising various geometrical techniques is implemented. Second, the four CNN algorithms are used to accomplish the feature extraction and classification operation in order to confirm the person's identity. The performance of the suggested model is tested and evaluated using the SDUMLA dataset. Our suggested method produced an accuracy of 98.11% with VGG16 and 99.53% with MobileNetV2 and 97.64% with Inception and 98.58% with Xception. According to experimental findings, the proposed approach performed well compared to existing techniques.

Keywords: Iris, CNN, Training, Convolution, Deep Learning, Image Recognition, Testing, Feature Extraction.

Résumé

L'insécurité intersectorielle, la montée de la criminalité et la piraterie sont des sujets de plus en plus discutés aujourd'hui. De plus, l'obligation de garantir l'identité des personnes est urgente en raison de la mobilité des personnes, des transactions de services financiers et de l'accès aux services. Les mesures de sécurité traditionnelles reposent sur des informations apprises précédemment (mots de passe, codes PIN) ou sur un accès basé sur des jetons (clés, badges et identifiants). Cependant, parce qu'ils ne peuvent souvent pas faire la différence entre les personnes légitimement autorisées et les fraudeurs, ces systèmes sont moins fiables dans de nombreux contextes. Dans ce cas particulier, nous avons choisi l'un de ces systèmes, un système de reconnaissance d'iris à apprentissage profond, pour être plus précis à analyser. un système qui utilise l'iris humain comme élément biométrique. Ce système est difficile à dupliquer. Il existe de nombreux avantages. tels que le faible coût et la facilité d'utilisation. Il y a deux étapes dans notre travail. Tout d'abord, pour compenser le manque d'échantillons de formation nécessaires pour former le modèle d'apprentissage en profondeur, une augmentation de données utilisant diverses techniques géométriques est mise en œuvre. Deuxièmement, les quatre algorithmes CNN sont utilisés pour accomplir l'opération d'extraction et de classification des caractéristiques afin de confirmer l'identité de la personne. Les performances du modèle suggéré sont testées et évaluées à l'aide de l'ensemble de données SDUMLA. Notre méthode suggérée a produit une précision de 98,11% avec VGG16 et de 99,53% avec MobileNetV2 et de 97,64% avec Inception et de 98,58% avec Xception. Selon les résultats expérimentaux, l'approche proposée a bien fonctionné par rapport aux techniques existantes.

Mots clés : Iris, CNN, Formation, Convolution, Apprentissage en Profondeur, Reconnaissance d'Images, Tests, Extraction de Caractéristiques.

ملخص

إن انعدام الأمن عبر القطاعات، والجريمة المتزايدة، والقرصنة هي مواضيع تتم مناقشتها أكثر فأكثر اليوم. علاوة على ذلك، هناك حاجة ماسة لشرط ضمان هوية الأشخاص بسبب تنقل الأشخاص ومعاملات الخدمات المالية والوصول إلى الخدمات. تعتمد إجراءات الأمان التقليدية على المعلومات التي تم تعلمها مسبقًا (كلمات المرور، رموز PIN)، أو الوصول المستند إلى الرمز المميز (المفاتيح والشارات والمعرفات). ومع ذلك، نظرًا لأنها في كثير من الأحيان لا تستطيع التمييز بين الأفراد المصرح لهم شرعًا والمحتالين، فإن هذه الأنظمة أقل موثوقية في العديد من السياقات. في هذه الحالة بالذات، اخترنا أحد هذه الأنظمة، نظام التعرف على قزحية التعلم العميق، ليكون أكثر دقة في التحليل. نظام يستخدم قزحية الإنسان كمقياس حيوي. من الصعب تكرار هذا النظام. هناك فوائد عديدة. مثل التكلفة المنخفضة وسهولة الاستخدام. هناك مرحلتان لعملنا. أولاً، للتعويض عن النقص في عينات التدريب اللازمة لتدريب نموذج التعلم العميق، يتم تنفيذ زيادة البيانات باستخدام تقنيات هندسية مختلفة. ثانيًا، تُستخدم خوارزميات الأربعة لإنجاز عملية استخراج الميزات والتصنيف من أجل تأكيد هوية الشخص. يتم اختبار أداء النموذج المقترح وتقييمه باستخدام مجموعة بيانات SDUMLA . أنتجت طريقتنا المقترحة دقة %98.11 مع VGG16 و %99.53 مع MobileNetV2 و %97.64 مع Inception و %98.58 مع Xception . وفقًا للنتائج التجريبية، كان أداء النهج المقترح جيدًا عند مقارنته بالتقنيات الحالية.

الكلمات المفتاحية: قزحية، تدريب، التعلم العميق، الشبكات العصبية التلافيفية، التفاف، التعرف على الصور، اختبارات، ميزة استخراج.