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Personal identification system based on hyperspectral palmprint

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Dedication

Charef Eddine BENAMARA

For my dearests, friends and family all, and a father who left this world in pursuit another journey. I solemnly devote this product of many sleepless nights to all of you, for I appreciate your companionship, for I cherish your support, for I never reward fondness by anything other than ten folds. My gratitude to you mother for your efforts, love and generous care. My gratitude to all of you siblings for standing by my side when I needed most. And finally, My gratitude to you friends, Mates, and teachers all, for your advice and guidance along the way.

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Dedication

Rabah MENZOU

I dedicate this work

To my family, a special feeling of gratitude to my loving parents, who never stop giving of themselves in countless ways, and who have taught me to work hard for the things that I aspire to achieve. May Allah protect them, To my brothers, who have never left my side. To my friends, classmates and teachers who have supported me throughout the process. I will always appreciate all they have done.

Many thanks to all those who have contributed from near or far to make this project possible.

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Abstract

Biometrics is the measurement and analysis of unique biological, physical, or behavioral traits (modalities) of individuals and turning them into a digital print that can be used as an identification or verification method. Furthermore, for a trait to be considered a modality, it must be universal, unique, permanent, collectible, and acceptable. Some modalities are better than others in some criteria, making some suitable for a particular task yet invalid in another. Biometrics are utilized in systems that can perform three main tasks: enrolling, identifying, and verifying. They also grant us the ability to use them in a direct, straightforward manner (unimodality) or by fusing several elements on several levels (multimodality) to achieve more accurate results. We can measure its accuracy through well-defined error metrics and performance curves.

While we have established some decent knowledge concerning biometrics, we have yet to define how to use them. One of the ways to use biometrics is through deep learning. In order for a machine to use biometric data, we are not only required to have an enhanced image that is focused on the region of interest. We must extract the features that differentiate one individual from another, which is a task done through the use of deep neural networks. The concept of deep learning is inspired by the cognitive ability of humans, which makes deep learning very capable of detecting objects. And from that comes the concept of Convolutional Neural Networks (CNN), which are special deep neural networks that mimic animals' visual systems. CNNs can be pre-trained in order to reduce actual training time and improve performance by producing a transfer-learning model. In our work, we used a database that contains palmprint hyperspectral images of 190 people. Each person has twelve pictures from both their left and right hands. Then, we performed band selection to select the most discriminating bands. After that, we trained and tested four transfer-learning networks for the purpose of performing feature extraction, and then used a classifier in unimodal and two multimodal approaches. We finally evaluated their performances and recorded their results.

Keywords: Biometrics, Palmprint, Unimodality, Multimodality, Identification, Hyperspectral images, Band selection, Deep learning, Transfer learning, Feature extraction.

Résumé

La biométrie est la mesure et l'analyse de traits uniques (modalités) d'individus et leur transformation en une empreinte numérique pouvant être utilisée comme méthode d'identification ou de vérification. De plus, pour qu'un trait soit considéré comme une modalité, il doit être universel, unique, permanent, et collectable. Certains sont meilleurs que d'autres dans certains critères, ce qui rend certains adaptés et d'autre invalides pour une tâche particulière. La biométrie est utilisée dans des systèmes qui peuvent effectuer trois tâches principales, l'inscription, l'identification et la vérification. Ils nous donnent également la possibilité de les utiliser de manière directe (unimodalité) ou en fusionnant plusieurs éléments à plusieurs niveaux (multimodalité) pour obtenir des résultats plus précis. Nous pouvons mesurer sa précision grâce à des métriques d'erreur et des courbes de performances bien définies.

Bien que nous ayons établi une connaissance décente concernant la biométrie, nous devons encore définir comment les utiliser. L'une des méthodes les plus récentes et avancées dans le domaine est l'utilisation de réseaux de neurones. Pour qu'une machine utilise des données biométriques, nous devons extraire les caractéristiques qui différencient un individu d'un autre, ce qui est une tâche effectuée grâce à l'utilisation de réseaux de neurones profonds. Le concept d'apprentissage profond s'inspire de la capacité cognitive des humains, ce qui rend l'apprentissage profond très capable de détecter des objets. Réseau de neurones convolutifs ou réseau de neurones à convolution, qui sont des réseaux neuronaux profonds spéciaux qui imitent les systèmes visuels des animaux. Les CNN peuvent être pré-formés afin de réduire le temps de formation réel et d'améliorer les performances en produisant un modèle d'apprentissage par transfert. Dans notre travail, nous avons utilisé une base de données qui contient des images hyperspectrales de l'empreinte palmaire de 190 personnes. Ensuite, nous avons effectué une sélection de bandes pour sélectionner les bandes les plus discriminantes. Après cela, nous avons entraîné et testé quatre réseaux d'apprentissage par transfert à des fins d'extraction de caractéristiques, puis utilisé un classifieur dans des approches unimodales et deux multimodales. Nous avons finalement évalué leurs performances et enregistré leurs résultats.

Mots-clés : Biométrie, Empreinte palmaire, Unimodalité, Multimodalité, Identification, Images hyperspectrales, Sélection de bande, Apprentissage profond, Apprentissage par transfert, Extraction de caractéristiques.

الملخـــــــــص

القياسات البيومترية هي قياست وتحاليل الصفات البيولوجية أو الفيزيائية أو السلوكية الفريدة للأفراد ورقمنتها لاستخدامها كطرق لتحديد الهوية أو التحقق منها. علاوة على ذلك ، لكي يتم اعتبار الصفة سمة، يجب أن تكون جامعة وفريدة من نوعها ودائمة وقابلة للتحصيل ومقبولة. بعض الأساليب أفضل من غيرها في بعض المعايير ، مما يجعل بعضها مناسبًا لمهمة معينة ومع ذلك ، فهي غير صالحة في مهمة أخرى. تُستخدم القياسات الحيوية في الأنظمة التي يمكنها أداء ثلاث مهام رئيسية ، وهي التسجيل والتعرف والتحقق. هذه السمات تمنحنا أيضًا القدرة على استخدامها بطريقة مباشرة (نظام أحادي السمة). أو عن طريق دمج عدة عناصر على عدة مستويات (نظام متعدد السمات) لتحقيق نتائج أكثر دقة. يمكننا قياس دقة النظام من خلال معايير الخطأ ومنحنيات الأداء.

بينما أنشأنا معرفة جيدة فيما يتعلق بالقياسات البيومترية، إلا أننا لم نحدد بعد كيفية استخدامها. إحدى طرق استخدام القياسات البيومترية هي التعلم العميق. لكي تستخدم الآلة البيانات البيومترية ، فنحن لسنا مطالبين فقط بالحصول على صورة محسنة تركز على منطقة الاهتمام. لكن يجب علينا استخراج الميزات التي تميز فردًا عن آخر ، وهي مهمة تتم من خلال استخدام الشبكات العصبية العميقة. مفهوم التعلم العميق مستوحى من القدرة الإدراكية للبشر ، مما يجعل التعلم العميق قادرًا جدًا على اكتشاف الأشياء. ومن هنا يأتي مفهوم الشبكات العصبية التلافيفية، وهي شبكات عصبية عميقة خاصة تحاكي الأنظمة البصرية للحيوانات. يمكن تدريب شبكات مسبقًا من أجل تقليل وقت التدريب الفعلي وتحسين الأداء نسمي النموذج المدرب بنموذج نقل التعلم. في عملنا ، استخدمنا قاعدة بيانات تحتوي على صور فائقة الطيف لبصمة الكف لـ ١٩٠ شخصًا. كل شخص لديه ١٢ صورة من كلتا اليدين اليمنى واليسرى بعد ذلك أجرينا اختيار النطاق لتحديد النطاقات الأكثر تمييزًا. ثم قمنا بتدريب واختبار أربع شبكات لتعلم النقل لغرض استخراج الميزات. ثم استخدمنا المصنف في نهج أحادي الوسائط ومنهجين متعددي الوسائط. قمنا في النهاية بتقييم أدائهم وسجلنا نتائجهم.

الكلمات المفتاحية: القياسات الحيوية ، البصمة ، الأحادية ، الوسائط المتعددة ، التعريف ، الصور الفائقة الطيفية ، اختيار النطاق ، التعلم العميق، نقل التعلم ، استخراج الميزات.

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List of Abbreviations

ANN Artificial Neural Networks

Avg Average

CMC Cumulative Match Characteristic

CNN Convolutional Neural Network

CONV Convolutional

DNA DeoxyriboNucleic Acid

DRB Deep Rule Based Classifier

EER Equal Error Rate

FAR False Accept Rate

FC Fully Connected

FDPC Fast Density Peak-based Clustering

FRB Fuzzy Rule Based

FRR False Reject Rate

GAR Genuine Acceptance Rate

HSI Hyperspectral Image

ID Identification

IE Information Entropy

ILSVRC ImageNet Large Scale Visual Recognition Challenge

IT Information Technology

MAX Maximum

MIN Minimum

MSI Multispectral Image

MVPCA Maximum Variance Principal Component Analysis

NIN Networking-network

OCF Optimal Clustering Framwork

PIN Personal Identification Number

PPI Pixels Per Inch

prod Production

RCS Ranking on Clusters Strategy

ReLU Rectified Linear Units

ResNet Residual Network

RGB Red Green Blue

ROC Receiver Operating Characteristic

ROI Region of Interest

ROR Rank One Recognition

RPR Rank of Perfect Recognition

sum Summation

T_0 Threshold

VGG Visual Geometry Group

wsum Weighted Summation

wprod Weighted Production

General Introduction

Our civilization is built on our ability to live in a society and maintain our individuality, which makes accumulating wealth, knowledge, and achievements to gain a legacy and provide a heritage a very desirable outcome. Hence, the birth of the naming concept: a concept that grants individuality. We tend to associate people's appearances with labels or names for ease of communication and data organization [1]. Recently, the amount of data being processed has been increasing drastically, causing complications in identifying individuals manually and also in combatting all potential identity theft, resulting in a rise in security concerns and transaction fraud. Therefore, we resorted to machines. Machines are capable of processing massive amounts of data with great accuracy. We rely on that fact while collecting descriptive data called biometric data (DNA, fingerprint, face,...) and linking that data to its owner's identity, enabling our machines to identify an individual using the thing that can never be separated from them, namely their bodies. This action will not only make our lives easier but more accessible and secure [2].

In the following pages, we will discuss and explore biometric systems in general and emphasize palmprint recognition systems. For that reason, since palmprint is a highly accessible modality, it is as effective as many other modalities for recognition, and for that reason, it has gained much traction. In our study, we will utilize hyperspectral imaging to provide an abundance of information about the palmprint, conveying all the details perfectly and ultimately producing a system with a high recognition rate. This outcome will be supported by the use of outstanding transfer learning algorithms as feature extractors. The points that will be discussed in each chapter are as follows:

First chapter: This chapter will define biometrics and introduce its modalities, systems, and evaluation.

Second chapter: This chapter will aim to provide a brief introduction to deep learning algorithms, compare them to machine learning, and explain some core concepts surrounding them.

Thrid chapter:In this chapter, we will demonstrate our approach to achieving our desired results.

CHAPTER 1

BIOMETRIC TECHNOLOGY’S GENERAL CONCEPTS

1.1 Introduction

In the time we live in, with enormous amounts of data flowing everywhere at every second, the efficiency of the manipulation of said data has become crucial. The way we access our private data plays a significant role in how efficiently we perform different tasks, which is not provided by the current more traditional access methods since they are quite an inconvenience and do not provide much security. Entering a piece of data to grant access to other data suffers from many drawbacks. As it is evident in passwords, which the user can forget easily, leading to complications or even complete data loss, which is very common. Another drawback to passwords is that they are weak identification methods. Commonly, we notice that data strings are used as ID numbers that trigger access to other pieces of data (confirmation/rejection or a larger pool of data). Furthermore, the latter weakness drags on to similar triggers such as names, emails, and others. Due to all these issues, it has become apparent that we need to find a better access method, a method that is permanent, secure, easy to use, reliable, and unique to every potential user. The best fit for those conditions is biometrics.

This chapter covers the fundamental principles of biometrics. First, we introduce the concepts and diverse modalities of biometrics. Following that, we explain the general architecture as well as the different functionalities of a biometric system. After that, we present the drawbacks of these systems. To overcome these issues, we present the concept of multimodal biometric and its different types. Finally, methodologies for evaluating the biometric system are provided.

1.2 Biometrics

1.2.1 Biometrics Definition

The term biometrics is derived from the Greek words bios and metron, which mean "life" and "measure," respectively. The combination of those two words yields the meaning "measurement of life," or as we know it, biometrics [3]. More specifically, biometrics is the measurement and analysis of unique biological, physical, or behavioral traits of individuals and turning them into a digital print that can be used as an identification or verification method. What makes biometrics very valid and viable is that it is irreplicable and very precise. Examples include, but are not limited to, fingerprint, face, DNA, palmprint, hand geometry, iris, voice, and signature [4]. Examples are listed in the following figure 1.1.

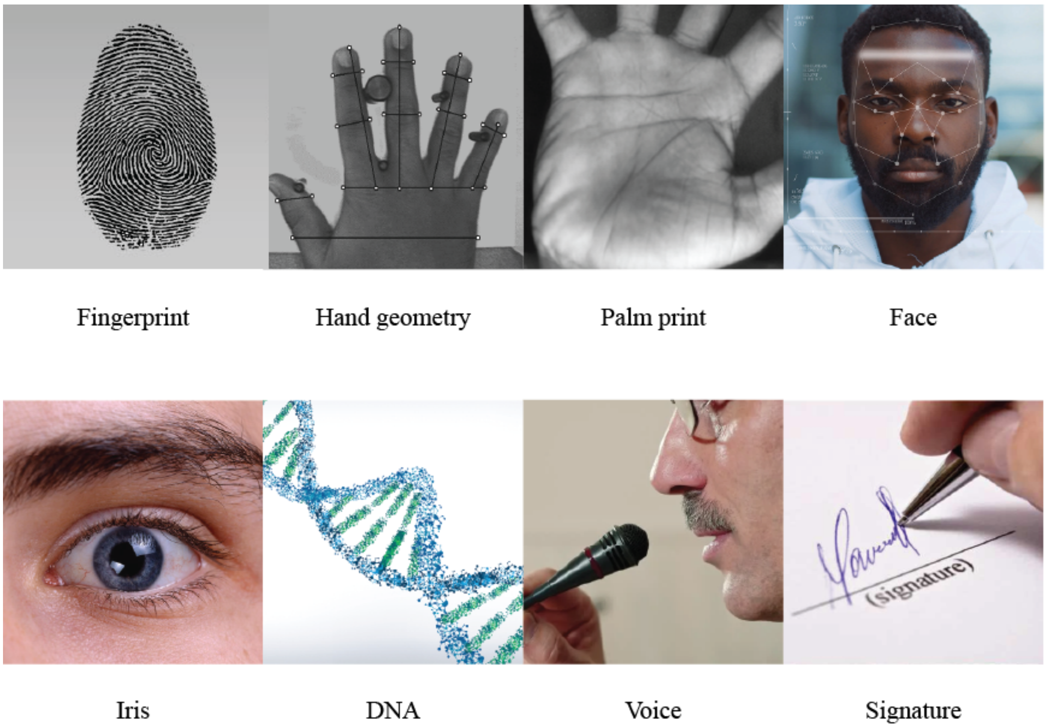

Figure 1.1: Examples of different biometric traits

1.2.2 A Brief History of Biometrics

Biometrics usage has a very long history. For example, fingerprint recognition dates back to at least 6000 B.C., making it the oldest known biometric identification method [5].

The Assyrians, Babylonians, Japanese, and Chinese utilized fingerprints to sign official documents and conduct economic transactions on clay tablets. According to an explorer Joao de Barros, Chinese merchants used ink to stamp the palm prints and footprints of children on paper to distinguish them from one another [5].

In the 1890s, Alphonse Bertillon was an anthropologist and police desk clerk in Paris, France. set out to solve the problem of identifying serial criminals who used fake names each time they were arrested. He came up with the concept of Bertillonage, which is a system of various body measurements to identify a person. However, this system was quickly considered unreliable as a consequence of many people sharing the same body dimensions [5].

In the 19th century, Sir Francis Galton conducted a detailed study concerning fingerprints and published it, where he claimed that the likelihood of two fingerprints being identical is one in 64 billion. Galton's identification relied on minutiae of the fingerprint, which are certain small details in fingerprints. The latter is still in use to this day [5].

In 1974, in the dorm of the University of Georgia, hand geometry was used to facilitate the food service. Consequently, in the 20th century, many biometric technologies were employed by humans in their daily lives [5].

1.3 Choice of Biometric Modalities

Biometric modalities are biometric traits that can be used to verify an individual's identity. There are many modalities of many classes with different uses.

1.3.1 Classification of Biometric Modalities

Biometrics are classified into three categories [6]:

1. ***Morphological biometrics***: Based on specific physical characteristics that are permanent and unique to every individual, for example, fingerprints, faces, palmprints, iris, hand geometry.

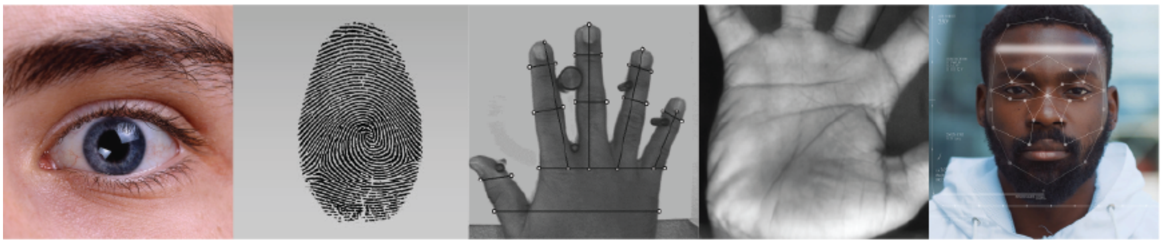

Figure 1.2: Examples of morphological biometrics

2. ***Biological biometrics***: A class of biometrics that analyzes biological data about an individual (saliva, DNA, blood).

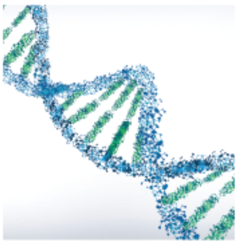

Figure 1.3: Example of biological biometrics

3. ***Behavioral biometrics***: It consists of studying the behavior of an individual (gait, keystroke dynamics, signature, voice recognition).

Figure 1.4: Examples of bihavioral biometrics

1.3.2 Biometric Modalities Criteria

In practice, any morphological, biological or behavioural trait that satisfies the following criteria can be called a biometric modality [7]:

1. ***Universality***: It must be carried by everyone who needs to be identified.
2. ***Uniqueness***: It must vary among people.
3. ***Permanence***: It must be permanent and unchanged throughout a person's life.
4. ***Collectability***: It must be collectable and measurable.
5. ***Acceptability***: It must not trouble the users during the accusation process of the trait.

Some application cases might require a trait that is more unique yet can compromise on acceptability (high-security areas). In other application cases, we can sacrifice a bit of uniqueness to gain more universality and acceptability (low-security areas). In short, during the selection of the modality, the use case must be considered, and the benefits and compromises must be weighed down. A few examples of biometric modalities evaluated according to the previously mentioned criteria are listed in the table 1.1.

1.3.3 Comparative Study of Different Biometric Modalties

There are many modalities that can be used for acquiring one's identity. Therefore, as described in table 1.2, it is expected to find advantages and disadvantages in the most commonly used biometric modalities. Comprehending these advantages and disadvantages can aid in selecting the most fitting trait for a specific application [9].

1.4 Biometric Systems

A biometric system's structure is made up of main modules. This section will explore these modules and the issues involved in their design, implementation, and evaluation [4].

Table 1.1: Properties of biometric modalities according to the following properties: (U) Universality, (N) Uniqueness, (P) Permanence, (C) Collectability, (A) Acceptability, (E) Performance (the number of stars in the performance column is related to the obtained value of Equal Error Rate (EER) (extracted from [8]).

Biometric	U	N	P	C	A	E
DNA	Yes	Yes	Yes	poor	poor	*****
Blood	Yes	No	Yes	poor	no	*
Gait	Yes	No	poor	Yes	Yes	***
Keystroke	Yes	Yes	poor	Yes	Yes	****
Voice	Yes	Yes	poor	Yes	Yes	****
Iris	Yes	Yes	Yes	Yes	poor	*****
Retina	Yes	Yes	Yes	Yes	poor	*****
Face	Yes	No	poor	Yes	Yes	****
Hand Geometry	Yes	No	Yes	Yes	Yes	****
Hand veins	Yes	Yes	Yes	Yes	Yes	*****
Ear	Yes	Yes	Yes	Yes	Yes	*****
Fingerprint	Yes	Yes	Yes	Yes	Medium	****

Table 1.2: Advantage and disadvantage of biometric modalities (extracted from [9]).

Method	Advantages	Advantages
Fingerprint	- Reliable - Distinctive - Accurate	- Susceptible to injury - Susceptible to Dry skin
Hand geometry	- Small template - Unaffected by skin condition	- Susceptible to injury - Large scanner size - Low distinctiveness
Face	- Efficient process - High acceptance	- Altered with time - Altered by surgery - Ineffective among twins
Iris	- Unique and robust - Distinctive	- Complex and expensive - Very intrusive
Voice	- High acceptance - Low training requirement	- Altered with time - Low accuracy - Susceptible to illnesses
Signature	- High acceptance - Low training requirement	- Varies every time - Low distinctiveness
DNA	- High distinctiveness - Unaltered with time	- Expensive - Low acceptance

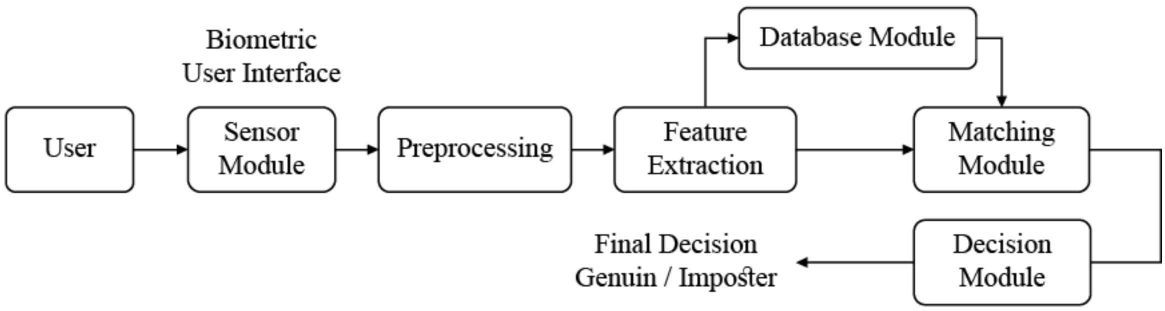

Figure 1.5: Generic biometric system architecture.

1.4.1 Biometric System Components

1. ***Sensor Module***: A user interface incorporating the biometric sensor is necessary to measure or collect the user's raw biometric data. For example, an optical fingerprint sensor could be used to scan the friction ridge pattern at the tip of the finger. A good user interface is essential for a biometric system's effective implementation [4].

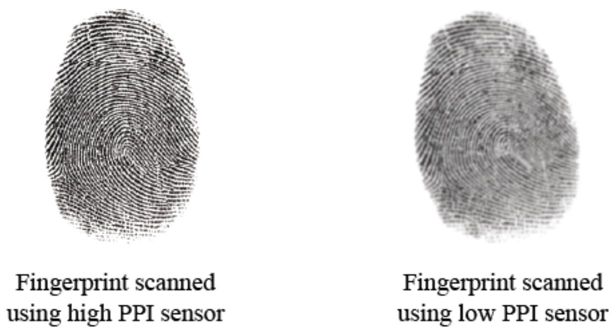

Figure 1.6: Effect of the sensor's PPI on clarity of fingerprint scans.

2. ***Feature Extraction Module***: Using an image captured by the sensor is not an efficient way to identify an individual because not all the information captured by the sensors is discriminative. Therefore, feature extraction is required. Its purpose is to extract feature values of a biometric trait by applying the feature extraction algorithm, which carries only the necessary information to recognize a person. Those feature values are called ”template”. For example, we do not use the entire fingerprint scan captured by the sensor. Instead, we use feature extraction to obtain the minutiae (locations where the friction ridges exhibit some anomalies) [4].

3. ***Database Module***: The biometric system database acts as a repository for biometric data. During the registration process, the feature set extracted from the raw biometric sample (i.e., the template) is registered in the database along with specific personal identifying information (such as name, PIN, address, and others) [4].

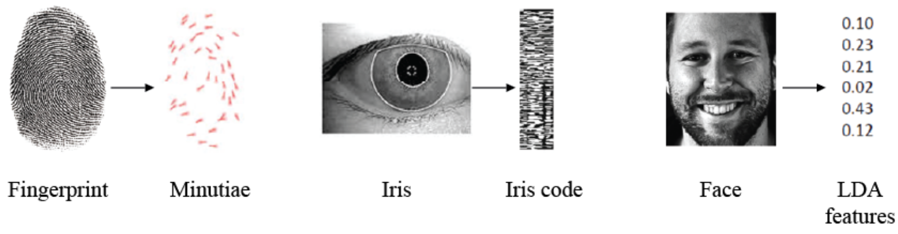

Figure 1.7: Commonly extracted features from fingerprints, iris, and face.

4. ***Matching Module***: A biometric matcher generates match scores by comparing query features to stored templates. The match score determines how similar the template and query are. As a result, a higher match score implies a more accurate match between the template and the query. A distance score is calculated when a matcher considers the dissimilarity between two feature sets. Thus, a lower distance score indicates a more significant similarity. For example, the degree of similarity in a fingerprint-based biometric system can be determined by the quantity of matching minutiae between the input and template feature sets (match score) [4].

5. ***Decision Module***: After receiving the match score from the matching module, the decision module compares that match score to a threshold that the system administrator predefines. After that, according to the comparison result, the decision module will decide whether an individual is genuine if the matching score exceeds the threshold or an imposter if the threshold exceeds the matching score. [9].

1.5 Biometric System Conception

In general, a biometric system is divided into two phases: enrolment and recognition. The first phase is intended to register users, while the second phase can conduct both verification and identification modes. These phases are covered in more detail below [4].

1.5.1 Enrolment

Both verification and identification techniques need enrollment. It is the preliminary phase in which a user's biometric data is recorded for the first time in the system. During this step, one or more biometric modalities are taken and saved in the database as templates. This stage is critical since it has a real impact. [10].

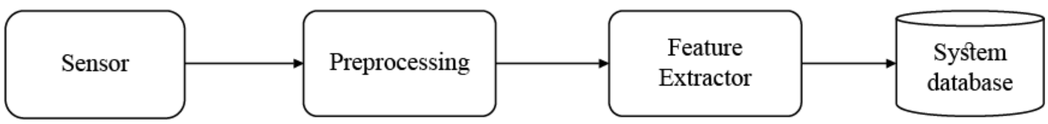

Figure 1.8: Enrolment phase of a biometric system.

1.5.2 Verification

In verification, the user claims an identity, and the system attempts to confirm or deny that claim. In this situation, the query is only compared to the template associated with the claimed identity (a one-to-one match). If the user's input and the template of the claimed identity have a high degree of similarity, the claim is considered "genuine". Otherwise, the claim would be denied, and the person would be labeled as an "impostor". Verification is frequently used in the prevention of unauthorized users from gaining access to services or information [4], and the decision rule is given by:

$$(I, x^A) = \begin{cases} genuine, & \text{if } s \geq \eta \\ impostor, & \text{if } s \leq \eta \end{cases} \tag{1.1}$$

I is claimed identity, x^A is a query feature set, s is a match score, Where η is a pre-defined threshold.

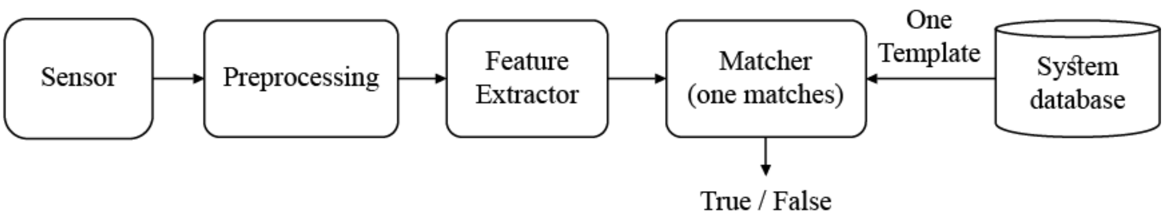

Figure 1.9: Verification function of a biometric system.

1.5.3 Identification

Identification means that the system recognizes a user by looking for matches in all user templates recorded in the database. The system performs a one-to-many comparison to create a user's identity (or fails if a user is not registered in the system database) without the requirement to claim their identity [10]. The decision rule can be defined as follows:

$$x^A \epsilon \begin{cases} I_{n0}, & n_0\text{=arg} \max\limits_{n} s_n \; and \; s_{n0} \geq \eta \\ I_{N+1}, & \text{otherwise} \end{cases} \tag{1.2}$$

x^A is a query feature set corresponding to the identity of the user I, where $I \; \epsilon \; \{I1$, $I2, \cdots, IN, IN+1\}$. Here, $I1, I2, \cdots, IN$ correspond to the identities of the N users enrolled in the system and $IN+1$ indicates the case where no suitable identity can be determined for the given query. Sn is the match score, η is the decision threshold [4].

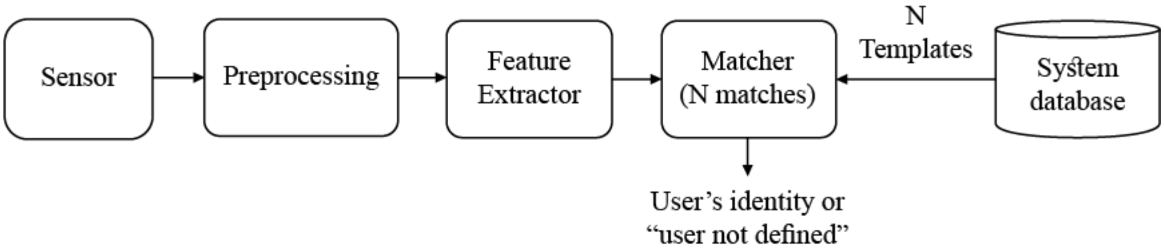

Figure 1.10: Identification function of a biometric system.

1.6 Multimodal Biometric Systems

1.6.1 Multimodal and Unimodal Systems

The main difference between multimodal and unimodal systems is the fact that unimodal systems use one trait for recognition. In contrast, multimodal systems use the fusion of multiple traits for the same function [11]. The reason why multimodal systems are considered more effective than unimodal systems is that the latter have a few drawbacks, which are [12]:

1. ***Noisy data:*** The susceptibility of biometric sensors to noise, such as fog or dust, which leads to the wrong rejection.

2. ***Intra class variation:*** The biometric data obtained during the recognition phase will not be similar to the data collected during enrollment to create a template. This is referred to as intra-class variation. Large intra-class variation raises a biometric system's False Rejection Rate (FRR).

3. ***Interclass similarities:*** Different individuals can always have very similar traits. These similarities can cause an increase in the False Acceptance Rate (FAR) of a biometric system.

4. ***Non universality:*** Due to medical circumstances, a few individuals are incapable of providing the required trait, which, in turn, makes them incapable of using the biometric system.

5. ***Spoofing:*** Spoofing is possible with unimodal biometrics, as the data can be imitated or fabricated.

1.6.2 Different Multimodal Types

There are five types of multimodal biometric systems, which are as follows [13]:

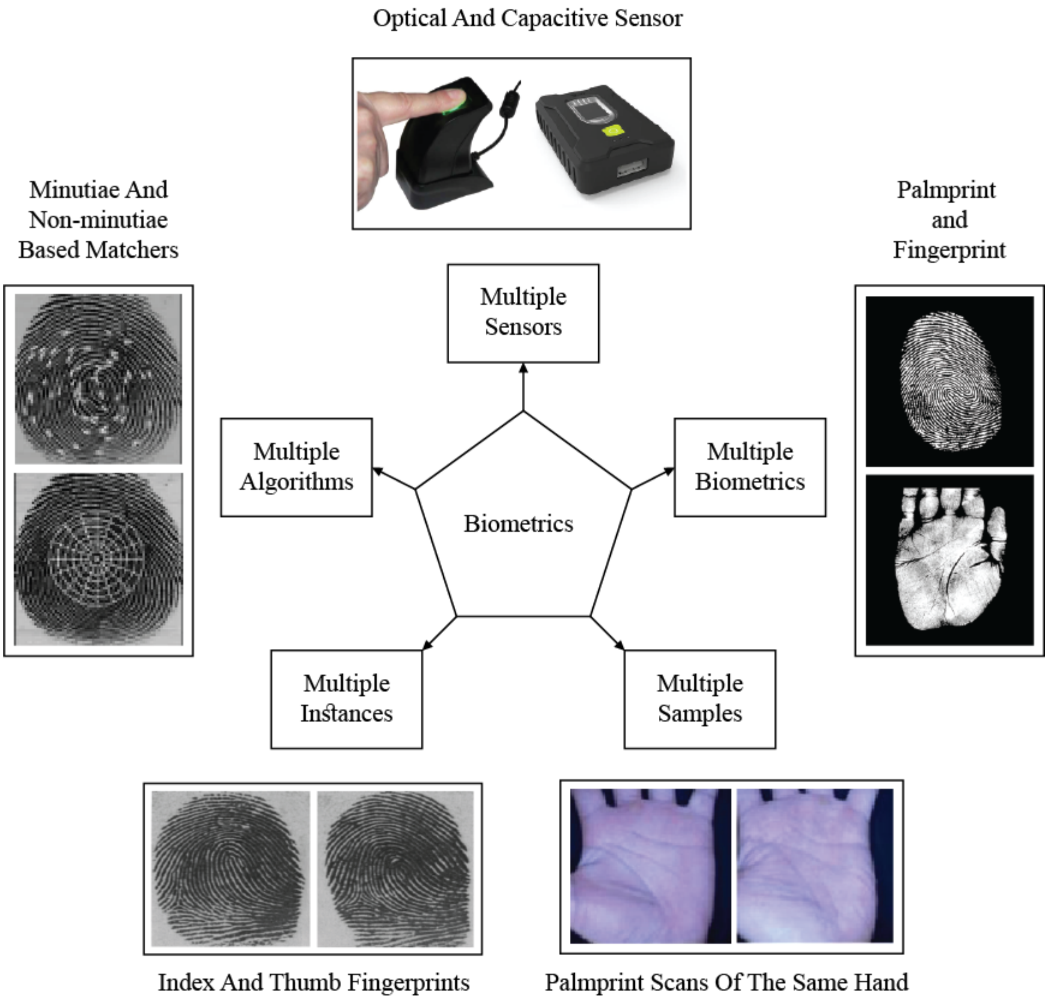

Figure 1.11: Different types of multimodal biometric system [14]

1. ***Multi-sensor systems:*** Combination of several sensors to acquire the same modality. For example, both optical sensors and multispectral sensors may be used for fingerprint acquisition.

2. ***Multi-sample systems:*** Association of several images of the same biometric trait. For example, the collection of many images of a face in various positions, expressions, or lighting.

3. ***Multi-algorithm systems:*** The use of several algorithms to process the same acquired image. For example, a hand biometric that can be represented by its shape and texture features.

4. ***Multi-instance systems:*** Combination of several instances of the same modality. For example, the left and right index fingers can be used to confirm a person's identity.

5. ***Multi-biometric systems:*** The use of several different biometric traits, such as iris and palmprint.

1.6.3 Multimodal Biometric Systems Fusion Levels

According to the literature, several modalities can be combined to improve the accuracy of biometric systems. As illustrated in figure 1.1, the fusion strategy can be used at four different levels: sensor level, feature level, matching score level, and decision level [10].

1. ***Sensor-level Fusion*** In the field of image processing, this approach is known as image fusion. This type of fusion is rarely employed because it requires homogenous data. Therefore, sensor-level fusion may be achieved by employing multiple compatible captures of instances generated by the same biometric trait, or multiple instances of the same biometric trait detected by a single sensor. But it is not feasible if the data instances are incompatible.

2. ***Feature-level Fusion:*** After the feature vectors are extracted separately from the modals, they get fused to form a single feature vector. The goal of this type of fusion is to get robust features if the data are homogeneous (made from the same modality and extracted using the same method) or more information if the data are heterogeneous (made from different modalities or extracted using different methods).

3. ***Score-level Fusion:*** This is the most frequently utilized sort of fusion since it can be applied to all types of systems. This method merges the resultant scores provided by the different systems to get a single matching score.

4. ***Decision-level Fusion:*** when each system produces a binary result in the form of YES or NO and the decision system makes a final decision based on a collection of those results, This is referred to as "Decision-level Fusion". The most commonly used strategy is majority voting, which generates the final decision based on the number of votes provided by each system.

1.7 Biometric Systems Evaluation

The performance evaluation of a biometric system is a critical phase in developing a biometric verification/identification system. This section examines the various performance data and charts used in exhibiting and discussing testing strategies for a biometric system. As previously mentioned, biometric applications are classified into two types, which are verification and identification. It is critical to distinguish between them here since they will influence the sort of performance evaluation utilized. [9].

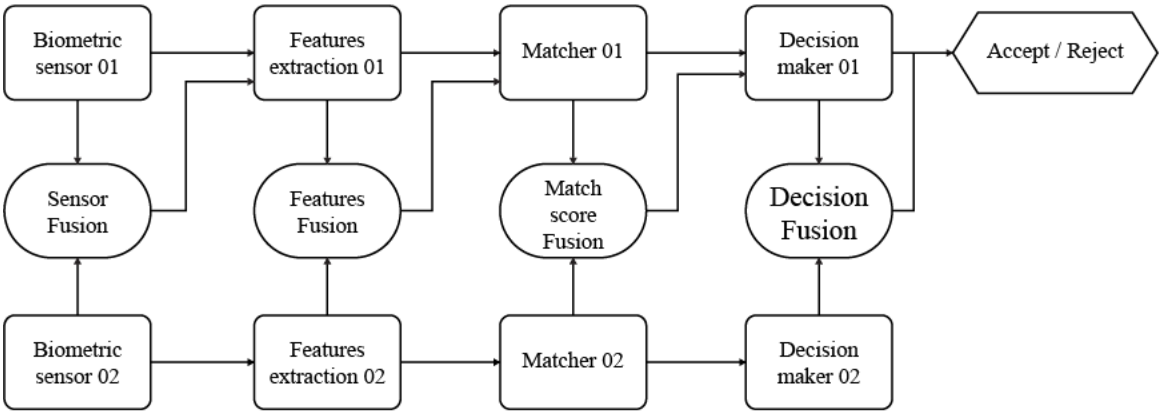

Figure 1.12: Fusion levels in multimodal biometric systems.

1.7.1 Error Rate Metrics

In the context of biometric system design and assessment, various metrics are employed. Some are used in the verification application, while others are used in the identification application (open-set / closed-set). The most commonly used metrics are listed below [9].

1. ***False Acceptance Rate (FAR)***: It is the probability of a biometric system wrongly approving unauthorized individuals.

$$FAR = \frac{number\ of\ people\ is\ falsely\ accepted\ (FA)}{the\ total\ numberof\ the\ impostor} \tag{1.3}$$

2. ***False Rejection Rate (FRR)***: It is the probability of a biometric system incorrectly denying access to an authorized individual.

$$FRR = \frac{number\ of\ people\ is\ falsely\ rejected\ (FR)}{the\ total\ number\ of\ genuine\ user} \tag{1.4}$$

3. ***Equal Error Rate (EER)***: The point when the FAR is equal to the FRR. The theoretical distribution of probability ratios of genuine users and impostors is shown in figure 1.13.

4. ***Genuine Accept Rate (GAR)***: It indicates the percentage of genuine individuals whom the system has approved. The formula is as follows:

$$GAR(\%) = 100 - FRR\ (\%) \tag{1.5}$$

5. ***Rank One Recognition (ROR)***: The percentage of individuals who are recognized by a biometric system based on a rank variable known as ROR. The ROR rate is determined when rank is equal to one.

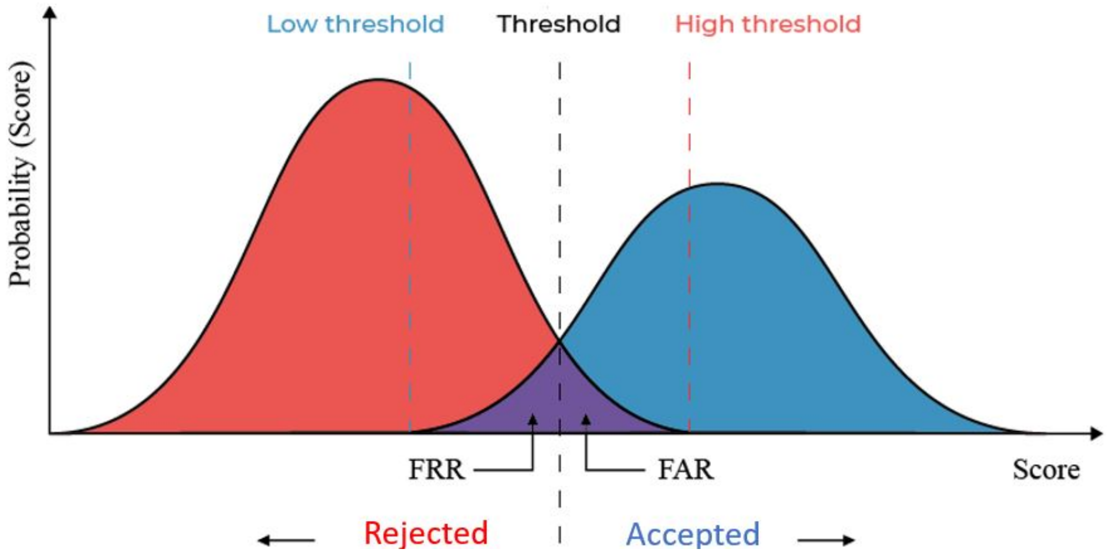

Figure 1.13: Score distributions for genuine users and imposter users [9].

6. ***Rank of Perfect Recognition (RPR)***: This rate is defined as the rank in which the identification rate achieves 100% accuracy, or at least attempts to. When RPR rises, the corresponding identification rate falls, implying a lower level of security.

It should be noted that the previously mentioned performance assessment metrics may be utilized for both biometric functionalities (identification/verification). The FAR and FRR are commonly employed in verification and open-set identification modes. For the closed-set, the ROR and RPR metrics are often used [9].

1.7.2 Performance Curves

Using specific curves, the performance of a biometric system for different parameters is graphically represented. The logarithmic scale is sometimes used to make graphs more accessible and understandable, especially when comparing biometric systems with similar data. These curves are [9]:

1. ***Receiver operating Characteristic curve (ROC)***: It is a common way for representing the technical performance of a biometric system in a specific application (usually in verification and open-set tasks). The ROC curve is a graph that shows the relationship between FAR and FRR (alternatively GAR against FAR).figure1.14 is an illustration of the ROC curve.

2. ***Cumulative match characteristic curve (CMC)***: It is a graphical representation used to evaluate the performance of a closed-set biometric identification system. The identification rate is plotted against the rank on a CMC curve. figure 1.15 shows an example of this curve.

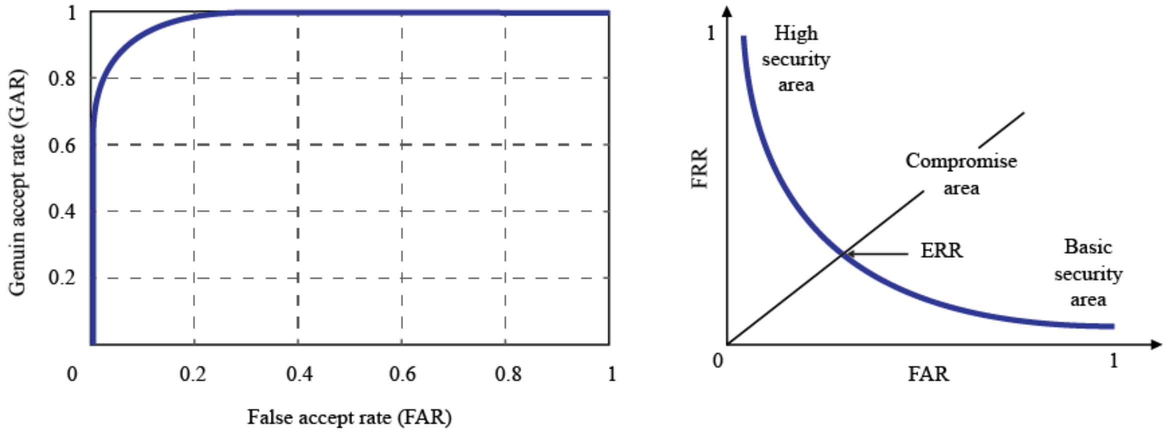

Figure 1.14: Receiver Operating Characteristic (ROC): (a) GAR against FAR when the decision threshold varies, (b) FRR Variation according to the FAR when the decision threshold varies [9]

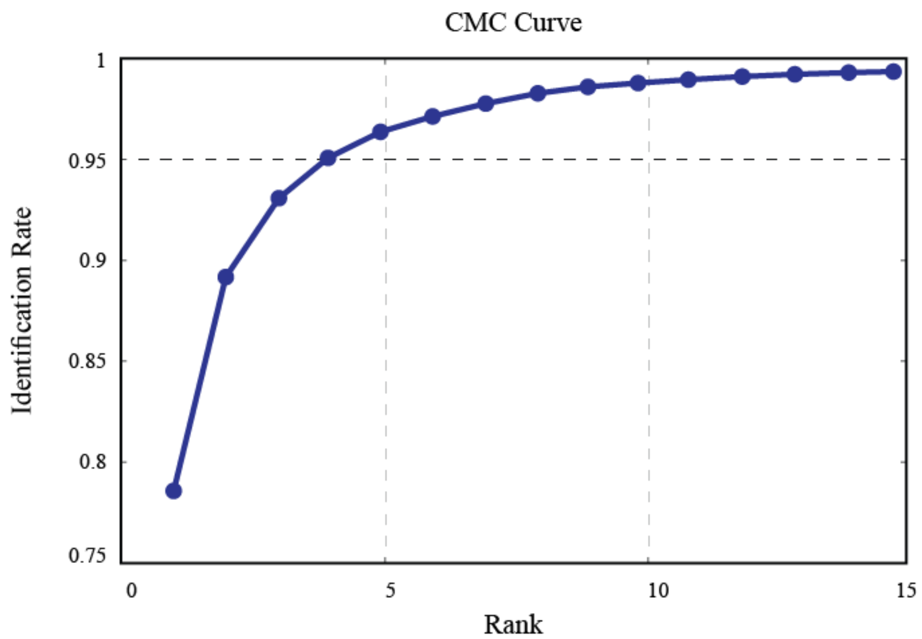

Figure 1.15: Cumulative match characteristic curve (CMC) [9]

1.8 Conclusion

This chapter was a well-rounded introduction to biometric technology. Within it, we provided many definitions and numerous concepts. Moreover, we provided some biometric techniques and the structure of a biometric system. In addition, we discussed unimodality, multimodality, and fusion levels and how these concepts contribute to a more desirable result. Finally, we concluded this chapter by going over the evaluation of a biometric system and how it helps us decide if a biometric needs enhancement and how urgent that enhancement is.

CHAPTER 2

PROPOSED HYPERSPECTRAL PALMPRINT IDENTIFICATION SYSTEMS USING DEEP LEARNING APPROACHES

2.1 Introduction

Building a biometric identification system requires the most optimal methods and techniques to be performed in perfect order to grant the most accurate results. There are various techniques and methods that can perform various tasks in each approach of biometric identification systems. The choice of those variables can affect the accuracy of the system to a high degree. Therefore, we must be meticulous in our choices to ensure a favorable outcome.

2.1.1 Deep Learning and Machine Learning

Learning is the process of the acquisition and accumulation of knowledge or skills through study, experience, or being taught. Humans learn countless concepts, solely to perform various tasks independently. We can say that machines have independently learned when they possess the ability to modify the structure, program, or data according to a pre-defined input. Now that an idea of what learning is for machines is established, we can define both machine learning and deep learning as modern techniques of image processing and data analysis, with great potential, which greatly assisted the field in growing incredibly popular among the IT community due to the doors they unlocked through their capabilities of classification and detection. Yet, deep learning is different to machine learning because it is a specialized subset that is a sophisticated and mathematically complex evolution of machine learning [15]. For example, in an image classification task, deep learning can select the best feature among all the features you offer. But traditional machine learning techniques don't have this capability.

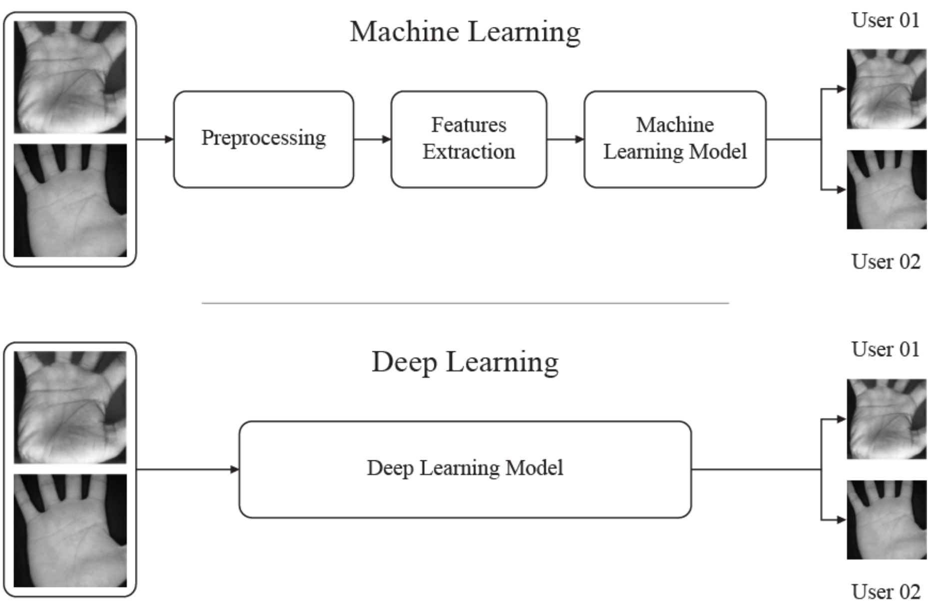

Figure 2.1: Difference between Machine learning and deep learning.

2.2 Artificial Neural Networks (ANN)

2.2.1 Artificial and Biological Neural Networks

The introduction of the concept of an ANN was first established through the paper under the name "A Logical Calculus of Ideas Immanent in Nervous Activity," written by the neurophysiologist Warren McCulloch and the mathematician Walter Pitts as early as 1943. McCulloch and Pitts demonstrate a computational model of how biological neurons enable more evolved species to perform tasks with high complexity. This was the first architecture for an ANN [16].

Biologically, the building stone of a nervous system is the neuron. Which is a cell composed of a cell body housing the nucleus and other complex components, one very long extension called the axon, many branching extensions called dendrites which serve as inputs receiving information from other neurons, and the terminals which serves as outputs giving the information to other neurons. The information traverses the neuron from the dendrites to the cell body to the terminals, using chemical electrolytes through a phenomenon known as action potential (as evident in figure 2.2) [16].

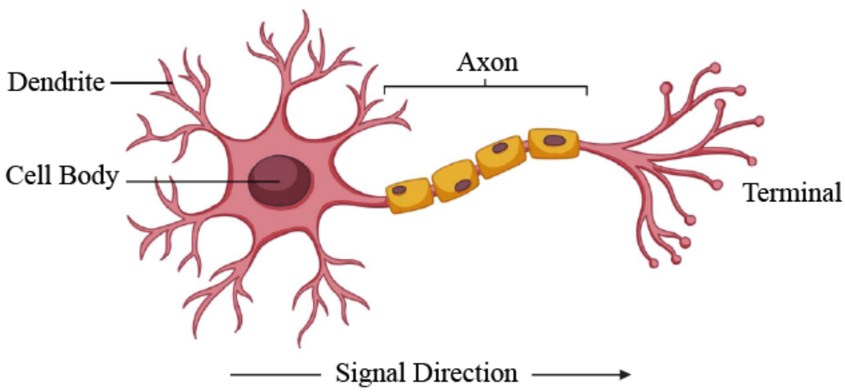

Figure 2.2: Structure of a biological neuron.

Computer engineers admired this magnificent product of nature, and the summit was to produce a system that mimics the functions of the human brain. Hence the birth of artificial neural networks (ANN).

ANNs are composed of neurons. The neurons have inputs that can be either the input data of the neural network or the output of the previous neurons, and neurons also have outputs that can be either the inputs of the following neurons or a portion of the network's output. Neurons have weighted connections to other neurons, which means that the connections have weights that resemble the relative importance of the input. Initially, the values of the weights are established randomly. After that, these values get adjusted through the training process [17].

2.3 Convolutional Neural Networks (CNN)

A Convolutional Neural Network (CNN) is a special type of deep learning architecture derived from animals' visual systems. A CNN's generalizing ability is significantly more efficient than other architectures. It possesses the ability to identify highly abstracted features of objects and identify them more efficiently, which makes it very powerful in image processing. However, it is effective in other fields, such as voice and natural language processing [18].

Since the 1980s, convolutional neural networks (CNNs) have been employed in image recognition, inspired by research into the visual cortex of the brain. CNNs have achieved phenomenal performance on several challenging visual tasks in recent years due to increases in computational power and the quantity of accessible training data, which was a progress-preventing factor for a long time. Examples of the employment of CNNs in modern technologies are self-driving vehicles, automatic video categorization systems, and others [16].

2.3.1 Types of Layers in a CNN

1. ***Convolutional Layers (CONV layers)***: A CONV layer contains a set of convolutional filters. A filter (or a kernel) is a matrix of numerical values. Each value is referred to as the "weight of the filter." As in an ANN, the weights of filters are assigned random numbers at the beginning of the training phase. After that, the weights will be tuned and adjusted with each training cycle to ensure better feature detection [18].

   As it is evident in figure 2.6, the bright pixels on the results are the edges that the filter has detected. Also, we notice that different filters detect different types of edges, as the first filter detected the top edges, the second filter detected the left-side edges, the third filter detected the bottom edges, and lastly, the fourth filter detected the edges on the right.

2. ***The Rectified Linear Units (ReLU)***: The ReLUs are considered activation functions. They follow CONV layers to generate non-linearity in the network. The ReLu helps the network achieve decision functions and reduce overfitting [19].

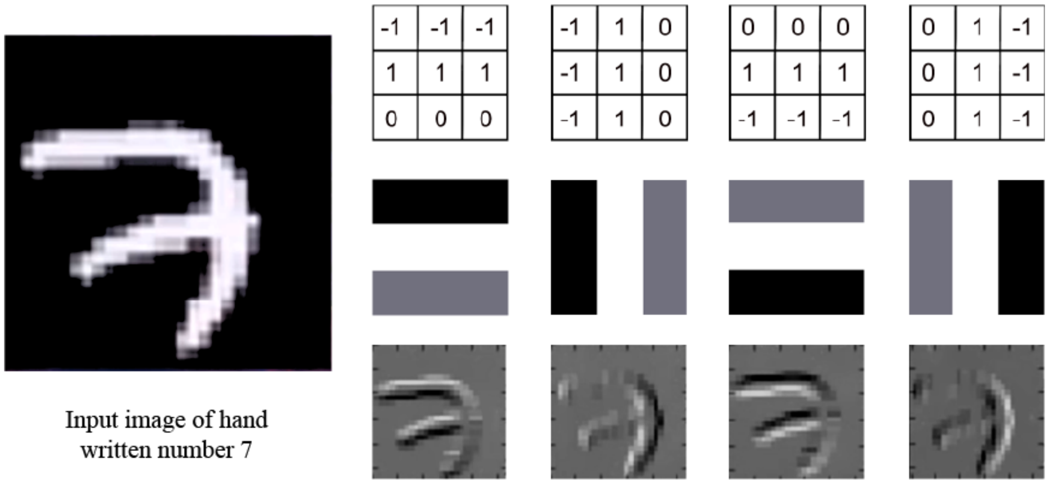

Figure 2.3: edge detection using a CNN on a hand written number 7.

3. ***Pooling Layers***: The pooling layers, or down-sampling layers, are applied to reduce the spatial size of feature maps in a manner that prioritizes saving the most relevant information from the feature maps, subsequently reducing the number of parameters and computation in a CNN and controlling overfitting. There are three operations in a pooling layer's filter, which are: maximum (Max), minimum (Min), and average (Avg). The most commonly used operation in these operations is the Max operation. These filters slide over the input data and apply the previously mentioned operations [19].

4. ***Fully Connected Layers (FC)***: As in ordinary Neural Networks, neuron in an FC layer have connections to all neurons in the previous layers. And that is where we distinguish between FC and CONV layers, since CONV layers' neurons are only connected in a local region [19].

2.4 Proposed Hyperspectral Palmprint Identification System

To create a robust and reliable biometric system that performs identification on hyperspectral images of palmprints, we utilize multiple components or stages starting with band selection to eliminate redundancy and noisy data from the hyperspectral images, ultimately reducing the size of its extensive dimensional data. Band selection results in selecting the most representative bands from which we extract their region of interest. After that, we perform feature extraction, employing CNN models. This is known as "off-the-shelf Pre-trained Models as Feature Extractors", which is one of the transfer learning strategies. Following that, we use a DRB classifier to obtain the scores. At this stage, we can either use a unimodal system by using each band separately or a multimodal system where we fuse the scores (score-level fusion) we obtain for more accurate results. All components used to compose this system are listed in the few following titles.

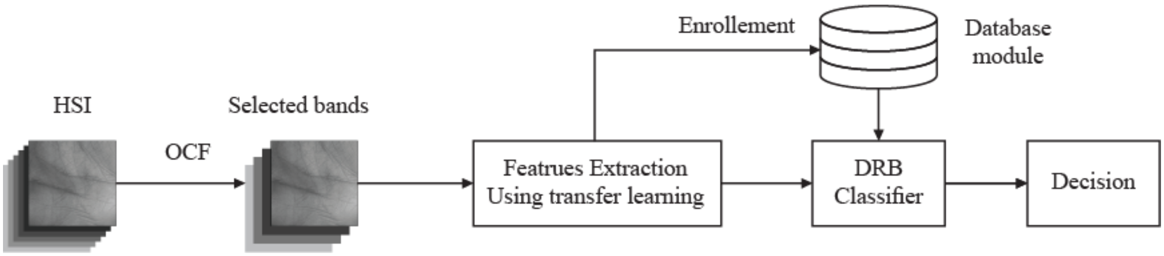

Figure 2.4: Proposed hyperspectral palmprint identification system.

2.4.1 Hyperspectral Image (HSI)

A hyperspectral image is a data cube that contains hundreds of 2-dimensional images. Conveying an abundance of information that is unique and undetectable by the usual RGB images or even multispectral imaging [20]. Both multispectral and hyperspectral imaging capture objects in a series of spectral windows. Both of them are efficient methods for collecting a multitude of spectra. Where we draw the distinction between them is that hyperspectral imaging consists of substantially more finely divided spectral channels than multispectral imaging [21].

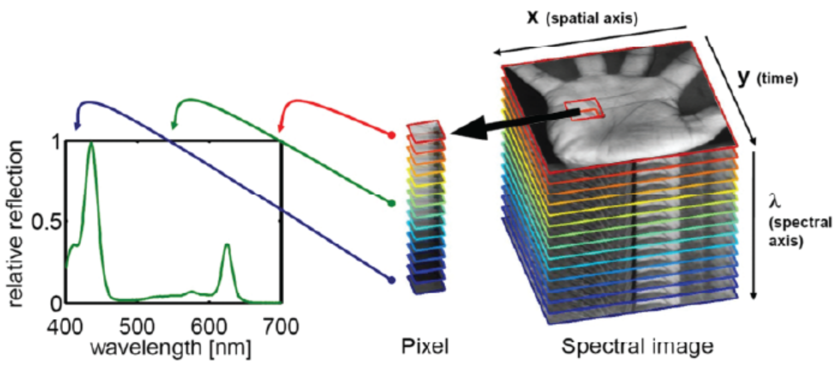

Figure 2.5: Hyperspectral Image Data Cube .

2.4.2 Region of Interest (ROI) Extraction

The images of the same palmprint obtained at various times will have different degrees of rotation and translation, and also, the size of the palmprint might differ, which makes it necessary that before we proceed with feature extraction and recognition of palmprints, we must extract the effective palmprint's region of interest that contains the main definitive features. Region of interest extraction is a critical stage that facilitates image alignment, enhances the efficiency of feature matching, and finally has a beneficial impact on recognition results [22].

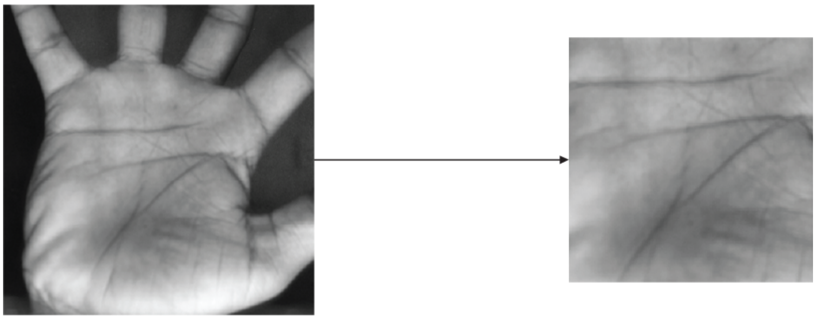

Figure 2.6: palmprint ROI.

2.4.3 Feature Extraction

Feature extraction is a crucial task in any pattern recognition application. The chosen feature extraction method determines the quality of the system's performance due to its selection of the most distinctive and discriminant features. In other words, the job of a feature extraction module is to extract only the distinctive features out of the raw data, forming a new representation that is unique and irreplicable [9]. One of the ways we can perform feature extraction is through transfer learning.

2.4.4 Transfer Learning

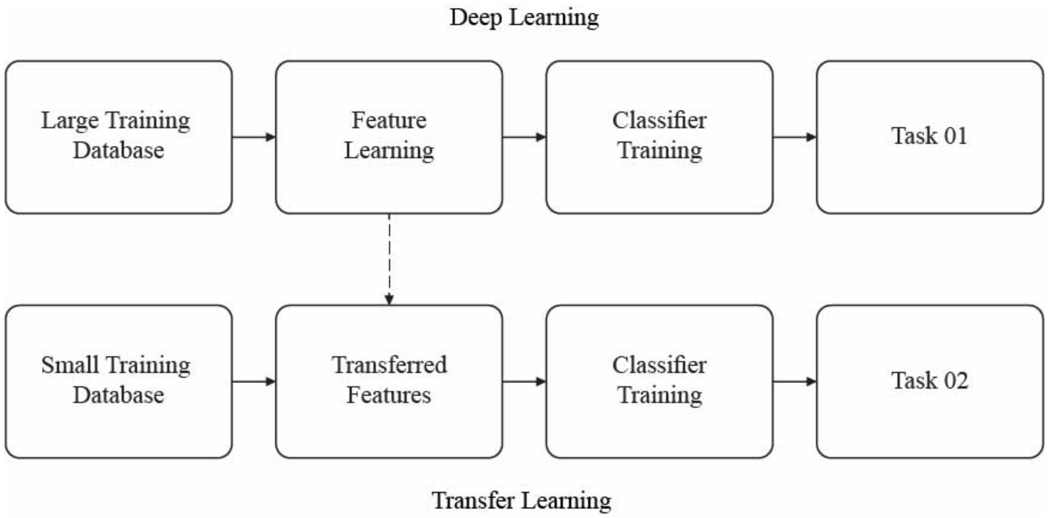

Figure 2.7: Transfer learning-achieving fast training times with limited dataset

Transfer learning is the process of training a network to perform a task (source task) in a certain domain (source domain) using a large database. And then use the same network to perform another task (target task) in a similar domain (target domain) using less training data [23]. Humans' capability to utilize knowledge learned in one domain across many other domains was the inspiration for transfer learning. For instance, employers require their applicants to have a certain amount of experience, owing to the fact that their experience, although gained on a different task, is still useful in their new job [24].

2.4.5 Transfer Learning Advantages

Transfer learning improves performance in many ways, of which we mention three common ones, starting with enhancing the beginning performance of the transfer learning's target task in comparison to an ignorant counterpart's performance. In addition, it substantially reduces the time the network takes to learn the target task using transferred knowledge. Finally, improve the final performance level achieved in the target task [25].

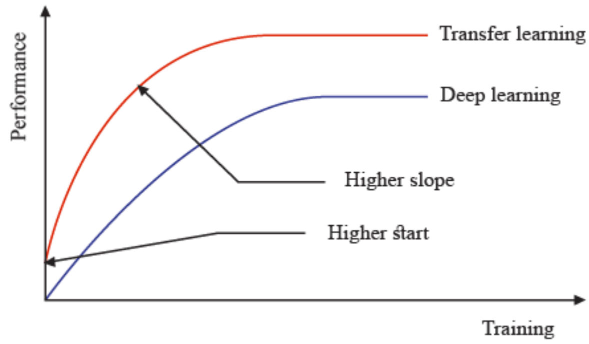

Figure 2.8: Comparing traditional deep learning and transfer learning [25]

2.4.6 Few Groundbreaking CNN Architectures

1. ***alexNet (2012)***: alexNet was created by Alex Krizhevsky, Ilya Sutskever, and Geoffery E. Hinton. Wining them the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition with top 5 test error rate of 15.3% [26]. alexNet is a CNN with eight layers. Five of them are CONV layers, and three are FC layers. As it utilizes ReLU as an activation function.[27].

2. ***VGG(2014)***: VGG or the Visual Geometry Group was submitted by Simonyan et al., awarding him second place in the ILSVRC 2014. Its layers pattern is modular, and it was made 19 layers deeper than AlexNet with the aim of demonstrating the relation of depth with the representational capacity of the network. What made VGG simple at that time was the fact that it decreased the size of the kernels from the usual 11x11 or 5x5 down to a stack of 3x3 kernels. This concept was proved through experiments that concurrent placement of small-sized kernels leads to results that are indifferent to those of bigger-sized kernels. In addition, the small size kernels provide the benefit of decreasing the computational complexity by reducing the number of parameters. As a consequence, a new trend of using smaller sized kernels arose widely [27].

3. ***GoogleNet (2014)***: GoogleNet won the ILSVRC 2014 competition. GoogleNet architecture's primary goal was to achieve great accuracy at a low computing cost (Szegedy et al. 2015) [27]. It proposed the new concept of inception block in CNN, which uses the split, transform, and merge ideas to incorporate multi-scale convolutional transformations. GoogLeNet's standard convolutional layer is replaced with small blocks employing the same networking-network (NIN) architecture concept, which replaces each layer with a micro-neural network. And also, GoogleNet used sparse connections. To get around the problem of redundant data, the purpose of GoogLeNet was to increase the learning capacity and improve the efficiency of CNN parameters [28].

4. ***ResNet (2015)***: Residual Network, commonly referred to as ResNet. Developed by Kaiming He and awarded the ILSVRC 2015. With the notion of residual learning in

CNNs and devising an efficient approach for deep network training, ResNet revolutionized the CNN architectural industry. It offered a 152-layer deep CNN. It was 20 times deeper than AlexNet and eight times deeper than VGG, with less computational complexity. ResNet is an excellent example of how the performance of image identification and localization tasks are greatly affected by representational depth and how crucial it is for visual recognition tasks. We see that in the fact that ResNet with 50/101/152 layers performs better image classification tasks than ordinary architectures with 34 layers [27].

2.4.7 Deep Rule Based Classifier (DRB)

CNNs falls short in many aspects, such as the required database size, its non-comprehensible internal structure, and its weakness while dealing with uncertainty. On the other hand, traditional fuzzy rule-based (FRB) systems cover those shortcomings, yet they are unable to achieve the high-level performance of deep learning classifiers. A combination of both approaches created the DRB classifier. DRB is a multilayer rule-based classifier used in image classification problems. It is data-driven and fully automatic. In short, this classifier is a set of IF...THEN...FUZZY rules that are fully comprehensible and self-organized. The classifier can updated constantly without fully retraining it, due to its non-parametric nature. Although, its training process is non-iterative and efficient, it can achieve remarkable classification accuracy [29]. The general architecture of a DRB classifier is presented in the figure 2.9 below.

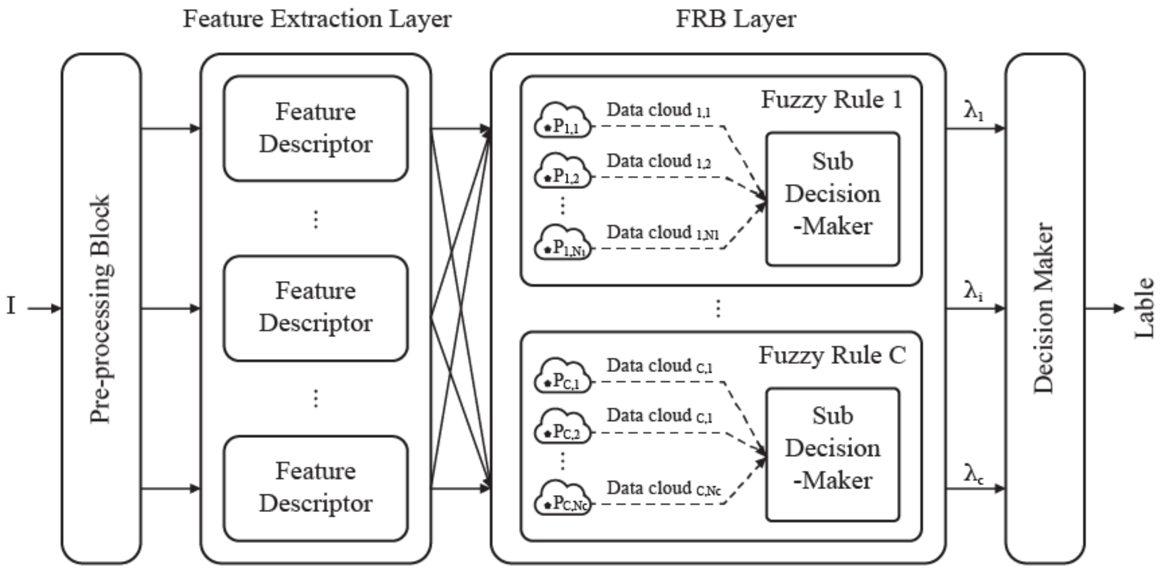

Figure 2.9: General architecture of DRB classifiers [29].

2.5 Conclusion

The few previous titles aimed to summarize and review core concepts surrounding deep learning algorithms, expand the readers' horizons beyond basic notions, and give a more in-depth overview. As a start, we provided a definition of deep learning and tied it to its more familiar inspiration, the biological brain and its neurons. Following that, we discussed ANNs and CNNs to a certain depth. After that, we explored an example of a biometric system that performs hyperspectral palmprint identification. In this section, we briefly mentioned a few stages that work together to ensure robustness and accuracy. The first step was to choose the bands, then to get the ROI, then to get the features using transfer learning, and finally to get the DRB.

CHAPTER 3

RESULTS AND DISCUSSIONS

3.1 Introduction

This chapter is dedicated to displaying and discussing the experimental results obtained through applying our identification system to a palmprint hyperspectral image database using transfer learning algorithms. We acquired the previously mentioned results by utilizing band selection. Moreover, we further improved the results by tinkering with and implementing the concepts of unimodality and multimodality.

3.1.1 Palmprint Advantages

Palmprints cover the shortcomings of many other biometric modalities. For instance, iris recognition has an expensive input device. Also, it is very intrusive to the extent that people might fear its damaging effects on their eyes. Another example would be fingerprint identification, because it requires high-resolution capturing devices. In contrast, low-resolution devices can capture palmprints without losing distinctive information. Likewise, it is not intrusive at all [30]. Palmprint recognition is suitable for applications with a larger targeted demographic. With that and all its advantages, it gained popularity among research academics [22].

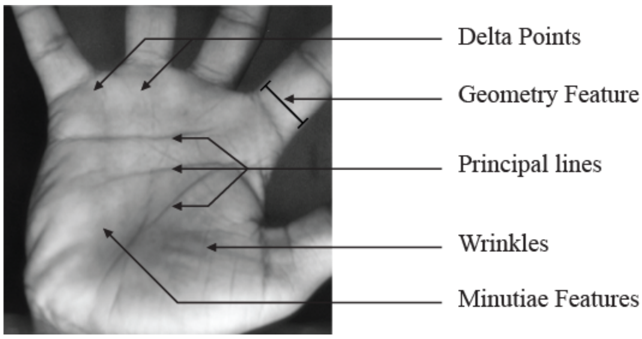

Figure 3.1: Different features of palm.

3.2 Database Description

The database used to conduct this experiment contains 314,640 hyperspectral images of palmprints collected from 190 people. Each person has 12 images of his left hand and another 12 images of his right hand. The hyperspectral images contain 69 spectra with wavelengths ranging from violet to near-infrared spectrum with a window between bands of 10nm (420nm-430nm-…-1100nm). Our database is organized through ranking, from the band with the shortest wavelength to the one with the longest. Therefore, 420nm is the first band, 430nm is the second band, and so on until we reach 1100nm, which is the 69th and last band.

3.3 Our Proposed Identification System

We propose a system in which we use band selection in order to eliminate redundancy and noisy data. The band selection method we used is OCF along with information entropy to select the most discriminant bands. The selected bands are 610nm, 690nm, 850nm, and 940nm for the left palmprint. 610nm, 760nm, 850nm, and 940nm for the right palmprint. After that stage, we utilized four transfer learning models as feature extractors, namely GoogleNet, AlexNet, VGG16, and Resnet50. The networks resulted in feature vectors that we fed into a DRB classifier to calculate the score vectors. After that, we fused our score vectors in three manners: unimodal system, multimodal system with four bands fusion, and multimodal system with fusion between all bands (four from the left and four from the right palmprints).

3.4 Assessment Protocol

3.4.1 Databases Separation

As we mentioned earlier, the palmprint image database contains 190 persons. Each person has 12 images of the left palmprint and 12 images of the right palmprint, which were taken in 4 bands. We chose six images from 12 images for training [1 3 5 7 9 11] and the other six [2 4 6 8 10 12] for the test (this applies to both the left and right palmprint images).

3.4.2 Work Environment

Physical environment: Due to the amount of time that it takes to conduct our experiments and their branching nature, we knew that in order to be efficient, we must use a high-end machine. We acquired a workstation with high computational capabilities with the following specifications:

- Computer: HP Z8 G4 Workstation.
- Memory (RAM): 96. 00 Go.
- Processor: Intel(R) Xeon(R) Silver 4108 CPU @ 1. 80 GHz 1. 80 GHz.
- System type: 64-bit operating system, processor x64.

Software environments: In recent years, with the advancements and achievements made in deep learning, MathWorks Inc. paid much attention to this aspect throughout the development of their renowned product, Matlab. It provides many features that help ease the experiments. Hence, we were prompted to use it. The environmental conditions used to conduct our experiment are:

- The software tool used by our system is: Matlab R2021a.
- The operating system used to run our software is: windows 10.

3.5 Experiments and Results

Our experiments aimed to compare different approaches with the same goal in mind: optimizing our identification system. We have experimented with various band selection approaches. We then tested four feature extractors in a unimodal system and two multimodal systems. The results are displayed in the following pages.

The following section aims to test and evaluate the unimodal and multimodal systems. To achieve that, we used our data set to train and test multiple transfer-learning architectures. In order to compare and contrast our different approaches and architectures, we chose the following criteria:

In open set identification: The Equal Error Rate (EER), and the T_0 (Threshold).

In closed set identification: The Rank one recognition(ROR), and the Rank of Perfect Recognition (RPR).

3.5.1 Unimodal Systems Test Results

With the aim of assessing the performance of the Unimodal system by utilizing our data set. We trained and tested our transfer-learning architecture with a single band at a time and recorded the following results:

Table 3.1: The unimodal identification system performance using the pre-trained networks GooglNet, AlexNet, ResNet50, and VGG16 as features extractors.

Feature extractor	Modality	Band(nm)	EER (%)	T_0	ROR (%)	RPR
GoogleNet	Left	610 (20)	2.1863	0.8260	89.2982	98
		690 (28)	0.5282	0.8230	97.7193	77
		850 (44)	0.1056	0.8480	99.4737	99
		940 (53)	0.0870	0.8470	99.5614	73
	Right	610 (20)	4.3389	0.7860	86.1404	185
		760 (35)	0.5263	0.8332	98.2456	65
		850 (44)	0.2587	0.7758	99.2105	46
		940 (53)	0.1764	0.8180	99.2105	111
AlexNet	Left	610 (20)	1.9368	0.7390	93.8596	126
		690 (28)	0.7008	0.7600	97.5439	156
		850 (44)	0.0880	0.7270	99.9123	57
		940 (53)	0.0880	0.7400	99.7368	54
	Right	610 (20)	3.2537	0.7420	90.4386	138
		760 (35)	0.2634	0.7812	99.1228	111
		850 (44)	0.0097	0.8530	99.9123	6
		940 (53)	0.0810	0.8140	99.8246	6
ResNet50	Left	610 (20)	1.3174	0.6470	94.9123	118
		690 (28)	0.0880	0.7937	99.5614	25
		850 (44)	0.0880	0.5559	99.8246	33
		940 (53)	0.0782	0.5716	99.9123	45
	Right	610 (20)	2.2127	0.6311	93.2456	112
		760 (35)	0.0135	0.7381	99.9123	16
		850 (44)	0.0005	0.9843	99.8246	3
		940 (53)	0	0.7947	100	1
VGG16	Left	610 (20)	1.1401	0.5845	95.3509	151
		690 (28)	0	0.9812	100	1
		850 (44)	0.0088	0.6006	99.8246	9
		940 (53)	0.0125	0.5304	99.9123	19
	Right	610 (20)	2.2798	0.5688	93.5088	118
		760 (35)	0.0824	0.5918	99.4737	7
		850 (44)	0.0139	0.6122	99.7368	4
		940 (53)	0.0685	0.5907	99.7368	9

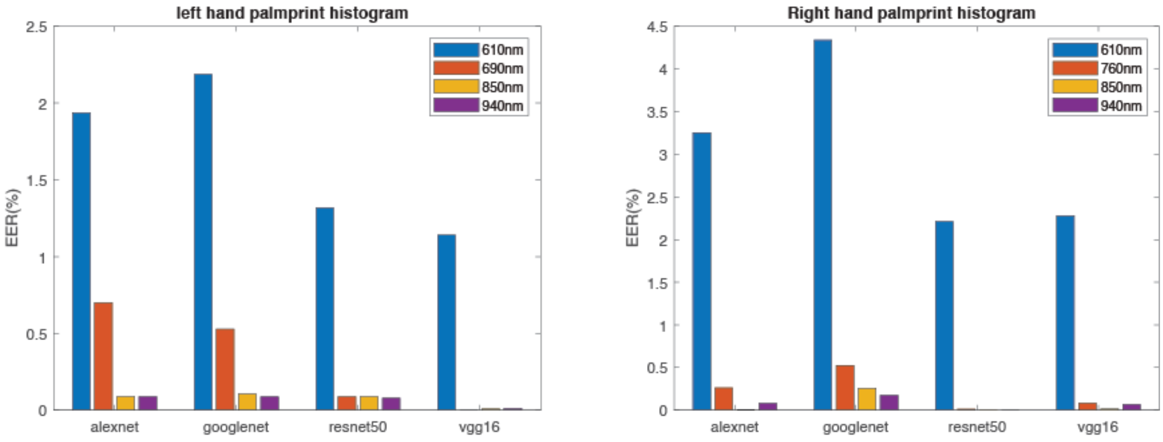

Figure 3.2: Histograms of EER(%) for the left palmprint (the left histogram) and the right palmprint (the right histogram).

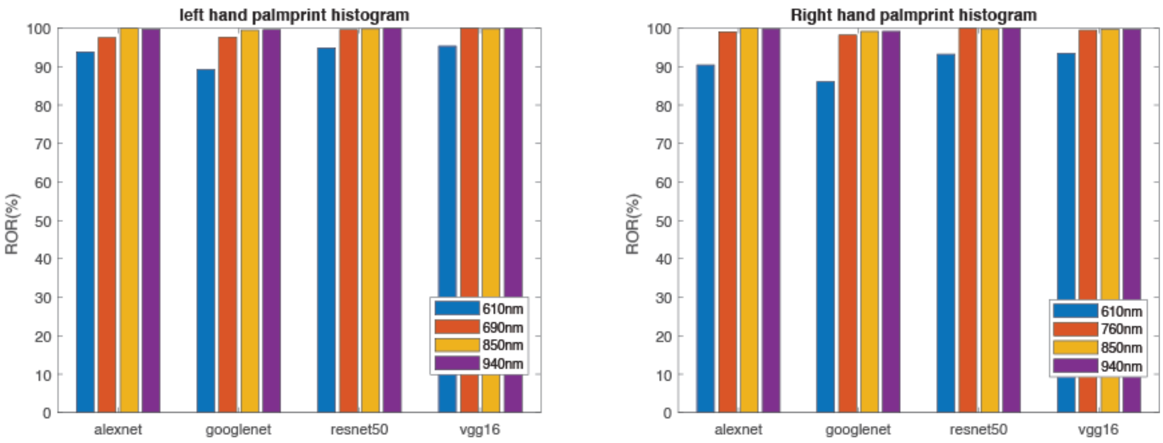

Figure 3.3: Histograms of ROR(%) for the left palmprint (the left histogram) and the right palmprint (the right histogram).

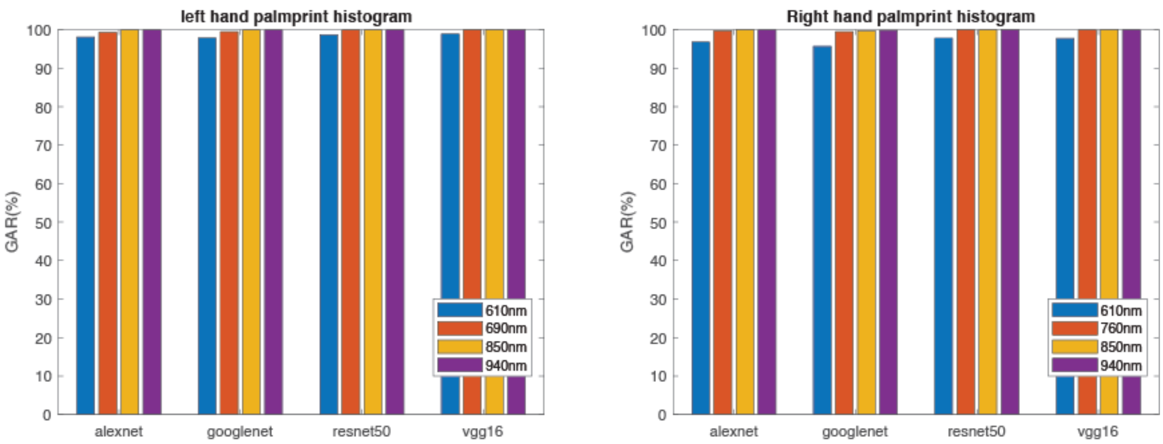

Figure 3.4: Histograms of GAR(%) for the left palmprint (the left histogram) and the right palmprint (the right histogram).

According to the results shown in table 3.1 and figures (fig.3.2 , fig.3.3 and fig.3.4) we notice:

In open set identification: What stands out in the table 3.1 is that some feature extractors gave perfect results in certain bands. As we see, the use of VGG16 as a feature extractor in the left palmprint using the 690nm band results in **EER** of 0% and **threshold** of 0.9812. And also, ResNet50 achieved a similar feat with the band 940nm, giving **EER** of 0% and **threshold** of 0.7947. From the histograms, we notice that ResNet50 and VGG16 show relatively low levels of **EER** compared to GoogleNet and AlexNet. As for the bands performance, we see the band 610nm in each palmprint sample for all the feature extractors gives the worst results in terms of **EER**. In contrast, the 850nm and 940nm bands gave the best results in terms of **EER**.

In closed set identification: We observe from the table 3.1 that the previous observations on the open set still apply to the closed set. We notice that we achieve an **ROR** of 100% and **RPR** of 1, using both ResNet50 and VGG16 with the right hand 940nm band and left hand 690nm band, respectively. Similar to the open set, the worst-performing band was 610nm, while the rest of the bands gave an **ROR** above 99%. Finally, we noticed that VGG16 achieved the lowest **RPR** levels among all feature extractors.

3.5.2 Multimodal Systems Test Results

This stage of experiments aims to improve the results given by the unimodal biometric identification system by using information from various bands and instances (left and right palmprint). Firstly, we present the performance of multimodal biometric systems based on fusion at a score level between four bands in each palmprint instance, which can be viewed in table 3.2 and the graphs below. After that, we demonstrate the performance of the same biometric systems but this time we fuse all bands as shown in table 3.3 and the following graphs. Also, it is worth mentioning that we experimented with four fusion rules: the simple sum rule (**sum**), the weighted sum rule (**wsum**), the product rule (**prod**), and the weighted product rule (**wprod**).

Table 3.2: The multimodal identification system performance using Fusion at score level between 4 bands.

Feature extractor	Modality	Method	EER (%)	T_0	ROR (%)	RPR
GoogleNet	Left Bands	Sum	0.0880	0.7680	99.9123	14
		WSum	0.0880	0.7806	99.9123	61
		Prod	0.0880	0.4049	99.9123	19
		WProd	0.0880	0.7937	99.9123	64
	Right Bands	Sum	0.0880	0.7974	99.5614	42
		WSum	0.0880	0.7913	99.4737	53
		Prod	0.0880	0.4561	99.5614	45
		WProd	0.0880	0.7971	99.4737	55
AlexNet	Left Bands	Sum	0.0051	0.8342	99.8246	7
		WSum	0.0880	0.6806	99.9123	39
		Prod	0.0084	0.4606	99.8246	9
		WProd	0.0880	0.6883	99.9123	40
	Right Bands	Sum	0	0.9556	100	1
		WSum	0.0042	0.8821	99.8246	5
		Prod	0	0.9447	100	1
		WProd	0.0042	0.8824	99.8246	5
ResNet50	Left Bands	Sum	0.0014	0.8327	99.9123	5
		WSum	0.0014	0.7753	99.9123	8
		Prod	0.0028	0.5001	99.9123	8
		WProd	0.0037	0.7663	99.9123	14
	Right Bands	Sum	0	0.8325	100	1
		WSum	0	0.7947	100	1
		Prod	0	0.4990	100	1
		WProd	0	0.7947	100	1
VGG16	Left Bands	Sum	0.0005	0.9445	99.9123	2
		WSum	0	0.9812	100	1
		Prod	0.0009	0.7502	99.9123	3
		WProd	0	0.9812	100	1
	Right Bands	Sum	0.0056	0.6954	99.8246	3
		WSum	0.0102	0.6258	99.7368	4
		Prod	0.0051	0.2287	99.8246	3
		WProd	0.0107	0.6256	99.7368	4

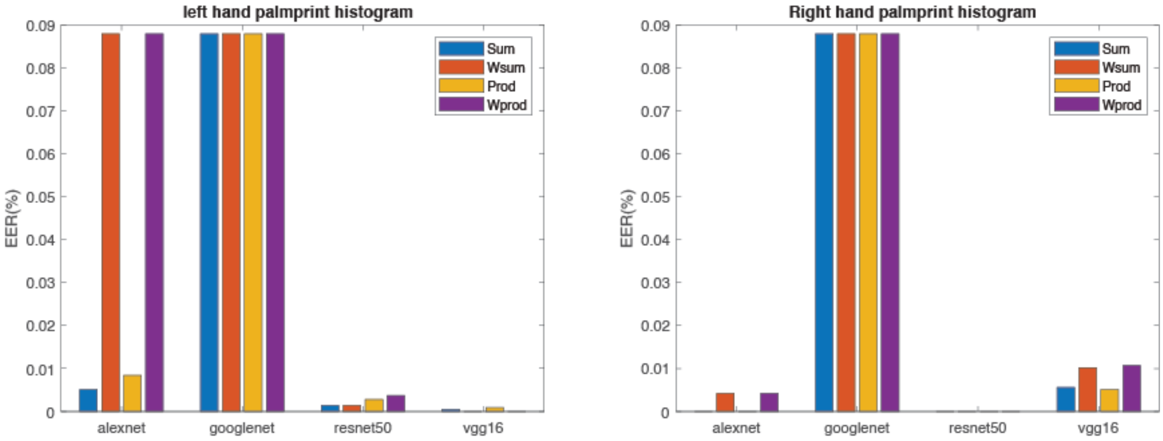

Figure 3.5: Histograms of EER(%) using fusion between four bands for the left palmprint (the left histogram) and the right palmprint (the right histogram).

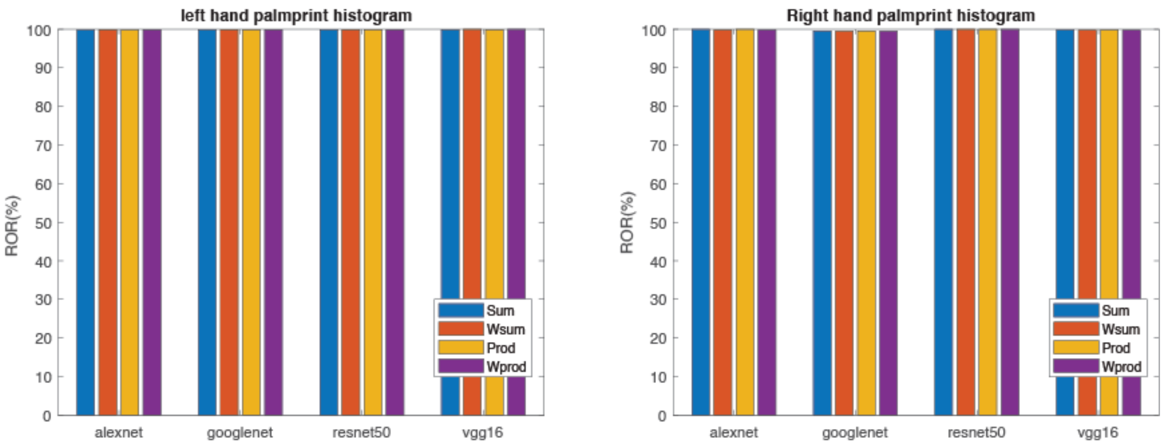

Figure 3.6: Histograms of ROR(%) using fusion between four bands for the left palmprint (the left histogram) and the right palmprint (the right histogram).

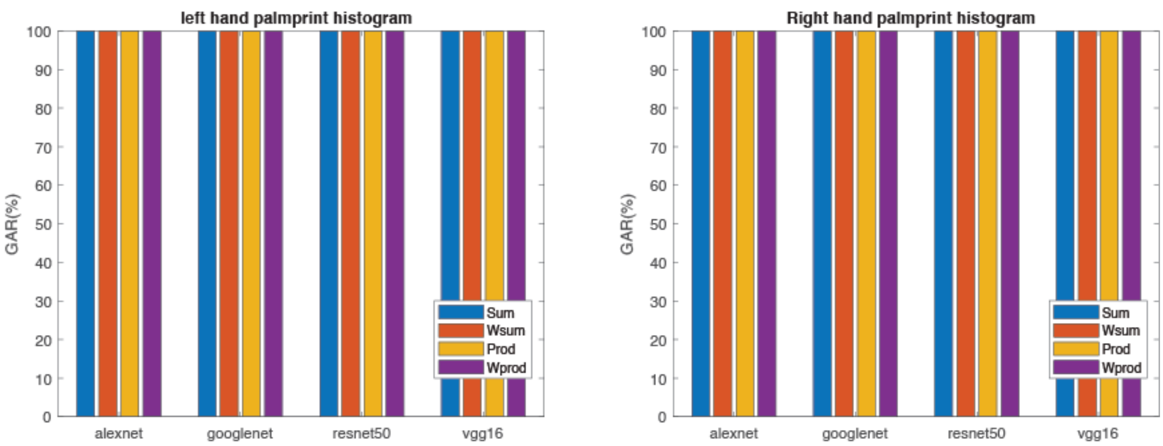

Figure 3.7: Histograms of GAR(%) using fusion between four bands for the left palmprint (the left histogram) and the right palmprint (the right histogram).

According to the results of table 3.2 and figures (fig.3.5 , fig.3.6 and fig.3.7), we notice that multimodal systems outperform unimodal systems:

In open set identification: The table 3.2 supports the notion that using fusion methods can reduce the **EER** significantly. We notice as we use GoogleNet that the **EER** is decreased to 0.088%. Moreover, we achieved **EER** of 0% in both cases of AlexNet on the right palmprint and VGG 16 left palmprint bands fusion with **sum** and **prod** fusion methods. As for ResNet50, we achieved 0% **EER** across all fusion methods in the right palmprint bands.

In closed set identification: The results reveal a very significant improvement of **ROR** compared to the unimodal system. As it is apparent with the use GoogleNet, all the **ROR** levels of both right and left palmprints are higher than 99%, which is a notable feat compared to **ROR** of unimodal systems. Whereas the 610nm bands achieved the lowest **ROR**, wherein both left and right palmprints, we recorded 89% and 86% respectively, which is still an improvement of 10% and 13% compared to the unimodal system. As a final note, we notice 100% achievement of **ROR** in cases of using AlexNet on right bands using **sum** and **prod** fusion methods, ResNet50 on right bands in all fusion methods, and VGG16 on left bands using **wsum** and **wprod** fusion methods.

Table 3.3: The multimodal identification system performance using Fusion at score level between all 8 bands (left and right).

Feature extractor	Method	EER (%)	T_0	ROR (%)	RPR
GoogleNet	Sum	0	0.8099	100	1
	WSum	0.0005	0.9739	99.9123	2
	Prod	0	0.2649	100	1
	WProd	0	0.9792	100	1
AlexNet	Sum	0	0.7583	100	1
	WSum	0.0005	0.9629	99.9123	2
	Prod	0	0.1373	100	1
	WProd	0.0005	0.9753	99.9123	2
ResNet50	Sum	0	0.5750	100	1
	WSum	0	0.7947	100	1
	Prod	0	0.0201	100	1
	WProd	0	0.7947	100	1
VGG16	Sum	0	0.6469	100	1
	WSum	0	0.9812	100	1
	Prod	0	0.0294	100	1
	WProd	0	0.9812	100	1

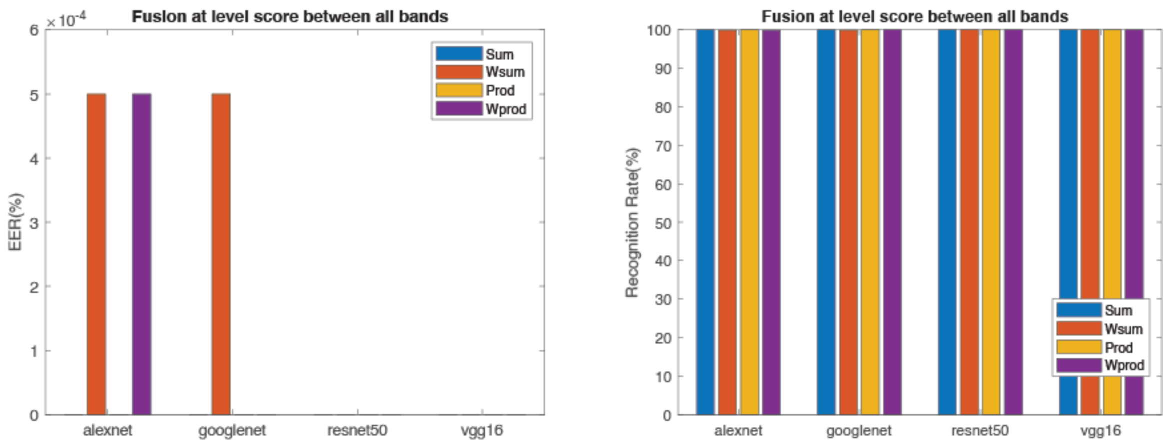

Figure 3.8: Histograms of EER(%) (the left histogram) and ROR(%) (the right histogram) using fusion between all bands.

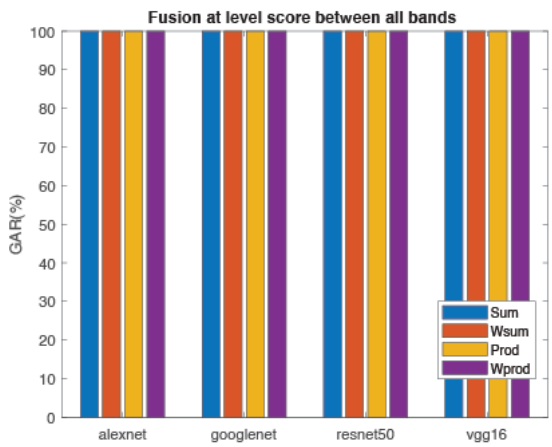

Figure 3.9: histogram of GAR(%) using fusion between all bands.

According to the results of table 3.3 and figures (3.8 and 3.9), we notice that in multimodal systems using fusion between all bands of both the left and the right palmprints results in a noticeable improvement.

In open set identification: We derive from the table 3.3 the fact that all feature extractors in all fusion methods resulted in a null **ERR**. Excluding the two feature extractors, AlexNet with the (**wsum** and **wprod**) fusion methods and GoogleNet with the (**wsum** fusion method (in all three situations, the **ERR** recorded was equal to 0.0005%). Even though the two exceptions did not perform like the others, they are still remarkably better than the previous fusion between four bands.

In closed set identification: As per usual, the open set results were similar to the closed set. Using all the fusion methods, we have achieved 100% **ROR** in the two feature extractors, ResNet50 and VGG16. But, for the AlexNet, the two fusion methods (**Wsum**

and **Wprod**) both gave **ROR** of 99.9123%. And, with GoogleNet, we recorded a **ROR** of 99.9123% using the (**wprod**) fusion method.

3.6 Conclusion

In this chapter, we constructed a personal identification system based on hyperspectral palmprint images in three approaches: one unimodal and two multimodal. We started by reducing the volume of the HSIs in the dataset by performing band selection, which highlighted the most representative and discriminative bands using OCF for the representation task, and with information entropy, which is a ranking method that is used for the discrimination task. After acquiring the most representative bands, we used a well-known transfer-learning architecture to perform feature extraction. Specifically, ResNet50, VGG16, GoogleNet, and AlexNet. Therefore, according to the results, we concluded that the two former architectures performed better than the two latter architectures. Besides that, for the approaches we used, we affirmed that multimodal systems outperform unimodal systems. Furthermore, we can even achieve continual progress if we collect multiple biometric instances, as in the previously mentioned proposal of fusing right and left palmprints with different specters.

General Conclusion

Through our advancements in technology, we are becoming more and more dependent on data, data that is growing in size and becoming very crucial and impactful in our lives. Consequently, managing that data has become a very daunting and sensitive task. And with that, people become very concerned about their safety and very paranoid about potential fraud and identity theft. Biometrics is a viable and secure option. Using a part of an individual's body to determine their identity is as secure as possible. Other than that, acknowledging that some biometrics are more effective in some situations than others, we decided on using palmprint identification. On the grounds that it suits tasks that need to be processed quickly without interfering much with the user's daily life due to its acceptability, it is also secure due to its acceptable distinctiveness.

We used a unimodal system and further improved the obtained results by using a multimodal system. The system's input was a hyperspectral image database, which we used to train and test multiple transfer-learning architectures, which functioned as feature extractors that fed into a classifier. Our first goal was to reduce the immense amount of data stored in each image of our database by using band selection to eliminate redundancy and reduce calculation time. After that, we established the results for the unimodal system, which yielded decent results, yet, there was room for improvement. We then used a multimodal system in which we fused the score vectors of four bands in multiple methods, which increased the accuracy of our system by a considerable amount. At this stage, our results were near-perfect, prompting us to take the fusion one more step by fusing all the bands from the left and right hands. This gave us our desired result of 100% accuracy across the board, apart from a few methods, which gave a very small error of 0.0005%. This result confirmed to us the claim that the palmprints and transfer learning algorithms are capable of resolving a lot of issues with traditional identification methods.

As we approach the end of this journey, we look forth to what can be done in this field and how to further improve. The options that can vary to produce different results that can better suit different circumstances to cover the shortcomings of the approach we took. An assumption can be made concerning improving our work by experimenting with more transfer learning architectures such as DenseNet or NASNet, or by using other transfer learning strategies such as model architecture extraction or partial fine-tuning.

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