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By: Amel BENABDALLAH

Subject

Biometric Recognition System based on Analysis and Classification of Physiological Signals

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Système de Reconnaissance Biométrique à base d'Analyse et Classification de signaux physiologiques

Publicly defended, on 11/12 /2025, before the jury composed of:

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"Whoever travels a path in search of knowledge, Allah will make easy for him a path to Paradise. People do not gather in the houses of Allah, reciting the book of Allah and studying it together, but that tranquility will descend upon them, mercy will cover them, angels will surround them, and Allah will mention them to those near him."

– Prophet Muhammad (PBUH)

Dedication

To my beloved parents and grandmother,
whose love and support have always been there for me, I am eternally grateful.

To my dearest little family, my Husband and my daughters,
for having faith in me and being patient with me.

To my dear brothers “Anes” and “Othmane” and my little son and brother “Dr. Omar El Farouk”,
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To my Professors,
Thank you for sharing your knowledge and professionalism.

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To my colleagues and friends,
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Amel BENABDALLAH Sp. BENHAMED

ملخص

تستكشف هذه الأطروحة المجال المبتكر لأنظمة التعرف على القياسات الحيوية، مع التركيز على تحليل وتصنيف الإشارات الفسيولوجية كوسيلة لتحسين عمليات تحديد الهوية الشخصية والتوثيق . وتركز المناقشة على مختلف الإشارات الفسيولوجية التي تم دمجها في إطار عملنا البيومتري المطور، مثل تخطيط كهربية القلب وتخطيط القلب وإشارات ضغط الدم المستمر ، مع تسليط الضوء على أهميتها في التطبيقات البيومترية. ومن خلال استخدام تقنيات متقدمة للتعلم الآلي والشبكة العصبية الاصطناعية وخوارزميات معالجة الإشارات ودراسة الاستئصال، توضح الدراسة الحالية كيف توفر هذه الإشارات نمطاًا مميزاًا فريداً لكل فرد، ومناسباًا للمهام المتعددة لنظام القياسات الحيوية المقترح. بالإضافة إلى ذلك، تتناول هذه الأطروحة التحديات التي تواجهها تطبيقات العالم الحقيقي . تُثري النتائج المقدمة مجموعة البيانات وتهدف إلى المساهمة في مجموعة المعارف المتنامية في مجال تكنولوجيا القياسات الحيوية، وتسليط الضوء على إمكانات تحليل إشارات ضغط الدم كحجر زاوية لأنظمة التعرف على القياسات الحيوية من الجيل التالي. يقدم هذا البحث رؤى قيمة للبحث العلمي في مجال القياسات الحيوية الطبية التي تحسن الكفاءة التشغيلية من خلال زيادة رضا المرضى من خلال الحد من الخطأ في التعرف على الهوية، مع تقليل التكاليف والأخطاء الطبية ومنع الاحتيال على أصحاب المصلحةْ.المتعلقة بخصوصية البيانات، والحاجة إلى نماذج تصنيف قوية.

كلمات مفتاحية: بيومترية ، الاشارات الفيزيولوجية ، خصوصية الهوية و التوثيق ، اشارات القلب ، اشارات كهربية القلب ، ضغط الدم المستمر ، الذكاء الاصطناعي .

Abstract

This dissertation explores the innovative domain of biometric recognition systems, focusing on the analysis and classification of physiological signals as a method to improve personal identification and authentication processes. The discussion delves into various physiological signals fusion into our developed biometric framework, such as electrocardiography (ECG), Impedance Cardiography (ICG) and Continuous Blood Pressure (BP) signals highlighting their significance in biometric applications. By employing advanced machine learning techniques and ANN, signal processing algorithms and ablation study, the current study demonstrates how these signals provide unique characteristic pattern to each individual tailored with multitasks of the proposed biometric system. Furthermore, this dissertation addresses the challenges faced in real-world implementations, including data privacy concerns, and the need for robust classification models. Results indicate the Fine Gaussian-SVM model achieved an 88.14% accuracy during training, with a recall of 95.09%, precision of 94.33%, and a Kappa coefficient of 87.7%. In the test set, FG-SVM demonstrated 93.33% accuracy, balanced recall and precision of 93.33%, and a Kappa coefficient of 92.9%. The Bi-layered ANN model exhibited superior training performance, attaining 93.3% accuracy, 94.56% recall, 93.17% precision, and a Kappa coefficient of 93.1%. Notably, in the test set, Bi-layered ANN achieved perfect accuracy, recall, precision, and Kappa coefficient of 100%. The presented findings enrich the dataset, aim to contribute to the growing body of knowledge in biometric technology, showcasing the potential of blood pressure signal analysis as a cornerstone for next-generation biometric recognition systems. This research offers valuable insights for academic and healthcare sectors which enhance operational efficiency by improving patient satisfaction through mitigate misidentification of patients, while also minimizing costs, medical errors, and preventing fraud of stakeholders interested in the future of biometric authentication solutions.

Key words: Biometrics, Physiological signals, identification, authentication, ECG, ICG, CBP, classification, SVM, ANN.

Résumé

Cette thèse explore le domaine innovant des systèmes de reconnaissance biométrique, en se concentrant sur l'analyse et la classification des signaux physiologiques comme méthode d'amélioration des processus d'identification et d'authentification des personnes. La discussion porte sur divers signaux physiologiques fusionnés dans notre cadre biométrique développé, tels que l'électrocardiographie (ECG), la cardiographie d'impédance (ICG) et les signaux de pression artérielle continue, en soulignant leur importance dans les applications biométriques. En employant des techniques avancées d'apprentissage automatique et ANN, des algorithmes de traitement du signal et une étude d'ablation, l'étude actuelle démontre comment ces signaux fournissent un modèle caractéristique unique à chaque individu, adapté aux multiples tâches du système biométrique proposé. En outre, cette thèse aborde les défis rencontrés dans les mises en œuvre réelles, y compris les préoccupations relatives à la confidentialité des données, et la nécessité de modèles de classification robustes. Les résultats indiquent que le modèle Fine Gaussian-SVM a atteint une précision de 88,14 % pendant la phase d'apprentissage, avec un rappel de 95,09%, une précision de 94,33 % et un coefficient Kappa de 87,7 %. Dans l'ensemble de test, FG-SVM a obtenu une précision de 93,33%, un rappel et une précision équilibrés de 93,33 % et un coefficient Kappa de 92,9 %. Le modèle ANN bicouche a affiché des performances de formation supérieures, atteignant une précision de 93,3%, un rappel de 94,56 %, une précision de 93,17 % et un coefficient Kappa de 93,1 %. Notamment, dans l'ensemble de test, le modèle ANN bi-couche a obtenu une exactitude, un rappel et une précision parfaits, ainsi qu'un coefficient de Kappa de 100 %. Les résultats présentés enrichissent l'ensemble de données et visent à contribuer au corpus croissant de connaissances en matière de technologie biométrique, en mettant en évidence le potentiel de l'analyse des signaux de pression artérielle en tant que pierre angulaire des systèmes de reconnaissance biométrique de la prochaine génération. Cette recherche offre des perspectives précieuses pour la recherche scientifique en biométrie médicale qui améliorent l'efficacité opérationnelle

en augmentant la satisfaction des patients grâce à la réduction des erreurs d'identification, tout en minimisant les coûts, les erreurs médicales et en prévenant la fraude des parties prenantes.
Mots clés : *Biométrie, signaux physiologiques, identification, authentification, ECG, ICG, CBP, classification, SVM, ANN.*

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List of Abbreviations

BIS : Biometric Identification System

BAS : Biometric Authencation System

CBPS : Continuous Blood Pressure Signal

ICG : Impedance Cardiography

MBEBI : Multi-Modal Biometric (ECG-BP-ICG)

BioAPI : Biometric Application Programming Interface

ANN : Artificial Neural Network

Bi-ANN : Bi-Layer Artificial Neural Network

SVM-RFE : The Support Vector Machine-based Recursive Feature Elimination

List of Algorithms

Introduction

Pattern recognition involves the description, identification, classification, and interpretation of objects or phenomena by processing and analyzing diverse data that characterise them [1]. Following decades of development, pattern recognition technology has become a highly advanced instrument that is used extensively in domains such as fingerprint and face recognition, handwritten character identification, character recognition, speech recognition, remote sensing image analysis, industrial fault detection, and precision guidance, revolutionizing automated and biometric systems [1]. Current recognition methods, often rely on the client-server paradigm, in which the machine plays the role of the server and the person user as a client, rely heavily on traditional authentication techniques. Such techniques include possession- based tokens such as ID cards or usernames and passwords [2]. These ancient systems are increasingly inadequate, leading to serious security vulnerabilities that hackers and malicious actors exploit to gain unauthorized access to privileged rights, including sensitive medical data. For this concept, biometrics are a significant way for securing communication in biomedical sensor networks and wearable devices. [3], [4], The birth of biometric systems starts with the common recognition of traits such as fingerprint, iris, or face recognition. However, research has expanded to hand geometry, then the vascular pattern, and even DNA. Since the late 1990s, there has been a revolution in biometrics, and they play a crucial role in security access. This technology revolutionized the world and replaced older identification technologies [5]. The term ”biometrics” refers to ”the automated recognition of individuals based on their behavioral and biological characteristics”, as defined by the (ISO/IEC JTC1 SC37) standards [6]. Several physiological (static) and behavioral (non-static) biometric characteristics have been utilized. The exploration of physiological signals reveals some of the most fascinating aspects of these methods. To begin with, these signals capture unique characteristics among individuals, making them particularly laregely resilient against attempts at deceit [7], [8]. Furthermore, the rapid advancement of non-invasive wearable sensors available off-the-shelf makes it increasingly easy to collect such signals [9], [10]. Third, physiological signals can serve as a means of detecting the presence of a living subject [11]. Physiological signals are considered as biometric traits because they are not readily observable. Such signals include ECG, EEG [12], and PPG [13]. Specifically, A Canadian business namely ”Nymi” has created an authentication system that uses wrist-worn pulse sensors as an alternative to fingerprint recognition ; on the other hand, a Pentagon device uses infrared lasers to identify each people’s unique heart features. Thus, visually detecting ECG differences between patients is difficult due to the small changes in amplitude and duration. To address this constraint, pattern recognition methods are commonly used for quick, objective, and reliable identification. Consequently, the ECG has achieved an incredible niche as a source of security and privacy in the form of a biometric, and researchers have begun investigating its use as an emerging biometric modality to identify and authenticate individuals [14], [15], [16]. A typical ECG biometric identification technique is broken down into three steps : as a first stage, preprocessing is primordial, then feature extraction, and finally a decision is made by classification. In particular, that among the three, feature extraction is particularly crucial because it affects the information provided to classifiers and has a significant impact on overall identification performance. Existing ECG identification algorithms are often classified into two types based on feature extraction : fiducial and non-fiducial [17]. In existing literature of ECG-based Identification approaches mainly rely on extracting fiducial points such as P, Q, R, S, and T waves as mentioned by Biel *et al.*[18], [19] these 360 fiducial features were extracted from 12-lead ECGs to classify subjects, achieving early promising results in biometric identification, but the number of leads and features engendered time-consuming in processing phases. After that, Nemirko *et al.*[20], [21] demontrated the variability of using only single-lead ECGs with linear discriminant analysis to achieve a 96% rate of recognition. However, many of these methods depend heavily on pre-processing steps such as denoising, which can be complex, time-consuming, and require careful parameter tuning. For example, traditional denoising algorithms often demand significant effort to optimize and may not effectively handle noisy signals, limiting their practicality [17]. Compared to prior work, the study of introduces a novel approach that omits the need for explicit denoising. Instead, it employs a wavelet transform combined with a prior knowledge-based feature selection targeting the QRST complex, which is less sensitive to noise. Furthermore, the use of a stacked sparse autoencoder for feature learning facilitates robust recognition while maintaining computational efficiency. Experimental results on popular databases (ECG-ID and MIT-BIH-AHA) demonstrate that this method achieves high recognition accuracy (up to 96%) using raw signal. These two research studies focus on biometric identification systems using the same databases containing ECG signals and develop an algorithm using the Fourier decomposition method (FDM) and phase transform (PT) to extract features from ECG signals for biometric identification. Compared to the study of [22], the ECG signals are divided into frames containing beats, capturing interbeat and intrabeat variations, and decomposed into Fourier intrinsic band functions (FIBFs), then different classifiers were used, such as Random Forest (RF), Ensemble Subspace Discriminant (ESD), and Support Vector Machine (SVM), on three datasets : MIT-BIH (on-the-person), ECG-ID and CYBHI (off-the-person), the method achieved identification accuracies of 91.07% (CYBHi), 97.92% (MIT-BIH), and 98.45% , in the other hand, Islam *et al.*[22] highlights the reliability of ECG-based biometric authentication testing by multiple deep learning models, including transfer-based, CNN-based Siamese network, and LSTM. Experiments on MIT-BIH datasets achieved identification accuracies of 98.99% (MIT-BIH) and 99.54%

(ECG-ID). However, for verification, the CNN-based Siamese model achieved 86% accuracy on the ECG-ID dataset. In recent years, research has shown that our bodies offer cryptographic keys for sensors attached to our bodies by way of measuring a physiological value extracted from our vital signs and physiological signals [23]. As a first investigation, the Electrocardiogram (ECG) has proven to be appropriate. According to [24], physiological signals such as Electrodermal Activity (EDA) and Blood Volume Pulse (BVP) measured via PPG are captured by wearable devices used for biometric recognition based on deep learning models, achieving up to 98.85% accuracy on real-world datasets, but the latter contains only 17 persons. Other angle of study ,focus on a biometric identification system that used machine learning with physiological signal (electromyography, phonocardiogram, and electrocardiogram) fusion. These signals were collected from 32 participants using the BIOPAC MP-36 system. Two types of cepstral features were extracted : gamma tone cepstral coefficients (GTCCs) and Mel-frequency cepstral coefficients (MFCCs), which were analyzed for their spectral properties ; the highest accuracy, 98.4%, was achieved using GTCC features with both the fine K-nearest neighbor (KNN) and linear discriminant classifiers [25]. A systematic review covers data acquisition techniques and the impact of emotional and physical states on biometric recognition performance based on ECG signals, noting accuracies [85-98]%, despite emotional stress or varying conditions, improving robustness of biometrics based on physiological signals [26]. In this context, the design of an appropriate acquisition protocol for physiological signals, especially

ECG. For instance, Jyotisho *al.* evaluated their model using three ECG databases on the person and two-off-the person, the results showed the model performs well for both on-the-person ECG and off-the-person ECG data [27]. In the same line of research, Srivasta *al.* [28] used one database acquired on-the-person and the other off-the-person, and even mixed together in a large database, their approach achieved identification accuracies around 99% for each individual databases and approximately around 98.5% for the combined dataset. The authors proved the robustness of their ECG biometric method from signal acquisition methods.

After a thorough and detailed review of existing research, it is apparent that there is a predominant focus on electrocardiography signals, often neglecting other pivotal physiological markers such as impedance cardiography (ICG) and blood pressure (BP). Integrating these signals brings a fresh perspective to biometric identification for several compelling reasons. Primarily, the continuous blood pressure signals offer crucial insights into vascular health and the autonomic nervous system (ANS). Additionally, ICG signals capture mechanical, electrical, and hemodynamic aspects of cardiovascular function. In this research, the integration of electrocardiography (ECG), impedance cardiography (ICG), and blood pressure signals is explored for the development of a comprehensive biometric identification model.

In accordance to this latter, research has emphasised the findings that physiological signal-based biometrics can play a primordial role in recognition and achieve high performance in identity verification. A study on multimodal physiological signals, including heart rate (HR), breathing rate (BR), palm electrodermal activity (P-EDA), and perinasal perspiration (PER-EDA), reported a top-1 accuracy of 88.74% and a top-5 accuracy of 99.51% using a convolutional neural network (1D-CNN) optimized with sequential model-based optimization [29]. This highlights the effectiveness of deep learning techniques in processing raw signal data for classification. PhD theses have further explored specific physiological signals. For example, Rig Das's thesis [30], ”Biometric Recognition Using Deep Learning”, focused on EEG and finger vein patterns, demonstrating the effectiveness of convolutional neural networks (CNNs) for feature extraction and achieving high accuracy in biometric recognition systems.

Although e-Services are in their early years in nations like **Algeria**, where the fraudulent events are small, it is estimated that over 17 million Americans were victims of one or another identity theft incident in 2014 [31], [32]. Statistics confirm that government and large private organizations are the most targeted ones. Every year, the number increases.

Today, what used to be a futuristic concept has become a reality today. Biometric technology is extensively employed in numerous real-world applications. They used in a wide range of purposes across various domains, including identity verification, authentication, and personal recognition. Biometric systems are utilized for purposes such as enhancing safety, securing access, preventing crime, supporting forensic investigations, facilitating medical applications, and security.

As passionate about biomedical engineering invention and data, we search for a specific problem in this sector to offer solutions, and thanks to the integration of numerization and e-health in medical fields in our country of Algeria, for this reason we focus on applying biometric systems based on physiological signals, because in healthcare they play a critical role in patient identification, securing sensitive medical data, and improving care by ensuring treatments are accurately attributed to the correct individuals. Current identification methods and physiological signals (e.g. Electrocardiography or Electroencephalography) face limitations in accuracy due to physiological factors or variability from environmental security vulnerabilities such as spoofing and accessibility issues for diverse individuals.

Although biometric recognition systems (BRS) based on physiological signals have reached a mature stage of development and technologies, there remain significant challenges tasks still require further improvement and continuous research. In this thesis, we focus primarily on the heart organ as a vital source of physiological signals not discovered yet and underexplored for biometric applications ; in particular, there are three major contributions in the thesis : as a first a new physiological signals namely Continuous Blood Pressure was integrated in the domain of multimodal biometrics after different trials and investigations due to it universality, accessibility and low cost acquisition of this signal ; in addition Blood pressure is a multifaceted parameter shaped by intricate physiological and neurological factors, which must be comprehensively integrated to develop a robust predictive model. The purpose of our thesis is to create a holistic framework that accounts for these interdependent influences, enabling accurate blood pressure modeling and advancing personalized healthcare solutions and this complexity is relevant in biometric systems, as these systems can benefit from incorporating various influences on blood pressure to enhance their accuracy and effectiveness. second, several new features were investigated in this research to improve the biometric system ; thirdly, novel classification algorithms, which led considerable boost in recognition performance. The main objective of this research area is to advance patient recognition methods in healthcare by deepening the understanding of biometric technology as a globally viable identification system. This current study investigates the efficacy of integrating physiological signals (electrocardiogram (ECG), blood pressure, and impedance cardiography (ICG)) into biometric systems, proposing solutions to improve their accuracy and security. Based on biometrics, healthcare facilities can enhance the accuracy of patient data. By expanding the knowledge base in this domain, we aim to deliver effective solutions that improve patient identification and safety across healthcare facilities. The chapters highlight the advantages of biometric systems, encouraging healthcare professionals and institutions to adopt these technologies to enhance patient safety. This ensures that physiological data and the right information are assigned to the correct patient, which is crucial for effective treatment and care planning, thus reducing the risk of medical errors and data breaches.

The thesis comprises four concise chapters, each providing valuable insights and pertinent details about our research area, structured as follows :

Chapter 01 This chapter serves as an introduction to biometrics, offering essential insights into its historical development and the biometric recognition process. Describes the core functionalities of biometric technology and its diverse applications in various sectors. The chapter emphasizes the transition from traditional identification methods to modern biometric systems, highlighting the advantages and challenges associated with this technology. The following sections delve into specific aspects of biometrics, providing a comprehensive understanding of its role and impact.

Chapter 02

This chapter is devoted to the concept of biometric recognition derived from physiological signals, providing a constitution for the biometric system. It elaborates on the methodological approach adopted throughout this dissertation, encompassing the successive stages from the preprocessing stage and culminating in identification decisions through machine learning techniques, highlighting its effectiveness in analyzing non-stationary signals, particularly the new multimodal physiological signals dataset under investigation.

Chapter 03

Divided into two integral parts, each delineating sophisticated methodologies and cutting-edge technologies in the domain of biometric identification/verification and characterization (fiducial vs. non-fiducial), offering a concise overview of the integration of physiological signals as biometric modalities, outlining their applications and advantages, and noting their notable impact on the field of medical health monitoring. As a second part, a comparison study between biometric systems begins with an ECG-based biometric identification framework, and then, with the apparition of wearable devices, we focus on the strategic amalgamation of these physiological signals, namely photoplethysmography (PPG) signals.

Chapter 04

Outlines our developed biometric system, detailing the biometric recognition framework modules and methodolody followed with multiclassification techniques based on two different classifiers leveraging machine learning and artificial intelligence with hyper-parameter functionalities.

Chapter 05

In this final chapter, we evaluate our contributions through an in-depth analysis of significant hybrid signals (Electrocardiogram, Impedance Cardiogram and Blood Pressure) and it also discusses the criteria used to assess the performance of biometric system comprehensively.

Chapitre 1

Theoretical Foundations of Biometric Recognition

1.1 Introduction

Pattern recognition is a cornerstone of human interaction, enabling the identification of individuals and the interpretation of their physiological and behavioral characteristics. In the context of modern technology, where machines, control systems, wearable devices, and information technologies are increasingly integrated into daily life, it is imperative that these systems emulate human-like recognition capabilities through *biometric systems* to verify or identify individuals, enhancing security in various applications ranging from healthcare monitoring to mobile device access. In this preliminary chapter, we present an overview of the theoretical foundations of biometric technologies and systems. Section 1.2 provides a detailed examination of the core definitions of biometric recognition, and then we outline the key challenges and motivations driving the adoption of this technology, emphasizing their key role in modern security and identification frameworks. Subsequently, Section 1.3 traces the historical evolution of biometrics, beginning with fingerprint systems to advancing technologies based on identification in different sectors, highlighting key milestones and technological systems that have shaped its development. Thus, in Section 1.4 we compare two categories of biometric systems and illustrate their practical significance if the system is uni-modal based on only one trait or multi-modal biometric system 1.6 combining different identifiers.

1.2 Reasons for Adoption of Biometric Technologies

In recent years, biometric technology has advanced rapidly, particularly in terms of security and identification. **B**iometrics is the science of recognizing individuals from their behavioral and/ or physical attributes, known as biometric modalities [46] as it is known that the word ”Biometric” is a Greek word that implies bios for (Life) meaning and metric which means (measure) [67]. Biometric systems are also called person identification system. Although biometric data are collected primarily to verify or establish a person’s identity, it often encodes additional information beyond an individual’s identity [47]. For instance, a facial image can reveal demographic details, such as gender and age [36]. Moreover, the physical and behavioral characteristics embedded in biometric data can subtly convey health-related information [39]. For example, the structural aspects of a person’s face may reveal underlying conditions like Down syndrome. Consequently, biometric data holds the potential to uncover health indicators that could support medical diagnoses. Depending on the specific application of the biometric system, it can function in either verification mode or identification mode. Both of which are fundamental concepts in the biometric field, yet they refer to distinct processes.

- In verification mode, the biometric system authenticates a person's or user's identity by comparing their newly captured biometric data with their pre-registered template(s) which are stored in the database. Usually in a verification system, the user claims an identity by providing a personal identification number (PIN), a user name, or a smart card, prompting then the system to perform a one-to-one (OvO) comparison to validate the claim. Verification systems are commonly used for positive recognition that prevents multiple people from using the same identity[34].
- In the identification process, an individual is recognized by matching their biometric template against all user templates registered in the database, without requiring the user to claim an identity. Identification is also known as negative recognition application because otherwise it fails to identify the subject if it is not enrolled in the database. Its purpose is to prevent a single person from using multiple identities by establishing recognition only using biometrics, relying solely on biometric traits for recognition [35].

In this context, the researchers Jain *et al.* [37] noted that automatic identification and authentication (verification) has become a critical technology through a variety of applications. It includes different fields such as security systems, domotic systems (smart homes), and the automotive industry, where secure user access is primordial.

However, when implementing these biometric systems, different main factors must be evaluated to guarantee their effectiveness and suitability for the intended application. As many researchers have stated [37], [38], these factors of the system include the conditions under which users interact with it, potential security risks, the scale of the user base, and the specific tasks the system will perform; for this reason, the selection of an appropriate biometric system depends on a range of characteristics. It is important and suitable to understand the characteristics of biometric systems in order to better understand the systems. The following are the characteristics of the biometric systems, as shown in the figure below 1.1:

Universality : every individual should possess the biometric characteristic; Distinctiveness : two individuals should be distinguished by their own and unique biometric traits; Permanence : the biometric feature should remain constant across time; Collectability : refers to the ability to measure biometric traits using practical technology or devices. Performance : the enrollment, feature extraction, and matching processes should take a limited period of time; Acceptability : the enrollment procedure should be accepted by a large parts of the users; Resistance to spoofing : The biometric attribute should be strong against attempts to spoof [49].

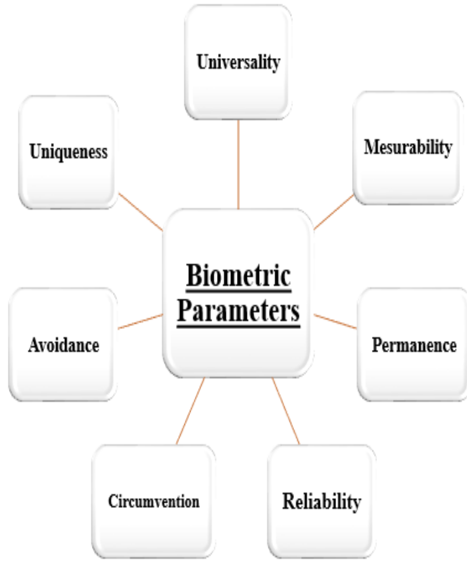


FIG. 1.1 : A biometric characteristic in various applications.

Biometric data refers to distinct physical, chemical, or other characteristics (such as iris patterns, facial features, or voice characteristics) used to establish a link between individuals and their identity. We encounter biometrics in our daily lives for both personal identification (for example, fingerprint analysis at a crime scene) and authentication (e.g., unlocking a smartphone using facial recognition). A key advantage of biometrics is the absence of preshared knowledge, unlike passwords. Most biometric attributes cannot be forgotten, lost, stolen, or easily forged, as they are unique to each individual. This inherent advantage has driven the continuous exploration of new and more reliable biometric data types since the pioneering use of fingerprint recognition in 1883 [59].

1.3 Evolution of biometric systems in different fields

1.3.1 Early developments

Biometrics has been employed informally for centuries, with various body parts and our behaviors serving as a means of identification throughout history. The study of finger images dates back to ancient China. However, the era of automated biometrics has only 40 years of history. In the late 1960s, the FBI (Federal Bureau of Investigation) pioneered this field and began to automatically check finger images. By mid-1970s a number of automatic finger scanning systems had become more widespread [53]. Beginning in 1996, and particularly in 1998, increased funding significantly boosted research and development in biometric technology. As a result, biometrics research has become more vigorous and has advanced beyond isolated studies in fields such as pattern recognition, signal processing, image processing, computer vision, and computer security. Current research efforts are primarily focused on the iris, ffingerprints, palmprints, voice, and handwritten signatures. Consequently, reports estimates that in 2001, homeland security expenditures from $56 billion to nearly $100 billion by 2005, which reflect a hightened global emphasis on security [40].

1.3.2 Evolution of biometric systems

Identimat was the first automatic commercial fingerprint scanner system and was installed by the FBI. In addition to fingerprint and hand geometry, various other biometric techniques have also been developed. Recognition methods based on retina, iris, and voice emerged during the 1970s, while signature and facial verification are relatively newer additions to this field [53].Beginning in 1996, and particularly in 1998, increased funding significantly boosted research and development in biometric technology. As a result, biometrics research has become more vigorous and has advanced beyond isolated studies in fields such as pattern recognition, signal processing, image processing, computer vision, and computer security. Current research efforts are primarily focused on the iris, fingerprints, palmprints, voice, and handwritten signatures. A series of prominent events highlights the growing attention biometrics is receiving in both industry and academia. For instance, in April 1998, the formation of the BioAPI Consortium marked a pivotal moment. This consortium was established to create a widely accepted and accessible API, aimed at standardizing and facilitating the integration of various biometric technologies. A notable trend in biometrics research is the collaborative involvement of companies, governments, and universities in advancing biometric technology. In recent years, the number of companies offering biometrics-based security products and comprehensive security solutions has steadily increased. These products range from fingerprint capture devices and specialized cameras for digital retina image capture to software development toolkits and complete software solution packages.

1.4 Types of Biometric systems

1.4.1 Behavioral Biometric System

Behavioral biometrics is a category of biometrics that relies on analyzing human actions as opposed to physical traits. Typically, behavioral biometrics are primarily utilized in verification systems [52]. Here are some examples of behavioral biometrics :

Keystroke Dynamics : Analyzing the way a person types, including speed, rhythm, and pressure. Gait Analysis : Assessing the manner in which a person walks. Voice Recognition : Identifying individuals based on their speaking patterns, pitch, and tone.

Notably, behavioral biometrics are considered arguably more repreplaceable than physiological biometrics due to the context in which they are used can frequently be altered as shown in the Figure 1.2.

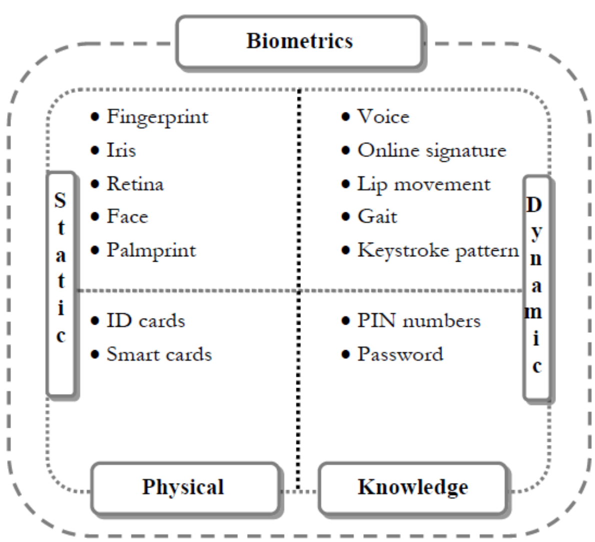


Fig. 1.2 : Different techniques of authentication, depicted from [90]

1.4.2 Physical Biometric System

Physical biometric systems are security systems that consist of using a part of human body that uses biological data to authenticate and identify individuals. These systems are increasingly integrated into various sectors, ensuring robust security to access building devices or sensitive informations and enhancing user experience. However, they also raise significant ethical and privacy issues that must be addressed as the technology evolves. Here are some applications of physical biometric systems :

- Security and Access Control : Used in secure facilities, airports, and offices.
- Smartphones and Devices : Commonly used for unlocking phones and tablets.
- Banking and Financial Services : Provides secure access to accounts and transactions.
- Healthcare : Ensures patient identity and secure access to medical records.
- Law Enforcement : Assists in identifying individuals and verifying identities

1.5 Principal Operation of Biometric System

The integration of biometric data systems and biometric recognition/identification technologies forms the biometric security systems. These systems serves a locking mechanism to control access to specific data. To gain entry and access to the biometric security system, an individual will need to provide their unique characteristics or traits, which will be matched to a database in the system. If there is a match, the locking system will provide access to the data for the user. The locking and capturing system will activate and record information from users who accessed the data. The relationship between the biometric and biometric security system is often linked to a lock and key system. The biometrics security system is the lock, and biometrics is the key to open that lock [41]. In light of many studies [41], [56]the principal components of a biometric system and its functionality, the general principle of the latter is at its core that a biometric system functions as a sophisticated pattern recognition technology that operates by first acquiring biometric data from an individual, such as an image or signal. This data is then analyzed to extract unique features, encapsulating the person's characteristic physiological or behavioral traits. Finally, this set of characteristics is then compared against a template set, which is essentially a digital record of the individual's biometric data stored in a secure database [51], and the action is executed according to the result of the comparison.

In detail, the principal functionalities of a biometric system revolve around the processes of enrollment as a first step, verification, and identification. These functionalities ensure that the system can accurately capture, analyze and compare biometric data for secure authentication. We detailed the key of each functionality :

Enrollment : This is the initial step of collecting biometric data from an individual to create a reference template that represents their identity, accomplishing steps of processing the captured data, and then associating the template with the user's identity, such as name or ID number, for future comparisons [16].

Verification $(1:1Matching)$: This process generates a matching score. The newly captured data are compared with the stored template that corresponds to the claimed identity by comparing a user-provided biometric sample to their stored template.

Identification/ Recognition $(1vs.All)$: This involves identifying an unknown individual from a database of known individuals by finding the closest match in the database. The biometric system either assigns the identity of the closest matching profile (or a list of top matches) from the database to the unknown subject or rejects them. This functionality is used to determine who a person is, rather than confirming a claimed identity; all modules are summarized in Figure 1.3.

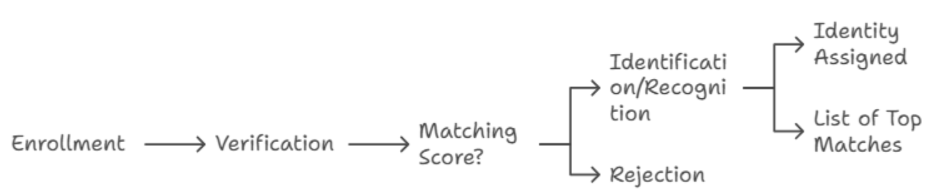


FIG. 1.3 : Biometric Recognition system

1.6 Uni-modal Biometric Vs Multi-modal Biometric

Biometric identifiers are useful for the development and conception of various biometric recognition systems. These are important in one sense oranother. But the choice of the biometric traits always depends upon the application, the availability of the dataset's samples, the level of complexities and the value of tolerance accepted. Moreover, biometric systems are separated into two main categories according to the number of modalities applied :

The biometric system that relies on a single type of identifier for identification and authentication is known as a unimodal biometric system [42], [43]. However, these systems often face challenges such as lack of distinctiveness, limited security, lower recognition accuracy, high intra-class similarity, and vulnerability to spoofing attacks due to their dependence on a single identifier. In addition, they often suffer from problems in the enrollment process because of non-universal biometric traits. Their performance can also be hindered by physical factors and environmental, such as noisy data or small sample sizes.

Characteristics	Unimodal Biometric Trait	Multimodal Biometric Traits
Biometrics	One type	Multiple types
Flexibility	Limited	Greater
Security	L	H
Privacy	Higher risk	Lower risk
Usability	H	L
Error Rate	H	L
Cost	L	H

Tab. 1.1 : Comparison of Multimodal and Unimodal Biometric systems (H : High Level, L : Lower Level)

Furthermore, unimodal biometric systems achieve less desired performances in real-world applications [44]. To overcome these issues, multimodal biometric systems offer a robust solution, as demonstrated in the table of comparison 1.1. [50].

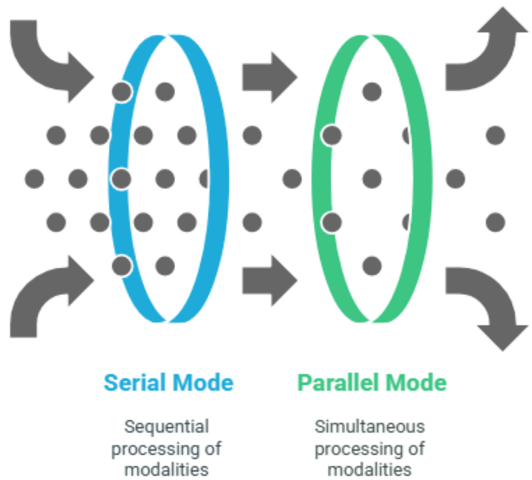


FIG. 1.4 : Multimodal Biometric Recognition Process

Multimodal biometric systems combine two or more types of identifiers (traits) for identification and/or authentication, applying different processes as demonstrated in Figure 1.4. Compared to unimodal systems, multimodal systems offer enhanced security against spoofing attacks and provide greater reliability and robustness, particularly in dynamic or challenging environments. Different search engines show that multimodal biometric recognition systems are the future of smart environments' security [45]. Combining traits like facial recognition, voice patterns, and signatures enhances security by providing multiple layers of verification [58].Systems that incorporate liveness detection can distinguish between real and fake biometric data, addressing vulnerabilities in traditional systems [57].In this thesis we aim to bridge the gap of this model category because this system has different factors influencing its robustness and reliability according to the scheme block in Figure 1.5.

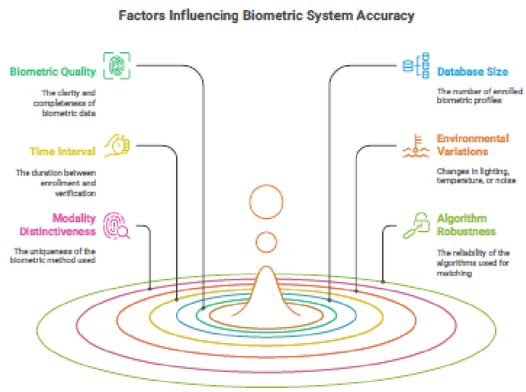


FIG. 1.5 : Factors influencing Biometric systems

1.7 Conclusion

In this preliminary chapter, we have provided some basic notions of the theoretical underpinnings of biometric recognition systems. An important part was devoted to establish a foundational understanding of its methodologies and principles. We explored the core concepts, including verification processes and identification tasks. Thus, these two processes are primordial in security and offer privacy for individuals, including in various biometric systems based on different modalities such as fingerprint, facial, voice and iris recognition. All these systems need to be scalable, secure and achieve high identification rate to ensure their validity and reliability. While also addressing challenges such as spoofing vulnerabilities, privacy concerns, and the need for robust algorithms. This theoretical foundation sets the stage for subsequent experimental chapters, which will delve into practical applications. Additionally, we will discuss emerging trends in biometric technology, particularly in the medical field, where physiological signals are increasingly being recognized as valuable biometric modalities. The integration of these signals into biometric systems has the potential to revolutionize patient identification and monitoring, thereby improving healthcare outcomes.

By bridging theoretical concepts with practical applications, we aim to provide a comprehensive overview of the current state and future directions of biometric recognition systems. In the next chapter, we examine mathematical and statistical frameworks, including pattern recognition with machine learning techniques, system design and emerging trends of biometric technology in the medical field using physiological signals as biometric modalities.

Chapitre 2

Architecture of the Biometric Recognition System : Methodology

2.1 Introduction

The first chapter covered biometric techniques in general and their applications in many industries, as well as the process of identifying and recognizing individuals. In this chapter, we go deeper into the process of building a feasible biometric system based on physiological signals, explaining each component of the framework of our biometric recognition system. This chapter comprises two main sections : The first Section II.1, Physiological Signals in Biometrics : provides a concise overview of signals as biometric characteristics, detailing their theoretical foundations and inherent nature. Section II.2 provides greater attention and specific information on various signal processing techniques, starting with the acquisition of unprocessed data and segmentation approaches. Ultimately, various metrics are applied to assess our biometric system and integrated into the blockchain system, ensuring that each individual's biometric data are securely recorded and matched to their profile. This integration enables the system to continually learn and adapt, resulting in improved performance over time.

2.2 Physiological signals in Biometric Recognition

Physiological signals reflect the electrical activity of a specific body part [142]. Thus, the electrical activity provides information on the physiological condition. Physiological signals can now be obtained non-invasively and without contact because of the current technological progress. This capability is particularly useful when physical interaction is not possible or is impractical, dangerous, or just not possible. Recently, these signals were integrated into the Biometric Identification System (BIS) verifies the authenticity of a specific physiological or behavioral characteristic proposed by its users [130]. The primary phase, known as enrollment, involves training the system to capture and digitally represent the subject's biometric traits as feature prototypes. Users then interact with the BIS, which records their biometric information, then generates a digital profile, and compares it against stored templates in a database to verify the user's identity.

2.2.1 Signal processing techniques

For a systematic analysis, it is essential to pre-process physiological signals to minimize distortion. Numerous researchers suggested physiological signals noise reduction utilizing : Moving Average (FIR), Notch, Adaptive Filters. Moving Average filters are user friendly and simple to use, yet, the original signal tends to be distorted during abrupt amplitude changes, for instance ECG signals especially at the begining of the R peak [140].

The Notch Filter also known as a band rejection filter. These filters reject and/or remove signals from a specific frequency band called the frequency range for the stop band and pass signals above and below it. This filter demonstrates superior efficacy in reducing power line interference, achieving a maximum signal-to-noise ratio as denoted in [141](equal to $33.53dB$) in compared to alternative approaches. However, the limitation of notch filters is that they are constrained to a certain frequency, hence eliminating only one frequency component at a time.The design of a low pass prototype filter can then become a band stop. Therefore, the transfer function is demonstrated in the Equation 2.2.1 as follows :

$$H(s) = \frac{s^2 + \omega_z^2}{s^2 + \frac{\omega_p}{Q}s + \omega_p^2} \tag{2.1}$$

Where : ω_z : is the circular frequency of a zero ; ω_p is the circular frequency of the pole ; Q is the quality factor. $\omega_z = \omega_p$ for standardized notch ; if $\omega_z > \omega_p$ it is a low-pass notch filters ; if $\omega_z < \omega_p$ it is a high-pass notch filters.

Butterworth Bandpass Filter This filter removes noise in the signal from baseline wander and power-line interference [149]. It is one of the most widely used types, and even used in our study, it is applied for quality control with a varying frequency range of $[5-20$ Hz$]$ [150], $[0.5-40$ Hz$]$ [151], $[1-40$ Hz$]$ [153] for the ECG signal. With respect to PPG signals, a second-order Butterworth filter shows adequate performance with a bandpass of $[0.5-10$ Hz$]$ [152]. Finally, the use of ICG (Impedance Cardiogram) in the range $[0.8-35$ Hz$]$ [153] is prominent as a standard for studies in the BCG domain.

Adaptive Filters

In order to overcome such problems of fixed filters (requiring prior knowledge of both the signal and noise), adaptive filters were developed, which can automatically adjust their impulse responses to filter the signal in the input without needing much or any prior information about the signal or noise characteristics. Additionally, these filters can track the signal in dynamic or non-stationary conditions [141].

In addition to the previously mentioned filters, literature reviews have shown that the Discret Wavelet Transform (DWT) approach performs better than other methods when it comes to noise reduction. In this dissertation, we based on different experiments to clean signals used in our study, therefore, we investigate the performance of the wavelt-based denoising method.

Wavelet transform (WT)

Wavelet transform (WT) is a time-scale representation used in image processing, and various other fields. It analyzes the non-stationary signals at multiple scales. Furthermore, the original WT function, called 'mother wavelet', is employed for generating all basis functions [143].

The Discrete Wavelet Transform (DWT) of the signal $x[n]$ is expressed mathematically in the Eq. 2.2:

$$X\{a;b\} = \sum_{n=1}^{\infty} x[n]\psi_{a,b}[n] \tag{2.2}$$

Where $\psi_{a,b}[n]$ is the analyzing wavelet function. It is represented as follows .Eq 2.3:

$$\psi_{a,b}[n] = \left(\frac{1}{\sqrt{a}}\right) \times \psi\left[\frac{n-b}{a}\right] \tag{2.3}$$

Where a and b denote the dilation and location parameters of the wavelet, respectively [144].

Definition and Principle of Discrete Wavelet Transform (DWT)

The DWT is a fully discrete version of Continuous Wavelet Transform, which, the inner product of the signal to be analyzed with the basis wavelet is computed as defined in 2.4:

$$j_k(t) = 2^{j/2}\,\psi(2^j t - k), \quad k \in \mathbf{Z} \tag{2.4}$$

Where, j represents the level of decomposition, and $jk(t)$ forms an orthonormal basis of $L^2(R)$. In fact, the Discrete Wavelet Transform (DWT) presents various wavelet families like Haar, Daubechies [146], Symlets, coiflets, etc. Thus, the choice of the right wavalet family and it's order depends primarily upon the type of signal to be analyzed [144]. The main principle of DWT is that the filters bank are used to decompose the signal into a set of coefficients that describe the signal frequency content at given times by examining the low and high-frequency components of the signal, and DWT applies a low-pass filter (LPF) and a high-pass filter (HPF), respectively. The resulting coefficients from the LPF and HPF are called to as Approximation (A) and Detail (D), respectively, as shown in Figure 2.1.

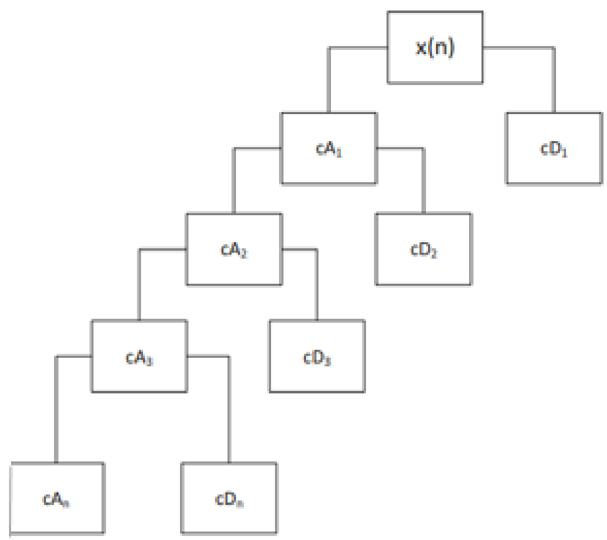


FIG. 2.1 : N Level Wavelet Decomposition

The wavelet based denoising algorithm is illustrated in the following steps : first, the signal is decomposed into different scales using the DWT technique, then thresholding of wavelet coefficients to remove noise, and the signal is reconstructed based on the inverse DWT ‘IDWT’ [145], as resumed in the algorithm 1.

The preprocessing stage is likely to be given a lot more weight in order to achieve notable

Algorithm 1 Wavelet-Based Denoising Algorithm

1: **Input :** Noisy signal $x(t)$
2: **Step 1:** Decompose the signal into different scales using Discrete Wavelet Transform (DWT)
3: Obtain approximation and detail coefficients at multiple scales.
4: **Step 2:** Threshold the wavelet coefficients
5: Apply thresholding function (e.g., soft or hard thresholding) to remove noise.
6: **Step 3:** Reconstruct the signal using Inverse Discrete Wavelet Transform (IDWT)
7: Use the modified coefficients to reconstruct the denoised signal.
8: **Output :** Denoised signal $\hat{x}(t)$

performance and quality with the appearance of deep learning technologies.

2.2.2 Signal Segmentation

Signal segmentation is the predominant signal preparation technique among the approaches surveyed . It is employed to constrain and limit the signal span for feature extraction, or to establish a fixed dimension (size) to facilitate template matching when the feature is the signal itself. In certain cases dedicated to physiological signals in general and for ECG signal specifically, segmentation follows the location of the reference point and involves the cropping of the QRS complex and/or additional waveforms [159] [160], or is intended to the entire heartbeat, or a significant part of the studied signal, is included and is therefore executed at predetermined distances before and after identified R-peaks or QRS complexes [160]. Additional research efforts involved the segmentation of signals utilizing sliding windows as demonstrated in Figure 2.2, with or without overlap, independent of the completeness of the heartbeat cycles contained within [161] and each window can be used to extract relevant features, such as heart rate variability or signal amplitude, enhancing the capability to identify patterns and anomalies in physiological data.

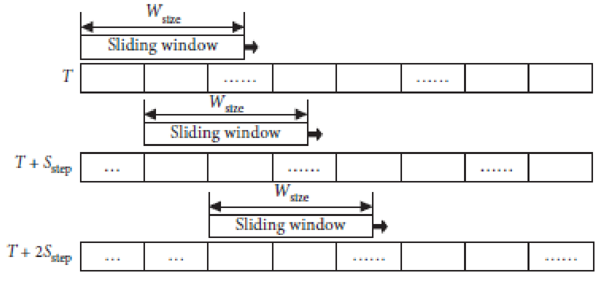


FIG. 2.2 : Segmentation using sliding window

2.3 Characterization of Physiological signals

Once the first two steps are done, the purchase should be ready for the next step, which is making features. This step is meant to turn the information that was picked up into a form that is even simpler. to help people make decisions by pointing out differences between subjects and the effects of leftover noise and intra-subject variability Physiological signals exhibit time-varying properties, indicating their non-stationary nature. Consequently, time-variant signal processing techniques are integral to the standard practices in biomedical signal analysis. The frequency of occurrence, along with the shape and time-frequency characteristics of transient signal components, holds significant diagnostic value, resulting in increased application of time-variant analysis methods [131], [132]. An additional example in characterisation of physiological signals is the temporal study of the cardio-respiratory system,in which the primary objective is the quantification of both short-term and long-term fluctuations of continuous oscillations (respiratory movements, blood pressure waves). Different feature extraction methods must be evaluated on the physiological signals before selecting the best performing feature extraction algorithms. When discussing biometrics in the context of healthcare, the goal is quite different. Measurement of medical data and extraction of certain clinical indicators to deliver useful diagnoses is the foundation of the process to provide valuable diagnosis ; for this reason, the characterization of physiological signals used for biometric purposes is a predominant part for our blockchain Biometric Identification System (BIS). The commonly used characteristics for biometric systems are based on physiological signals.

The commonly extracted features for biometric recognition system based on physiological signals fall into two principal categories : fiducial features based generally on time domain attributes, non-fiducial features extracted by using different approachs such as : frequency domain attributes, and time-frequency domain attributes.

2.3.1 Fiducial Approaches

Fiducial approaches are designated because they use as features the measurements of fiducial landmarks of the physiological signal in the time domain. The majority of the work on physiological signal(ECG, ICG, PPG ...) biometrics is based on single channel as proved by *Biel &. al* [19], each signal contains a form and a fiducial points, therefore, different studies was based on factor analysis, using PCA, on time, amplitude, area and slope features [108]. In addition, especially for ECG signal as mostly used several time intervals between the heartbeat waveforms P, Q, R, S, and T, as well as their onset and offset points, and the width of the P and T waveforms. Various studies improved that the complex QRS of the morphological features of ECG signal are most reliable for personal identification.

2.3.1.1 Time Domain Analysis

The earliest approaches to feature extraction were based on the time domain, where biomedical signals are examined with respect to their progression over time. Time-domain features provide a way to measure how the ECG signal evolves temporally. In most cases, the signal of interest is divided into segments or windows, enabling the extraction of features within each portion. This strategy is essential since ECG signals, similar to other physiological signals, are inherently non-linear and non-stationary [170]. A variety of techniques and methods can be applied for time-domain feature extraction.

The Autoregressive (AR) model is a widely used time-domain feature in EEG biometrics [137].

Autoregressive Model

It denotes a type of random process by indicating that the output variable is linearly dependent on its own previous values and on a stochastic term (an imperfectly predictable term), it is defined in the equation 2.5.

$$x(n) = -\sum_{i=1}^{p} a_i x(n-i) + e(n) \tag{2.5}$$

Where : $x(n)$ is the current values of one channel, a_i is the AR coefficients at delay i, $e(n)$ is the error at time, and p is the order.

2.3.2 Non Fiducial Features

New extracted features were investigated and proposed as research progressed toward off-the-person signals and fiducial detection became unreliable. Non-fiducial approaches are those that comprehensively extract features related to the waveform morphology by utilizing the entire signal (or segments of it).

2.3.2.1 Frequency Domain

Converting physiological signals data into the frequency domain can extract and distinguish the dominant frequency components.

Power Spectral Density PSD. Delineates the distribution of signal power within the frequency domain, defined in the Equation 2.6.

$$S_X(f) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t) e^{-j2\pi f t}\, dt \tag{2.6}$$

Where : $x(t)$ is the time-domain signal. $S_X(f)$ Power Spectral Density at frequency f. T Total time duration over which the signal is analyzed. j The imaginary unit. $e^{-j2\pi ft}$ Represents a complex exponential function, which is used for frequency analysis.

The *Fourier Transform (FT)* is an efficient method for converting the signal from time domain to the frequency domain [154]. Welch approach, with the FT method, is a prominent algorithm for estimating the PSD. Welch's method involves splitting input signals into overlapping segments and calculating the periodogram using the squared magnitude of the Discret Fourrier Transform (DFT) findings. This strategies was applied in various investigations. Mean frequency parameter known as intensity weighted mean frequency, spectral edge frequency, Peak frequency or the dominant frequency, spectral entropy and the intensity weighted bandwidth, these are the main frequency domain features used to analyse PPG signals as a biometric trait. The Energy of specific frequency ranges,and Spectral Power (SP) are another two frequency domain features based on the PSD, which are calculated using Parseval's Theorem as denoted in 2.7.

$$\int_{-\infty}^{\infty} |x(t)|^2 \, dt = \int_{-\infty}^{\infty} |X(f)|^2 \, df \tag{2.7}$$

Where : $x(t)$ is the continuous time signal and $X(f)$ its Fourier transform.

2.3.2.2 Entropies Analysis

Entropy has become a suitable complexity metric in recent years for the analysis of time series from biological systems, including the heart, brain, and muscles [133]. As a general definition, entropy is the rate of information production by signals [135]. On the other hand. It means complexity measures for biological signal analyses, which increases with the degree of disorder in the system. The fundamental concept of entropy is used in many fields of science, such as : information theory, statistical mechanics, chaos theory, neural networks, mathematical linguistics, and taxonomy [133]. For the same reason that, entropy can be used as a measure of disorder or uncertainty in a system, which consider that if the degree of disorder is low, so the systems become organized. Therefore, the ideal system is when everything is in complete order and the entropy value is zero [133]. Different researchers have summarized the implementation of information entropy in medicine [147], [148] and provide more information about these applications.

Entropy Methods

Various types of entropy measures exist, including Shannon entropy (SE), Kolmogorov entropy, approximate entropy (ApEn), sample entropy (SampEn), multiscale entropy (MSE), and so on [134] as shown in the Figure 2.3.

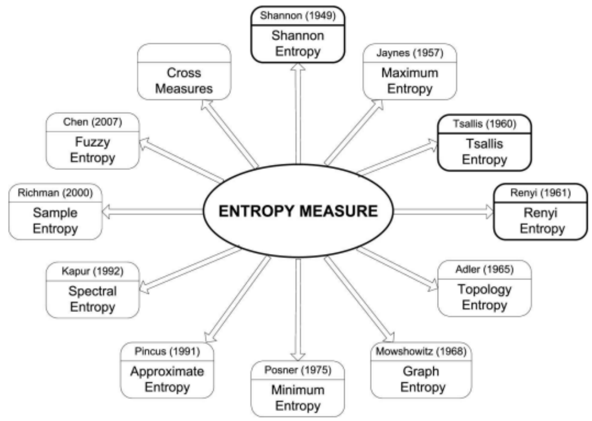


FIG. 2.3 : Forms of Entropy [133]

Shannon Entropy

Information entropy was proposed by *Shannon & al.(1949)*. The Shannon Entropy S of a random variable X that takes the values $x1, x2, ..., xN$, is defined as 2.8:

$$\text{Sen} = \sum_{i=1}^{n} p(x_i) \log_a \frac{1}{p(x_i)} = -\sum_{i=1}^{n} p(x_i) \log_a p(x_i), \quad a > 1 \tag{2.8}$$

Where : $p(x_i)$ are probabilities of acceptance by the random variable X values (x_i). Shannon entropy is characterized by a degree of uncertainty associated with the occurrence of the result. Notably that, a higher value of the entropy gives a more uncertain outcome and is more difficult to predict. Generally, the entropy of X is a measure of expected uncertainty obtained during the measurement of that variable [133].

Shannon entropy may be used globally, taking all data into account, or locally, in this dissertation, we calculate it around certain segmented intervals of physiological signals. This measure can provide additional information about specific and or rare events.

Renyi and Tsallis entropies are generalizations of Shannon entropy that depend on a parameter. If $p(x_i)$ is a probability distribution on a finite set, the Rényi entropy of order β is defined as in (2.9) :

$$\text{Ren} = \frac{1}{1-\beta} \ln \sum_{i=1}^{n} p(x_i)^{\beta} \tag{2.9}$$

Tsallis entropy has been used in different fields such as pattern recognition and computer science [157]. It is defined as in (2.10) :

$$\text{Ten} = \frac{1}{\beta-1} \left(1 - \sum_{i=1}^{n} p(x_i)^{\beta}\right) \tag{2.10}$$

Approximate entropy.

Pincus (1991) introduced approximate entropy, a method for quantifying regularity in data without a prior knowledge about a system. Approximate entropy is defined as 2.11:

$$\text{Appen} = \phi^{m}(r) - \phi^{m+1}(r) \tag{2.11}$$

The disadvantage of App_{en} is it's dependency with the record length and is often lower than expected for short records. Out of the two types of entropy measures : Approximate Entropy $(ApEn)$

and Sample Entropy $(SampEn)$ available in literature.

Sample Entropy

$(SampEn)$ overcome the lacks of App_{en}, and it is more suited for biological time series due to its independency on data length and more consistency than that in ApEn [136]. SampEn is the negative natural algorithm of the probability that 2 sequences for m points in a time series remain similar at the next point, where self-matches are not included, it is defined as 2.12:

$$\phi^m(r) = \frac{1}{N-m} \cdot \sum_{i=1}^{N-m} C_i^m(r) \tag{2.12}$$

Where : The probability $\phi^m(r)$ that two sequences match for m points is computed by counting the average number of vector pairs for which the distance is lower than the tolerance. Similarly, $\phi^m(r)$ is defined for an embedding dimension of $m+1$. It is calculated as 2.13:

$$\text{Sampen} = \ln \frac{\phi^m(r)}{\phi^{m+1}(r)} \tag{2.13}$$

Wavelet Entropy

Rosso &. al. [158] introduced wavelet entropy in 2001. It analyzes the complexity of the signal and informations content of multi-frequency signals by fusing the wavelet transform with the idea of entropy. Wavelet entropy measures the level of disorder in those components, offering insights into the signal's structure. The wavelet transform decompose a signal into components at different scales, extracting both time and frequency information. The shanon formula defines wavelet entropy, although in this case, the probability distribution relates to various resolution levels. It is often used as a feature extracted from biomedical signals lie : ECG , EEG, to identify different physiological states and detect abnormalities.

The entropy measurements that were discussed earlier have been utilized in physiological time series, such as, Electroencephalographic signals (EEG), Electrocardiographic signals (ECG), electrohysterographic (EHG is a non-invasive technique for monitoring uterine contractions by recording the electrical activity of the myometrium (uterine muscle) using abdominal surface electrodes).

Statistical features

Extracting statistical features from physiological signals is by far the least complex of the time domain feature extraction techniques. Using statistical mathematics programming languages, it becomes even simpler to implement with the use of native, built-in functions. Statistical analysis/feature extraction is not considered fiducial because knowledge of the actual signals characteristics is not needed [169], [174]. One popular application of statistical features can be applied for is for the use of subject recognition using physiological signals as a biometric trait. The feature extraction is what provides : The mean and the median features can be used to measure the central tendency of the ECG signal. The statistical dispersion of the ECG is captured by the standard deviation, range, and interquartile range features. The kurtosis and skewness features are typically used to measure the asymmetry and the sharpness of the peak of the signal distribution [100], [169], [174], these features are detailed and explained in chapter 04.

2.4 Feature Selection Methods

In the machine learning literature, feature selection methods are typically classified into three categories : filter techniques, wrapper strategies, and embedded approaches.

Filter-based feature selection

strategies employ the statistical properties of the predictor variables and their association with the response variable (the output) [157]. These strategies are beneficial for computational time.

Numerous filtering methodologies exist, including but not limited to Principal Component Analysis, a widely recognized unsupervised technique for dimensionality reduction that does not consider dependent characteristics. Linear Discriminant Analysis with Partial Least Squares. The common concept underlying these three approaches is the investigation of a linear separation among the features to find and differentiate binary or multi-class classifications. Despite their linearity, simplicity, and relatively low cost in diminishing input data dimensionality, the ranking process of pertinent characteristics remains ambiguous; in other words, there is no clear interpretation of the attribute rating procedure [155].

One-Way Analysis of Variance (ANOVA) algorithm is a statistic model to analyze the differences of means and variance among classes. Thus, it can be applied to explore the inter-class and intra-class variance of features [137].

Wrapper-based feature selection

procedures are utilized to develop a predictive model by combining several features to identify the subset that yields optimal evaluation performance. These methods are detrimental for processing time (consumer and slower). Consequently, they are inappropriate for use in feature subset selection for large-scale tasks. The Support Vector Machine-based Recursive Feature Elimination, abbreviated as SVM-RFE, is a notable wrapper technique that employs backward feature removal. The latter develops a model utilizing the complete collection of features. Subsequently, it computes the relevance score for each item. Ultimately, it discards the least significant features at each iteration, hence enhancing the model's performance efficiency. The traits ranked highest are the final ones excluded [155].

Embedded strategies

markedly differ from the two aforementioned approaches. This strategy involves the classifier automatically selecting important features throughout the fitting process, indicating that attribute selection occurs concurrently with model training [157]. The embedded method signifies an enhanced implementation of the Gradient Boosting framework. The word Boosting denotes the implementation of a strong learner, characterized by an optimistic precision rate, wherein classifiers are constructed using gradient descent to enhance the loss function. We refer to Extreme Gradient Boosting as an example of embedded techniques, which has been extensively utilized across several domains due to its remarkable scalability, concurrent processing capabilities, and adaptability [157].

In our thesis work, we conducted a feature selection process utilizing the renowned Relief-F algorithm and Minimum Redundancy Maximum Relevance (mRMR). This later pertains to the filter methods. The central concept relies on a distance measurement technique, specifically the well-known Manhattan distance.

2.5 Machine Learning in Biometric Identification

Machine learning (ML) is a technique that enables a system to predict future events. It employs different algorithms to analyse data, learning from it to forecast outcomes for previously unseen data. Essentially, ML seeks to identify patterns in historical data through a training process, resulting in a predictive model. Today, machine learning plays a significant role across diverse fields, aiding organizations in making informed decisions. It's important to note that ML is a crucial concept for enhancing the artificial intelligence (AI) of smart systems, reducing the need for human intervention due to the limitations of human cognitive and memory capacities. AI, a branch of computer science, focuses on mimicking human-like thinking in machines, with applications across various sectors, including industry, healthcare, security, transportation, energy, and commerce. Furthermore, artificial intelligence facilitates the development of modern technologies aimed at automating tasks and operating independently of human input [164]. machine learning (ML) has been demonstrated to be instrumental in the enhancement of biometric systems. ML algorithms has the ability of constantly learning and adapting to biometric users' changing patterns, and can improve accuracy and performance over time. A simple classification category for identifying or authenticating people based on the chosen similarity evaluation metrics is similarity-based pattern recognition [180]. In order to distinguish one individual from another in the authentication case, the system determines a suitable threshold based on similarity values after identifying both intra- and inter-class similarity ranges during enrolment. However, the classification results for the identification case go accepting or rejecting a threshold. In general, classification refers to a supervised learning approach. There are numerous commonly used supervised learning classifiers, such as : Support Vector Machines (SVM), Naive Bayes classifiers, K-nearest neighbors (KNN), Decision Tree (DT), Artificial Neural Network (ANN) [180]. In the literature, Support Vector Machines (SVM) and k-Nearest Neighbors (kNN), two prevalent decision algorithms, have demonstrated their efficacy in performance, even under heightened noise and variability. Nevertheless, it would be advantageous to identify a comparably precise alternative that does not necessitate re-training with each subject enrolment or update (as SVM requires) or the resource-intensive storage of all subjects' templates (as kNN entails). Artificial neural networks, including Deep Neural Networks, may address these challenges, However, researchers must invest efforts to achieve or exceed the performance levels provided by SVM and kNN. In our thesis research, we utilized several supervised classifiers to achieve various objectives : identification based on physiological signals and authentication of unhealthy individuals. During the experiment, we have used different approach to divide the data into test and training sets, but the most commonly used is cross-validation (CV).

K-Nearest Neighbors (KNN)

KNN is developed for classification and regression classification. Where the input is formed by the k-nearby apprenticeship observations in the employed data set, while the output depends on the objective behind using the KNN, whether for classification or regression ; for the first (classification), the outlet represents a class adhesion, where the test observation will be classified on the basis of a plurality vote of its closest neighbors, in other words, the object will be commonly attributed to the class among its k nearby neighbors. Typically, K-Nearest Neighbors (kNN) were chosen for identification because they use a majority rule to decide which points are closest or most similar to the input. In particular, earlier research experimented with various similarity metrics in kNN for recognition [164]. The k-NN algorithm classifies a data point based on the majority class among its k nearest neighbors in the feature space. The "distance" between points can be measured using various metrics, such as Euclidean, as demonstrated in equation 2.14, or Manhattan distance. In a multiclass scenario, the goal is to classify instances into more than two classes. The k-NN algorithm can handle multiple classes naturally since it simply counts the number of neighbors from each class.

$$d(x, y) = \sum_{i=1}^{n} (x_i - y_i)^2 \tag{2.14}$$

As shown in Figure 2.4, the algorithm attempts to determine the nearest neighbors among all examples in the dataset for each sample. Therefore, an increase in the size of the dataset can significantly increase the computational workload.

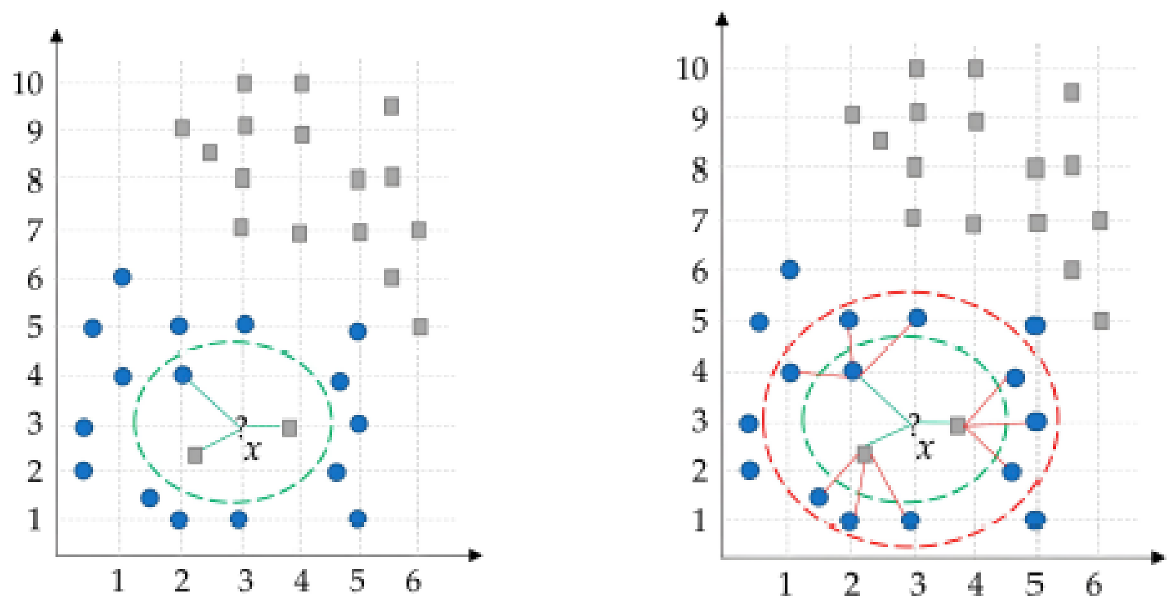


FIG. 2.4 : K-Nearest Neighbors Algorithm : (a) Low level neighborhood, (b) High level neighborhood.

Naïve Bayes Model (NBM)

NBM is a probabilistic model grounded in the Bayes theorem with the assumption that features are strongly independent. It has good performance when the dimension of the feature vectors is high. Assume that each element x_i of the vector of characteristics X of dimension M follows the Gaussian distribution and is statistically independent of each other; then the parameter Θ of NBM can be estimated using the maximum likelihood estimate using the training data. A Naive Bayes (NB) classifier can effectively manage missing attribute values by excluding the corresponding probabilities when calculating the likelihood of membership for each class. In addition, the NB classifier is based on the conditional independance of the class, which means that the influence of a particular attribute on a given class is independent of the influences of other attributes [165].

$$P(C_i \mid X) = \frac{P(X \mid C_i)P(C_i)}{P(X)} \tag{2.15}$$

In Bayes theorem shown in Eq. 2.15, as $P(X)$ is a constant for all classes, only $P(X \mid Ci)P(Ci)$ needs to be maximized. If the class prior probabilities are not known, then it is commonly assumed that the classes are equally likely, that is, $P(C1) = P(C2) = ... = P(Cm)$, and therefore maximize $P(X \mid Ci)$. Otherwise, maximize $P(X \mid Ci)P(Ci)$. The class prior probabilities are calculated by $P(Ci) =\mid C_{i,D} \mid /D$, where $\mid C_{i,D} \mid$ is the number of training instances belonging to the class Ci in D. To compute $P(X \mid Ci)$ in a dataset with many attributes is extremely computationally expensive [165].

2.6 Conclusion

Biometrics play a crucial role in the healthcare system, serving as a reliable means of identifying individuals based on unique physiological characteristics.

We start with a comprehensive overview of physiological signals as biometric traits, exploring their theoretical foundations and intrinsic properties which offer valuable insights into an individual's identity and health status. Next, we examine the efficacy of two signal processing techniques : the Wavelet-based denoising method and the Butterworth filter method applied in our dissertation. These techniques are applied to enhance signal quality, ensuring that the data used in our study is accurate and reliable. By effectively cleaning the signals, we aim to improve the overall performance of the biometric identification system.

Following the signal processing phase, we implement a feature selection process using established algorithms such as Relief-F and Minimum Redundancy Maximum Relevance (mRMR). These algorithms help identify the most relevant features of the physiological signals, thus optimizing the classification process and enhancing the accuracy of the system.

In addition, we investigate the role of machine learning (ML) in biometric recognition systems. ML algorithms are essential for distinguishing individuals during both authentication and identification processes.

Ultimately, we underscore the importance of machine learning as a foundational element in advancing the artificial intelligence (AI) capabilities of smart systems. By integrating ML techniques into biometric systems, we enhance their ability to accurately recognize and authenticate individuals, thereby contributing to improved security and efficiency in healthcare and beyond. This chapter highlights the potential of combining advanced technologies to create robust biometric identification systems that can adapt to the evolving needs of the healthcare sector.

Chapitre 3

ECG & PPG Signal as a Biometric trait

3.1 Introduction

Biometrics in healthcare is a technological solution to avoid patient identification errors by leveraging unique physiological characteristics of individuals.

This chapter delves into the development and application of biometric systems that rely on physiological signals, specifically electrocardiograms (ECG) and photoplethysmograms (PPG) as unimodal biometric modalities. We will explore various datasets, feature extraction methods and classification techniques, examining both healthy and unhealthy signal variations. The goal of this chapter is to underscore the potential and challenges of integrating these signals into effective, real-world biometric solutions, ultimately advancing personalized and secure identification technologies. Additionally, we will discuss enabling technologies and practical use case scenarios, considering diverse aspects of human characteristics. The feature extraction process begins with a set of measured data, producing derived values. These features, crucial in signal processing, pattern recognition, and machine learning, are designed to be informative and non-redundant, facilitating efficient learning and generalization. Biometric recognition systems based on physiological signals have become essential in modern security and identity verification, utilizing distinct physiological and behavioral traits for reliable authentication. Particularly ECG, Particularly ECG, have gained interest because of their potential for high accuracy recognition. ECG signals are unique to individuals, making them suitable as a biometric modality. Recent studies have focused on improving the robustness and accuracy of these systems under various conditions and challenges.

The characterization of signals is prominent, as proved in our preliminary study [61] the statistical features of ECG can used effectively for identification, achieving high accuracy rates with support vector machines (SVM). As an advanced approach, deep learning techniques, such as the combination of Transform and LSTM networks, have been applied to extract user-specific characteristics from both ECG and PPG signals, achieving high precision in identifying existing and new users [106]. As a challenge, the presence of cardiac pathologies, such as murmurs, can affect the morphology and rhythm of signals, potentially impacting the performance of biometric systems. It is crucial to consider these effects during signal analysis and classification [107]. Continuous and instantaneous identity recognition modes can be implemented using physiological signals, with machine learning utilities adapted to different application environments for enhanced security and flexibility [108].

By eliminating redundant data, the feature extraction process reduces data dimensionality, enhancing training efficiency, accelerating inference, lowering error rates in learned models, and minimizing the risk of overfitting. The features commonly used for physiological signal processing studies based on biometric recognition followed the same techniques as clinical considerations and fall into three principal categories : frequency domain attributes, time domain attributes, and time-frequency domain attributes [115].

3.2 Electrocardiogram Signal as a Biometric identifier

3.2.1 Electrocardiogram Signal (ECG)

Electrocardiogram (ECG or EKG) is a graphical representation of the heart over time 3.1, recorded using electrodes placed on the skin. These electrodes detect small electrical changes that are a consequence of electrical muscle depolarization followed by repolarization during each cardiac cycle (heartbeat) [60]. It is a useful and critical tool in medical diagnostics for assessing heart conditions.

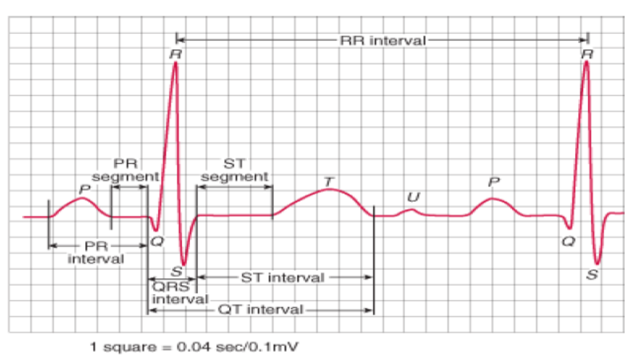


FIG. 3.1 : ECG Signal in Normal Sinus Rhythm [79]

In our initial study, we investigated the usability of ECG-fiducial characteristics by exploring the potential of using the $R - R$ interval as a biometric trait through different process steps, as demonstrated in Figure 3.2 .

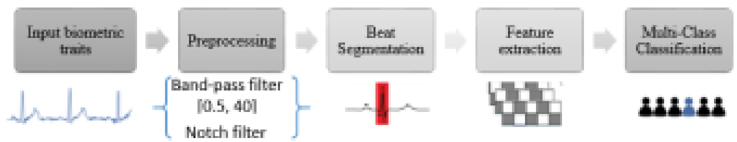


FIG. 3.2 : Process of the developed ECG-based biometric system

For this purpose, we extracted fiducial points, and we focused on R-R intervals as a biometric characteristic. This approach takes advantage of the scalability of data obtained from the ECG-ID and MIT-BIH databases. By analyzing these QRS complexes, we aim to assess their effectiveness and reliability in biometric identification systems. As a first study, we investigated the usability of QRS complexes as a biometric trait due to its scalability extracted from the ECG-ID and MIT-BIH databases, as shown in Figure 3.3.

Characteristic	**Description**
Heart Rate	60 to 100 beats per minute
P Wave	Duration : 0.06–0.11 s ; Amplitude : 0.1–0.3 mV
PR Interval	0.12–0.20 s
QRS Complex	Duration : 0.08–0.12 s ; Amplitude : 0.5–3.0 mV
ST Segment	Usually isoelectric
T Wave	Asymmetrical ; Amplitude : < 0.5 mV in limb leads
QT Interval	0.36–0.44 s

TAB. 3.1 : Characteristics of a Normal ECG Signal

3.2.2 Description of databases

Using biometric technologies, a smart healthcare system can revolutionize patient care, improve diagnostic precision, and improve administrative workflows [55]. Biometrics improve patient safety and expedite administrative procedures by allowing healthcare professionals to identify patients more quickly and securely. To apply this purpose, we need a well-collected database to verify the robustness and efficiency of biometric recognition algorithms. For this reason, the data used in this analysis were chosen based on results from recent research studies that reported a successful biometric recognition system with a satisfactory accuracy value as listed in Section 3.2.2. Electrocardiogram (ECG) signals and their intrasubject and intrasession validity. MIT-BIH is acquired in an on-the-person setting.

3.2.2.1 ECG-ID Dataset

This database [65] is produced to aid research into the use of the ECG for biometric identification. Its recordings of 20 seconds, Lead I ECG signal, each were obtained from 90 participants (44 men and 46 women, aged 13 to 75 years) and are available on Physionet's website [179]. The database contains between 2 and 20 recordings for each 90 volunteers (for a total of 310), collected during six months. Each record contains both raw and filtered ECG signals. A limb-clamp electrode at the wrists. Each recording is digitized at a sampling rate of 500 Hz with a 12-bit resolution with an amplitude range of ±10mV range. Each record includes annotations for 10 beats, marking R- and T-wave peaks. Notably, that in our investigation, we downloaded the raw data noisily ; it contained both high- and low-frequency noise components, which is typical for real-world ECG signals. This database is valuable for assessing intra- and inter-individual variability very useful in biometric investigations.

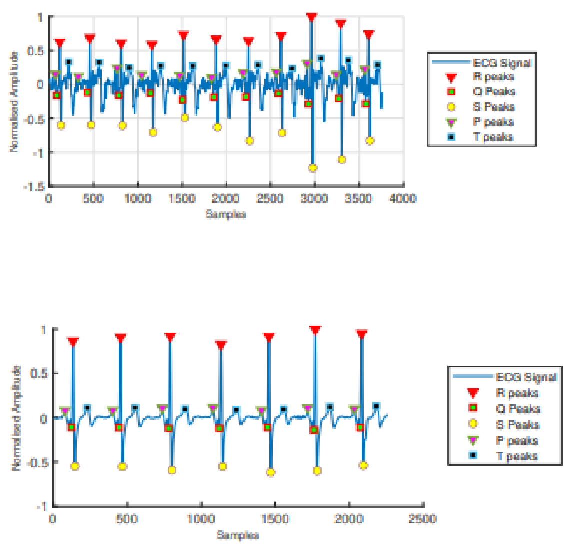


FIG. 3.3 : Comparison of fiducial points identified on ECG signals : (a) ECG-ID database, (b) MIT-BIH database.

3.2.2.2 The MIT-BIH Arrhythmia Database

The MIT-BIH Arrhythmia Database was utilized to investigate the reliability of ECG-based biometric recognition systems for individuals with arrhythmias, complementing the initial study of healthy subjects using the ECG-ID database. This database contains 48 half-hour ECG recordings from 47 different individuals, (one subject contributes two records : 201 and 202) ; each recording includes two ECG leads, typically Lead II (MLII) and a precordial lead (e.g. V1, V2, V4, or V5), varying by record. The subjects include 22 women (aged between 23 to 89 years) and 25 men (aged 32 to 89 years), with 60% of patients having various cardiac conditions, primarily arrhythmias, and the remaining were healthy individuals. For its universality attribute, the MIT-BIH Arrhythmia Database is suitable for testing the developed ECG biometric technique [64], [69], [93].Table 3.2 presents the main parameters of each ECG database. Signals are digitized at 360 Hz per channel with 11-bit resolution.

TAB. 3.2 : Parameters of the ECG datasets

Parameters	**ECG-ID DB**	**MIT-BIH DB**
Leads	I-lead filtered	MLII Lead
Total number of records	100	47
Records per user	2	1
Sampling rate	500Hz	360Hz
Record time	1min	1min
Electrode placement	Wrist	Chest
Health condition	Healthy	Arrhythmia

3.2.3 Fiducial Characteristics based on Pan-Tompins Algorithm

Revised Pan Tompkin's algorithm was implemented for identification of QRS complexes, by following this algorithm 2.

Algorithm 2 Pan–Tompkins QRS Detection Algorithm

Input : ECG signal

Step 1: Band-pass filtering

Apply low-pass and high-pass filters to remove baseline wander and high-frequency noise.

Step 2: Differentiation

Differentiate the filtered signal to highlight the slope information of QRS complexes.

Step 3: Squaring

Square the differentiated signal to make all data points positive and emphasize large differences.

Step 4: Moving window integration

Apply a sliding window average (integration) to extract waveform features in the QRS region.

Step 5: Adaptive thresholding and decision rule

Define thresholds based on signal and noise peaks.

Classify peaks as QRS complexes if they exceed the threshold.

Step 6: Post-processing

Apply a refractory period (e.g., 200 ms) to avoid multiple detections of the same QRS.

Output : List of detected QRS complexes

After following step-by- step the methodology explained in the flowchart, the results obtained are summerized in Table 3.3 and discussed. The table compares the proposed biometric model, which uses time-domain analysis of three-heartbeat ECG segments with Hurst-exponent and statistical features.

Against three prior studies for ECG-based recognition. The proposed method, tested on MIT-BIH and ECG-ID datasets using SVM with 10-fold cross-validation, achieves accuracies of 95.40% to 99%, rivaling [99] CNN-based approach (99.90% and 94.18% on PTB and ECG-ID datasets) and outperforming [98] cascaded CNN (94.3% across five datasets) and [63] Fourier-based method (97.92%, 98.45%, and 91.07% on MIT-BIH, ECG-ID, and CYBHi). Its simpler time-domain

TAB. 3.3 : The developed biometric model in comparison with other reported framework recognition.

Studies	Approach	Datasets	Classifier	Results
Li et al. (2020) [98]	Truncated 40% from R–R interval as heartbeat	5 datasets	Cascaded Convolutional Neural Network	94.3%
Dalal et al. (2021) [99]	Time–frequency analysis of segment of an ECG signal around the R-peak	PTB, ECG-ID	CNN models	99.90%, 94.18%
Fatimah et al. [63]	Fourier decomposition and phase transform on one or more heartbeats	MIT-BIH, ECG-ID, CYB-Hi	Random Forest and SVM	97.92%, 98.45%, 91.07%
Our method	***Time–domain analysis of short three-heartbeat ECG segments using Hurst-exponent with statistical features***	***MIT-BIH, ECG-ID***	***SVM with 10-fold Cross Validation***	***95.40%, up to 99%***

approach offers comparable or superior performance to complex CNN or Fourier-based methods, with potential computational efficiency, though dataset-specific accuracies and efficiency details would further clarify its advantages.

3.3 Biometric system based on PPG signals

Significant progress has been made in the field of biometric recognition, with photoplethysmography (PPG)-based systems showing promise as a study topic. In recent years, PPGs have been proven to have the ability to distinguish individuals [72] and they offer a potential remedy to vulnerabilities [13], especially With the widespread use of connected objects (IoT systems) and the massive increase in data exchanges, data has become a more visible target for cyberattacks. In ***2003***, PPG signals made their firt step in biometrics recording to the study of Gu *et al.* [101], This study was reported on 17 healthy subjects, and basic characteristics were extracted, thus resulting in an identification rate of 94%. Subsequently, the PPG signal's derivatives were then applied to biometric authentication as mentionned by [103] based on statistical methods, derivatives can precisely describe the features of a person's PPG signal and emphazise the ability of this signal to be used as bio-measures for identification tasks. Recent studies has analyzed PPG signals based on non-fiducial approaches for the purpose of human verification [104]. A comparative study with 42 participants was discussed assessing both non-fiducial and fiducial characterization methods, this latter was performed using discrete wavelet transform (DWT) and the feature vector was fed through neural networks and support vector machines [109].

Unlike previous studies that focused primarily on robust authentication, this research prioritizes the identification of unhealthy individuals. Following robust feature extraction, a machine learning classifier is applied to the BIDMC dataset, enabling precise identification and advancing the application of PPG-based biometrics in health-focused scenarios. PPG-based biometric systems are versatile, finding applications across various fields, such as health monitoring and fitness tracking. These systems can leverage a diverse array of sensors integrated in medical equipment, wearables, smartphones, and even digital cameras. Their experiments focused on recognition rates for features derived from the wavelet transform. In addition, they enhanced the results by applying a genetic algorithm to select an optimal subset of characteristics. The biometric recognition process can utilize either algorithmic methods or computational intelligence techniques, depending on the application's requirements. In addition, studies have shown that PPG signals possess sufficient discriminative power and stability to support a wide range of biometric applications. In the same context, Yang *et al.* [105] using three publicly available data sets : BIDMC, MIMIC II, and Capnobase. They applied a sliding window technique to segment the signals, followed by transforming them into a soft-max vector of the sparse representation. For the classification step, they compared RF, LDC, KNN, and NB algorithms by splitting 80% of the data for training and 20% for testing, but without employing a validation method such as 10-fold cross-validation. They achieved satisfactory accuracy scores, generally ranging from 85% to 100%.

3.3.1 Photoplethysmography Signal (PPG)

Photoplethysmography (PPG) is a non-invasive electro-optical technique that measures blood volume changes, reflecting arterial pulsatile activity [110]. Clinically, PPG signals are used to obtain information like blood oxygen saturation and heart rate to aid in diagnosing heart-related diseases. It meets the biometric criteria of universality, distinctiveness, permanence, and conductivity. PPG signals are easily acquired from finger- or wrist-worn devices like smartwatches, requiring less equipment than other physiological signals, making it a promising biometric trait. Much research has demonstrated that photoplethysmography satifies conditions of biometric, like uniqueness, robustness, universality, and adaptability [71]. Nowadays, the method of simple-feature extraction has been extensively studied and is used in PPG biometric recognition ; some promising results have been reported [70]. Compared to other physiological signals like electrocardiography (ECG) and electroencephalography (EEG), PPG signals offer significant advantages due to their low-cost acquisition, high accessibility, and portability. PPG can be conveniently measured using compact devices such as smartwatches or fitness trackers. Additionally, PPG signals can be collected from various body locations, including fingertips, wrists, earlobes, or even the forehead, providing flexibility in application. Unlike some biometric methods that require bilateral measurements, PPG only needs to be captured from one side of the body, enhancing its versatility for a wide range of human identification scenarios. Furthermore, PPG's non-invasive nature and compatibility with wearable technology make it highly practical and appealing for real-world biometric applications, such as continuous authentication in healthcare, security, and fitness monitoring [73].

Its ability to integrate seamlessly into everyday devices and adapt to diverse environments underscores its potential as a robust and user-friendly biometric solution. The state of the art in PPG-based authentication involves a typical processing chain : signal acquisition, signal conditioning (denoising), characterization of denoised signals, and finally, application for authentication or identification [13]. In this study, we propose a novel cancelable biometric identification system leveraging PPG signals, aiming to enhance its practical applications in real-world identification scenarios, specially among individuals with abnormal PPG signals. The proposed framework operates through a two-step process : first, it extracts robust features from the segmented PPG signals, and second, it employs a support vector machine (SVM) model for classification. Tested on the BIDMC dataset, our system achieved an impressive identification accuracy exceeding 95% across a cohort of forty individuals, with Area Under the Curve (AUC) results ranging from $[97.44\% - 100\%]$.

3.3.2 Followed Methodology

3.3.2.1 BIDMC Dataset

The BIDMC dataset [64], comprising electrocardiogram (ECG), pulse oximetry (photoplethysmography, PPG), and impedance pneumography signals collected from intensive care patients. The dataset includes 53 recordings, each lasting 8 minutes, of ECG, PPG, and impedance pneumography signals sampled at 125 Hz, collected from adult patients aged 19 to over 90 (including 32 females). Participants were randomly selected from a larger group of patients admitted to the medical and surgical intensive care units at Boston Medical Center.

Each recording includes :

Electrocardiogram (ECG) : Lead II ECG signals, capturing electrical activity of the heart. Pulse Oximetry (PPG) : Photoplethysmogram signals, measuring blood volume changes in peripheral circulation. Impedance Pneumography : Respiratory signals derived from chest impedance changes, used for manual breath annotations. Physiological Parameters : Sampled at 1 Hz. In this current study, we used PPG recordings from the BIDMC dataset to evaluate the effectiveness of our proposed biometric identification framework. By analyzing these recordings, we aim to extract relevant features that enhance the precision and reliability of individual identification in a clinical setting.

We specifically examine the PPG signals by extracting one-minute segments from the recordings for evaluation, working with data from 53 individuals.

Differents steps are applied to analyse and identify persons via heir PPG signals as illustrated in the algorithm 3 process of PPG -Based biometric Identification :

Algorithm 3 PPG-Based Biometric Identification

Input : 53 PPG signals (1 minute each)
Preprocessing of PPG signals
for each signal in PPG signals **do**
    Perform noise reduction
    Normalize the signal
end for
Segmentation
for each signal in PPG signals **do**
    Divide the signal into 10 segments
end for
Feature Extraction
for each segment **do**
    Extract time-domain features
    Compute Power Spectral Density (PSD)
    Extract frequency-domain features from PSD
end for
Feature Combination
Concatenate time-domain and frequency-domain features into a feature vector
Feature Selection
Apply Minimum Redundancy Maximum Relevance (MRMR) to rank features
Classification
for each classifier in Classifiers **do**
    Train the classifier with selected features
end for
Validation
Perform 10-fold cross-validation to evaluate model performance
Output : Class labels for each signal

3.3.2.2 Spectral Analysis Parameters of PPG Signals

Signal preprocessing techniques are applied to remove noise and artifacts, ensuring high-quality data for analysis by performing signal normalization to baseline drift present in the signals. Then, we have applied the low-pass Butterworth filter as illustrated in Figure 3.4., focusing on frequencies above 5 Hz as proven in literature [102]. Feature extraction methods, including frequency-domain, and statistical-based features, are explored to capture unique individual characteristics embedded in the PPG waveform.

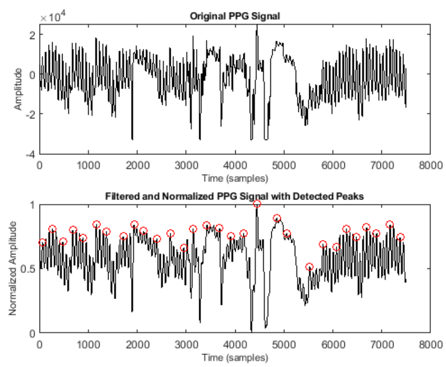


FIG. 3.4 : Original and Filtered PPG signal with detected peaks

In this research, we apply the spectral analysis characteristics of PPG signals by extracting power in specific frequency bands. These parameters provide valuable information on the autonomic nervous system activity, cardiovascular health, and the general physiological state.

3.3.3 Main Power Spectral Density Characteristics of the PPG Signal

The analysis of the Power Spectral Density in Figure 3.5illustrates how power is distributed across frequency components in the PPG signal.

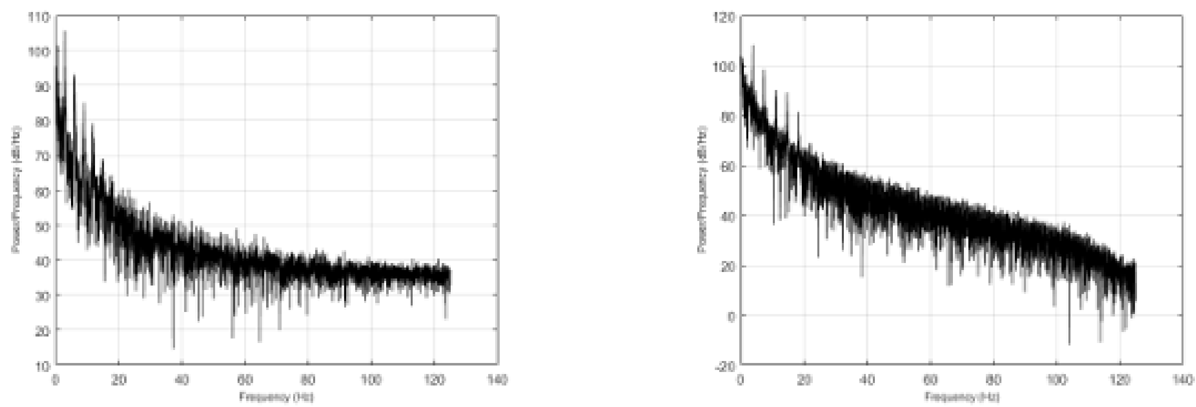


FIG. 3.5 : Power Spectral Density of PPG Signal : Record 20 and Record 40

Shows a decrease in power with increasing frequency. The highest power levels are concentrated in the lower frequencies, specifically in the fundamental and dominant frequency ranges of the PPG waveform. This pattern reflects the physiological rhythms captured in the signal, particularly those related to heart rate and autonomic activity. The rapid decrease in power at higher frequencies indicates that high-frequency components have minimal impact on the signal's overall variability, consistent with the dominance of lower frequencies in typical PPG signal characteristics. The ability to analyze PPG signals in real-world settings enhances their applicability in biometric monitoring, particularly in remote areas where traditional methods may be impractical [62]. Conversely, while PPG signals present a promising avenue for non-invasive monitoring, their susceptibility to artifacts and variability in quality can pose challenges in clinical settings, necessitating ongoing research to refine signal processing techniques.

The Power in Low Frequency (LF) Band, LF/HF Ratio, and the Total Power are described in table 3.4.

TAB. 3.4 : Frequency-Based Characteristics from Power Spectral Density

Feature	Description
LF Band	Combined sympathetic and parasympathetic activity.
HF Power	Power in PPG signal, 0.15–0.4 Hz.
VLF Power	Power in PPG signal, 0.003–0.04 Hz.
LF/HF Ratio	Ratio of LF (0.04–0.15 Hz) to HF (0.15–0.4 Hz) power.
Normalized Ratios	LF and HF power relative to total power.
Total Power	Total variability of the signal.

Subsequently, the ranked and selected features as shown in Figure 3.6 are fed into various machine learning classifiers, such as Support Vector Machine (SVM) with different kernels are employed to evaluate the identification performance. The contribution of this system focus on identification tasks and it is tested against variations in physiological states such as unhealthy cases.

As a result, the system demonstrates efficacy as a reliable and secure method for biometric identification, particularly in challenging cases involving abnormal signals. underscoring its effectiveness as a secure and resilient approach for biometric identification, particularly for those with atypical PPG characteristics. PPG signals offer valuable insights into an individual's clinical state, supporting personalization and reliable identification. Furthermore, physiological signals provide a unique advantage for continuous authentication systems, as they can be collected over extended

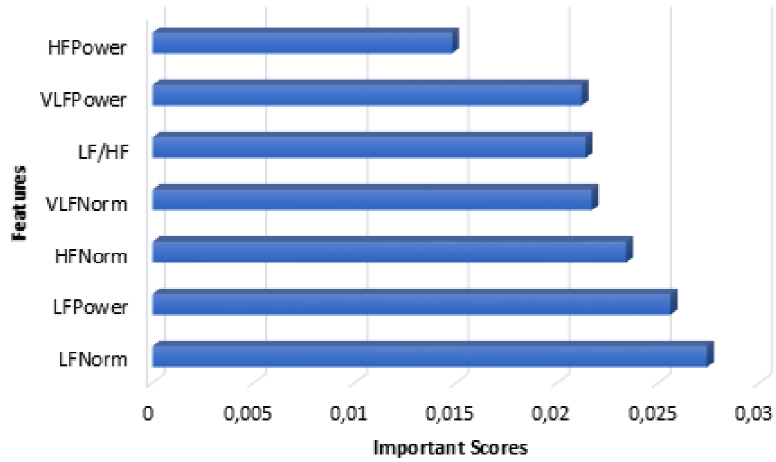


FIG. 3.6 : Feature importance scores sorted using Relief-F algorithm

periods without manual input.

3.4 Conclusion

The chapter on unimodal biometric systems provided a comprehensive investigation into the utilization of Electrocardiogram (ECG) and Photoplethysmogram (PPG) signals for individual identification.

The initial section delved into ECG biometrics, emphasizing the importance of leveraging both fiducial and non-fiducial characteristics to effectively differentiate between individuals. Fiducial features, such as specific points in the ECG waveform, allow for precise identification, while non-fiducial characteristics, which encompass broader waveform patterns, offer a more generalized approach. This dual focus enables a more nuanced understanding of individual cardiac signatures, enhancing identification accuracy. Furthermore, the chapter compared ECG signals from healthy individuals with those from individuals displaying various health conditions. This comparison illustrated the robustness of biometric technology, demonstrating its capability to maintain performance across different health statuses. By analyzing variations in ECG patterns, the study highlighted how specific anomalies can serve as unique identifiers, further solidifying the viability of ECG as a reliable biometric modality.

Following the discussion on ECG, the focus shifted to PPG signals for biometric identification. This section explored the unique advantages of PPG technology, especially its applicability in identifying unhealthy individuals where ECG might be less effective. The research revealed that despite the health-related complexities often associated with PPG signals, such as noise from motion artifacts or underlying health issues, these signals still hold significant promise. The analysis showcased how the variability in blood volume pulse, captured through PPG, can provide distinct identifiers even in compromised health states. To achieve this, the system sets an appropriate threshold based on the similarity values calculated from the intra- and inter-class similarity ranges established during the enrolment phase.

Collectively, the results from both ECG and PPG analyses indicate that these unimodal biometric options are not only promising but also adaptable to a range of health conditions. The findings suggest that integrating health status considerations into biometric systems could enhance their practical value, reinforcing the notion that biometric technologies can evolve to meet diverse user needs.

This adaptability positions ECG and PPG as viable solutions in the growing field of biometric identification, potentially leading to wider adoption in security, healthcare, and personal identification applications.

Chapitre 4

Development of a Biometric Recognition System Based on ECG, BP, and ICG Signals

4.1 Introduction

Biometric recognition systems based on physiological signals have potential security advantages. Unfortunately, they also have drawbacks, like the effect that diseases and physiological changes have on signal integrity. To solve these problems and raise the precision of identifying and resilience of these systems, our research propose multimodal biometric system by integrating ECG, BP and ICG signals with biometric systems.

Historically, the application of ICG has stagnated in comparison to the ECG mostly due to the lack of standardization and costly apparatuses. However, advances in affordable technology and signal processing techniques led to an increase in both research and clinical used of ICG [114], [115], and our research is the first to identify the blood pressure signal as a biometric modality. In light of the interest in developing robust physiological-based biometric systems that can handle various challenges, including the integration of multi-modalities and the use of deep learning techniques for improved performance [67]. A variety of procedures come together in the field of signal analysis to provide reliable pipelines for the automation of data processing. Physiological signals are employed in the medical field. It is growing more widespread. These days, it's common to work with enormous datasets that contain thousands of features. This is mostly because biological signal collecting can be done over periods of several hours, which is another difficulty in and of itself [169].

Physiological signals are measurable quantities obtained from the human body through suitable sensors, offering information on the pathophysiological condition of a patient. Processing these signals is crucial for providing valuable information, aiding physicians in diagnosis, and guiding treatment decisions. In addition, physiological signals are used recently to identify people and protect data as an optimal solution. It can also be used in unimodal and multimodal systems. One of the advantages of using these physiological signals is that the person is still alive. in Table 4.1, we found a brief comparison between different biometric modalities used in identification systems, focusing on physiological signals and including voice, which has a behavioral aspect but involves physiological characteristics. The modalities are evaluated across four criteria : environmental impact, cost and complexity, uniqueness, and security.

Biometric	Env. Impact	Cost & Complexity	Uniqueness	Security
Voice	High	Low	Low	Low
ECG	Low	Low	Moderate	Moderate
Fingerprint	Moderate	Moderate	High	Moderate
Iris	Low	High	High	Moderate
Palm Print	Moderate	Moderate	High	Moderate
DNA	Low	High	High	High
EEG	Low	High	High	High
Finger Vein	Low	High	High	High
Retina	Low	High	High	High
Hand Geometry	Moderate	Moderate	Moderate	Moderate
PPG	High	Low	Moderate	Moderate

Tab. 4.1 : Comparison of Physiological Biometric Modalities

4.1.1 Continuous Blood Pressure Signal (CBPS)

Blood pressure (BP) is one of the most crucial monitoring parameters in clinical medicine [68].In recent decades, the widespread of the oscillometry-based blood pressure wrist or arm cuffs have made home blood pressure monitoring more accessible and convenient. The BP signal undergoes changes along its course from the proximal aorta (aortic pressure) to the peripheral arteries (peripheral blood pressure) that may be modeled by wave reflection and pulse wave amplification phenomena [77], which is more explained in [68]that the coupling of electrical and mechanical processes in our heart leads to the ejection of blood into the arterial system, which influences blood velocity and creates a pressure wave that moves from the central arteries to the peripheral ones. This wave causes the arterial walls to expand as it travels and moves more quickly than the blood itself. The pressure oscillates between two extremes : the peak pressure during heart contractions (systolic blood pressure, SBP) and the lowest pressure in between beats (diastolic blood pressure, DBP). The average pressure of this wave, referred to as mean arterial pressure (MAP), is calculated using the formula 4.1:

$$\text{MAP} = \text{DBP} + 0.333(\text{SBP} - \text{DBP}) \tag{4.1}$$

Blood pressure signal is a complex parameter in other physiological signals because that has both physiological and neurological influences, and therefore these need to be included to obtain a robust model [68].

4.1.2 Impedance Cardiography Signal (ICG)

ICG signal (also called dZ/dt) measurement is a non-invasive method employed to extract crucial information or features related to heart activity [88]. It uses Thoracic Electrical Bioimpedance (TEB), a type of electrical impedance plethysmography [81], Known as impedance rheography, is consider as a diagnostic technique to assess the function of the body's internal organs on the basis of the impedance value or its changes in the examined area of the body. Impedance fluctuations occurring as a result of changes in the volume and velocity of the blood vessels, air in the lungs, as well as movements of organs and changes in their shape can provide information about the state and function of the body's internal organs [81] as demonstrated in Figure 4.1.

The values of $(dZ/dt)_{max}$, LVET are necessary to calculate the stroke volume and can be deter-

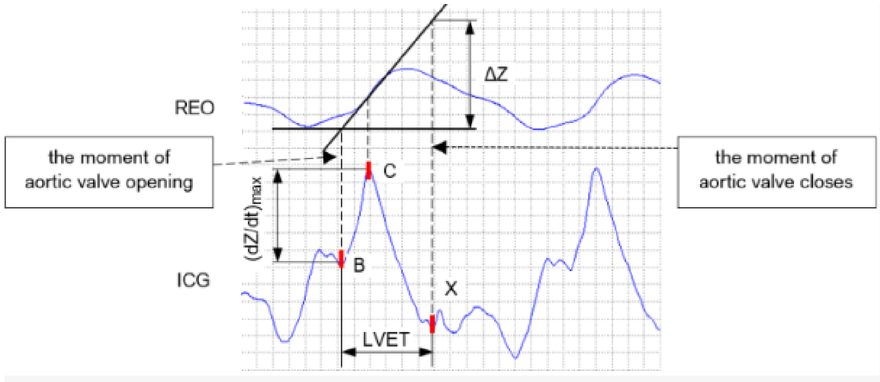


FIG. 4.1 : Identifying a bioimpedance change within a single cardiac cycle [156]

mined based on the positions of the characteristic points C, X and B located on the first derivative of the bioimpedance curve (ICG) [156]. Each of these points has a significant interpretation. Point B refers to the moment of the aortic valve opening, point C denotes a maximum blood ejection speed, while point X indicates the moment of the aortic valve closing [156].

A brief description of these fiducial points along with the hemodynamic parameters that are determined based on their locations in the ICG signal are introduced in Table 4.2.

Fiducial Point	**Definition**	**Hemodynamic Characteristic**
B	The onset of rapid upstroke towards the C point. It represents the moment of aortic valve opening.	PEP, LVET, SV, CO
C	Point with the greatest amplitude in one cardiac cycle. It represents the maximum aortic flow.	HR, SV, CO, Heather Index
X	The minimum ICG signal in one cardiac cycle. It represents the moment of aortic valve closing.	LVET, SV, CO

TAB. 4.2 : Description of Fiducial Points and Hemodynamic Parameters of the ICG Signal

An overview of the most often used hemodynamic parameters such as : CO, PEP, LVET, and the heather index that are deduced from the positions of the distinctive spots in the ECG and ICG signals are presented in the Table 4.3.

Hemodynamic Parameter	**Definition**
PEP (Pre-ejection period)	The time between electrical systole (Q point in ECG) and opening of the aortic valve (B point in ICG).
LVET (Left Ventricular Ejection Time)	The period of blood flow across the aortic valve. The time between B and X points in the ICG signal.
HR (Heart Rate)	The frequency of the heartbeat. The mean number of C points occurrences in one minute.
Heather Index	Cardiac contractility index defined as $C/(C-Q)$.
SV (Stroke Volume)	Amount of blood ejected from the left ventricle during one cycle.
CO (Cardiac Output)	Amount of blood ejected from the left ventricle in one minute.

Tab. 4.3 : Definitions of various hemodynamic parameters.

It is a technique used to monitor stroke volume, which also means continuous changes in left ventricular volume and various hemodynamic indices, including continuous cardiac output (CO), total peripheral resistance (TPR), ventricular ejection time (VET), pre-ejection period (PEP), heart rate (HR) and heart rate variability (HRV), which are critical for assessing autonomic nervous system function and thereby obtaining diagnostic information on cardiovascular functioning by sensing variations in thoracic impedance to the change in blood volume.

The first study discovered this trait denoted that ICG has been used as a biometric trait in a system based on a radiofrequency oscillator with an antenna and detector, which acquires contactless long-distance ICG for analysis and feature extraction, without comparable results of person

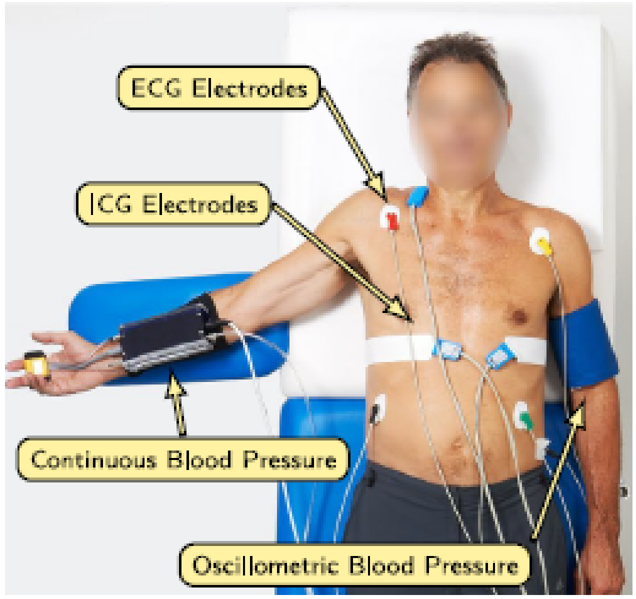


FIG. 4.2 : Location of reference sensors. [54]

recognition (Analytics for US Patent No. 8232866) [113].

4.2 A dataset of clinically recorded radar vital signs with synchronised reference sensor signals

This thesis represents the initial exploration of the dataset of clinically recorded radar vital signs with synchronised reference sensor signals in the field of biometrics. The database used was planned and implemented from a clinical evaluation of physiological radar signals. The measurements were monitored by medical staff at the University Hospital Erlangen. It [54] is a collection of continuous-wave radar systems and multimodal physiological signals recorded by the Task Force Monitor (TFM), used as a reference device measuring electrocardiogram (ECG), impedance cardiogram (ICG), and non-invasive continous blood pressure (BP) to determine hemodynamics and autonomic nervous system (ANS) parameters on 30 healthy subjects over 24 hours , monitoring vital signs through radar in conjunction with traditional medical sensors such as ECG and blood pressure monitors.

It also revolves around measuring values such as : heart rate, stroke volume, cardiac output, thoracic fluid content, total peripheral resistance and respiratory rates using radar pointed at the chest while subjects rest on a tilt table. Following a predetermined process, participants' as well as the local ethics committee's consents were obtained before the studies were planned. In general, measurements were made on 14 healthy male and 16 healthy female test volunteers. During the measurements, the heart's electrical activity measures the electrical activity of the heart over time. It helps in assessing the heart rhythm and detecting any abnormalities or irregularities. According to clinical standards, the four color-coded leads were attached. The ECG channels were digitalized with a precision $\pm 5 \mu V$ and a sampling rate of 2000 Hz. Through the use of an alternating, small current between two electrodes on the body, ICG measures changes in electrical impedance across the chest during the cardiac cycle. It provides information about stroke volume, cardiac output, and other hemodynamic parameters. Ohm's law states that the measured voltage is inversely proportional to the impedance. Post export, ICG raw signal was made usable with a sampling frequency of 1000 Hz. In general, the cuff-based technique is the most adopted non-invasive means of blood pressure measurement. Nonetheless, its drawback lies in the need for a 1–2 minute interval between measurements to minimize errors in obtaining continuous blood pressure data. Therefore, this technology is known as Continuous Noninvasive Arterial Pressure (CNAP) and is done by combining the measurement of an oscillometric BP cuff and a cuff at the fingers measuring the vascular unloading. The raw signal of continuous blood pressure which is given in mmHg, was processed to achieve usability, employing a sampling frequency of 200 Hz. Notably, this database takes into consideration the stimulation process, involving different scenarios such as the Valsalva maneuver (VM), breath-holding, and the tilt table test, which attempted to stimulate the individuals' autonomic nervous system and hemodynamics. In the context of biometrics, this paper investigates the application and analysis of Impedance Cardiogram (ICG), Electrocardiogram (ECG), and blood pressure measurements, estimating the period of the resting scenario was carried out with each subject and thus an average recording time of 2882 s per subject.

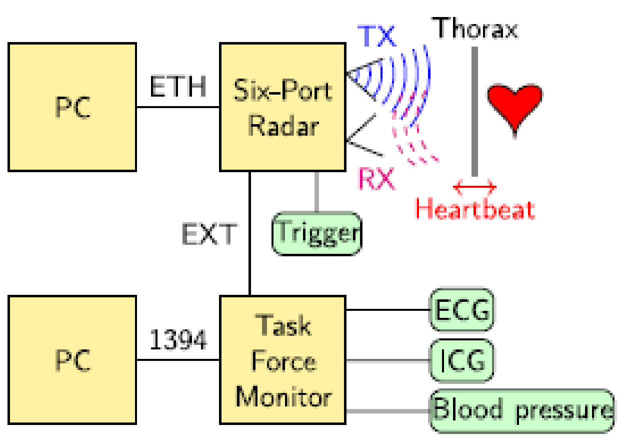


FIG. 4.3 : Block diagram of the system acquisition of ECG, ICG and CBP signals. [54]

4.3 Data Analysis Methods

Data pre-processing is a major step to prepare the data before moving to the classification model. This pre-processing can include several steps, for example, removing noise, balancing classes, and presentable and reliable data shape in the context of ECG signals [80]. The raw ECG , ICG and BP are typically contaminated with electrical artifacts. The most common of these are 50/60 Hz noises from nearby electronics and muscular artifacts from the movements of body parts. It is typical to preprocess these physiological signals to reduce or remove these artifacts to improve signal quality. Artifacts can be either rejected outright based on some criterion or corrected. We next discuss common methods of artifact rejection and correction according to each signal as detailed in the table 4.4.

4.3.1 Pre-processing stage

Pre-processing of ECG Signal

To enhance the quality of electrocardiogram (ECG) signals, processing is required to mitigate unwanted noise and artifacts. In this study, a digital band-pass Butterworth filter is implemented. This filter is configured with cutoff frequencies of [1 Hz to 20 Hz] on the light of Digital bandpass 4th order Butterworth filters [1, 40 Hz] was used to pre-process ECG [162] and a baseline drift of the ECG signal is removed. The primary objective of this approach is to isolate the desired signal frequency range, attenuating extraneous frequencies to ensure a filtered ECG output for reliable analysis and interpretation.

Noise Source	Description	Filters
Electrical	Medical devices [100 KHz–1 MHz]	Notch, Band-pass [78]
Hardware	ECG equipment	Low-pass, Adaptive
Muscle	Non-heart muscle contractions	High-pass, Band-pass
Electrode Motion	Skin-electrode movement	Adaptive, Notch
Baseline Wander	Inhalation affecting ECG baseline	High-pass
Power Line	[50/60 Hz] interference	Notch
Electrical Contact	Poor electrode adhesion	Adaptive

Tab. 4.4 : Noise Sources in ECG Measurements

Pre-processing of ICG Signal

In recent years, there has been a gradual increase in the study of impedance cardiogram (ICG) signals. The recorded ICG signal is further post-processed in order to extract certain characteristics. The recorded ICG signal is similar to a conventional aortic pulse waveform [74]. According to [75] recorded ICG signals were digitally filtered with a 4th-order Butterworth bandpass filter to remove the high frequency noise and artifacts and low-frequency drift. The lower and upper cutoff frequencies were set and 0.5 Hz and 25 Hz for ICG. The ICG bandpass filter cutoff frequencies are commonly used in the literature to remove respiration and low-frequency movement artifacts and including respiratory noises, motion noises [76], power line interferences, and more. Hence, selecting an effective denoising method becomes crucial for precise noise removal. In this study, the denoising of ICG signals was achieved using the eighth-order Daubechies wavelet family (db8) [89], [91], in the reason that the db8 wavelet is the most efficient denoising method which can filter the ICG signal with minimal degradation of the shape. Furthermore, the db8 wavelet method presents the lowest error rate for determining the amplitudes of the peaks C. To emphasize, the db8 wavelet is the most suitable method for denoising the ICG signal because It can facilitate the determination of the hemodynamic parameters and the diagnosis of cardiovascular diseases, which allow us to extract relevant features from the processed ICG signal obtained.

Pre-processing of BP Signal Cutting-edge research indicates that electrocardiogram (ECG) signals can effectively evaluate cardiac contractility, revealing a strong correlation with blood pressure (BP) fluctuations and variations [92]. In this thesis, a 4th-order bandpass Butterworth filter is applied, with cutoff frequencies configured between 0.1 Hz and 10 Hz to BP signals. This filtering approach, as previously described, ensures that baseline variations do not distort the underlying physiological data.

Following initial preprocessing, the physiological signals—namely impedance cardiography (ICG), ECG, and BP—are subjected to an advanced feature extraction phase. This critical process involves identifying and isolating key attributes from these signals, enabling a more precise and comprehensive analysis. The features derived from ICG, ECG, and BP significantly enhance the characterization of the physiological dataset, providing deeper insights into the complex patterns and dynamics embedded within the biometric signals under investigation.

4.3.2 Segmentation and Data augmentation

In the realm of biometrics, dividing physiological signals into distinct segments is a fundamental preprocessing step that prepares data for accurate feature extraction and individual identification. By carefully designing the segmentation process, researchers can optimize the trade-off between computational efficiency and feature richness [16], ultimately improving the system's ability to distinguish individuals based on their physiological signals. The findings of this study underscore the importance of tailoring segmentation strategies to the specific characteristics of signals and the goals of the biometric application. Segmenting physiological signals like blood pressure (BP), impedance cardiography (ICG), and electrocardiograms (ECG) is an essential preprocessing step in our biometric systems to get data ready for feature extraction. According to [93], the objective is to identify regions of interest, such as recurrent patterns, in these signals to streamline feature extraction, minimize intra-subject variability caused by physiological changes, and reduce the size of the data. In this investigation a buffer-based technique was used that slides a fixed size window across the signal in discrete steps to split each person's single continuous signal for ECG, ICG and

BP into five segments. The segments were 24,304 for BP, 196,300 samples for ECG, and 121,520 for ICG. As noted by *antic & al.* [113] each three recording intervals are divided into four non-overlapping windows consisting of 10 beats, which were used to create averaged segments. In our study, we tested different segments,in the first step we divided each signal into nine smaller segment experiments but it resulted in poorer model performance, indicating that five segments best balanced feature quality and segment size. Researchers and clinicians working on physiological-based recognition systems can gain important insights from this segmentation strategy, which enhanced the dataset and improved the machine learning model's capacity to capture complex blood pressure dynamics, generalize across signal variations, and increase biometric identification accuracy.

4.3.3 Characterization of Signals and Fusion technique

The pre-processed physiological signals, specifically Impedance Cardiogram (ICG), Electrocardiogram (ECG), and blood pressure, underwent a subsequent stage where a comprehensive feature extraction process was used. This pivotal step involved the identification and extraction of relevant features from the aforementioned signals, enabling a more nuanced and detailed analysis. The extracted features from ICG, ECG, and blood pressure contribute significantly to the overall characterization of the physiological data, facilitating a deeper understanding and interpretation of the intricate patterns and dynamics inherent in the biometric information under investigation. Feature extraction is a method in signal processing, pattern recognition and machine learning classification.

That begins with raw measured data and generates derived values called features. These features are crafted to be highly informative, accurate, precise and non-redundant enhancing subsequent learning and differentiating between individuals to be able to distinguish between them. By reducing data dimensionality by eliminating redundant information. This improves training and inference time, minimizes identification model errors, and mitigates the risk of overfitting.

4.3.3.1 Extracted features for MBEBI : Developed a multi-biometric system

In the present phase of extracted features, we meticulously examined various techniques for feature extraction from different physiological signals based on biometric recognition, aiming to distill essential information and patterns indicative of recognizing the right person according to its physiological traits and distinguishing other individuals. These extracted features act as the essential components building blocks that pave the way for the subsequent phase of our analysis, propelling us towards a comprehensive understanding and accurate biometric recognition system based on analysis of multi-modal physiological signals.

In the feature extraction phase, segmented signals are translated into a representation that minimizes the effects of intra-subject variability while amplifying discriminative traits in each signal and intra-class differences, ultimately enhancing multi-classification performance [93]. Identifying pertinent features that adeptly encapsulate the nuances of the processed signals, namely ECG, ICG, and BP signals, is integral to enhancing person identification accuracy. In literature [113], [163] ECG peak positions were extracted using the Pan-Tompkins method to extract fiducial features, while ICG peaks were extracted as a maximum value between two-time points of consecutive ECG peaks . To this end, in our study , we focus on non-hand crafted features on the light of the Table 4.5 of comparison between methods of extract characteristics. A set of sixteen (16) distinctive features has been meticulously chosen. For our intended biometric research, we adopted the stance that the more traits we could assess objectively, the better, rather than limiting our study to traditional methods. In the light of [176]for each measured aspect, a distribution of values was observed within each subject, and we calculated the mean, median, and standard deviation. Inter-quartile range, skewness, and kurtosis should be considered as distinct features.

These features, comprising Mode, Mean, Standard Deviation, Minimum, Maximum, Range, Variance, 3rd Quartile, Kurtosis, Skewness, Root Mean Square, MAD, Geometric Mean and Harmonic Mean, Shannon Entropy and Energy Entropy, collectively provide a comprehensive framework for characterizing and understanding the unique properties embedded in the signals. The careful selection of these features aims to contribute significantly to the precision and effectiveness of person identification processes. Presented below is a detailed list of the extracted features :

Feature 1: Mode

The mode is a measure of central tendency in statistics that represents the value or values that occur most frequently in a dataset. In other words, it is the data point(x_i) that have the highest fre-

Method used	Advantages	Disadvantages	Applications
Statistical features	Simple implementation, Computationally inexpensive	Not application-specific ; statistical features can be extracted for many types of data, and may not always be the best choice for physiological signals like the ECG	Biometric identification system with the use of ECG signals [174]
Pan-Tompkins	High detection accuracy even in the presence of noisy ECG signals, Allows for real-time ECG analysis, Does not require excessive computing power	The window size is determined empirically and thresholds depend on the accuracy of the heart rate determined in the previous segment—this can cause a domino effect of errors to occur	QRS detection, duration, amplitude and morphology for the diagnosis of cardiac diseases [172], [173].

Tab. 4.5 : Comparison of time domain feature extraction methods for (ECG, ICG, and BP) with their advantages, disadvantages, and applications

quency of occurrence. A dataset can have one mode (unimodal), more than one mode (multimodal), or no mode at all if all values occur with equal frequency.

Feature 2: Mean

The mean value of data samples can be found using the equation 4.2.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{4.2}$$

where ; n refers to the total number of data points, x_i represents each value or data point at i.

Feature 3: Standard deviation (STD)

The standard deviation is the square root of the variance, and it is expressed through the following equation 4.3. This parameter allows us to precisely quantify the dispersion and alterations induced in the blood pressure signals.

$$STD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{4.3}$$

where; n refers to the total number of data points, x_i represents each value or data point at i , and $\bar{x}$ is the mean value.

Feature 4: Minimum value (min)

The minimum value of data samples can be defined as in equation 4.4

$$\text{min} = \min(x_1, x_2, \ldots, x_n) \tag{4.4}$$

where $x_1, x_2, \ldots, x_n$ represents the processed data points.

Feature 5: Maximum value (max)

The maximum value of data samples can be found using the equation 4.5

$$\text{max} = \max(x_1, x_2, \ldots, x_n) \tag{4.5}$$

where; $x_1, x_2, \ldots, x_n$ represent the processed data points.

Feature 6: Range value

The Range value serves as a measure of dispersion, determining the gap between the maximum and minimum values within a sample. This can be articulated using the provided equation 4.6

$$\text{Range} = \max(\text{x}) - \min(\text{x}) \tag{4.6}$$

Feature 7: Variance

The incorporation of the variance feature in our biometric framework is essential for describing the variability within the investigated dataset. Variance is a traditional metric of statistical dispersion that quantifies the degree to which individual data points diverge from the dataset's mean. Variance offers essential insights into the distributional properties of physiological signals data by examining the dispersion of values. It quantifies the dispersion of the processed data around their mean, as articulated in Equation 4.7.

$$\text{Var} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2, \tag{4.7}$$

where ; n refers to the total number of data points, x_i represents each value or data point at i , and $\bar{x}$ is the mean value.

The use of variance as a feature allows for a detailed examination of the dataset's inherent variability, enhancing the understanding of signal dynamics. This statistical metric is particularly pertinent in our biometric analytical setting, where a comprehensive analysis of ECG, ICG, and BP data variability is crucial for informed decision-making. The formal definition of variance and its function within our analytical framework are clearly delineated, enhancing the methodological accuracy of our study.

Feature 8: 3^{rd} **Quartile** The equation for the third quartile is detailed in 4.8

$$Q3 = \frac{3(n+1)}{4} \tag{4.8}$$

where ; n represents the total number of the processed data points. The third quartile is a measure of statistical dispersion, representing the value below which 75% of the data falls. It is the median of the upper half of the processed data points.

Higher–order statistics : (HOS) is useful when dealing with non–Gaussian or nonlinear processes.

Feature 9: Kurtosis (K)

In the field of statistics, Also known as the ”fourth moment,” it is a measure of the tailedness of the probability distribution of a signal. kurtosis serves as a shape parameter assessing the asymmetry of a time series, which means that the kurtosis defines the sharpness of a peak relative to a normal distribution in a frequency distribution curve [175]. Its computation is determined by the equation 4.9.

$$K = \frac{E(x - \bar{x})^4}{\sigma^4}, \tag{4.9}$$

where $\bar{x}$ represents the mean of the data row x, σ is the standard deviation of x, and $E(\cdot)$ is the expected value.

Feature 10: Skewness (sK)

The skewness measures the asymmetry of a probability distribution. A positive skewness indicates a distribution with a longer right tail, It is the third moment of a signal. while negative skewness suggests a longer left tail. When the left and right sides of a central point are similar, the data set can be considered symmetrical [175]. The skewness value can be positive, zero, or negative. The skewness can be defined as in eq 4.10

$$\text{sk} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{n \cdot s^3} \tag{4.10}$$

Feature 11: Median Absolute Deviation (MAD)

The Median Absolute Deviation (MAD) is a statistical metric used to assess the dispersion of quantitative data. Unlike the standard deviation, MAD is particularly robust in the presence of outliers, especially those located at the extremes of a distribution. This robustness arises from the reliance on the median rather than the mean, which minimizes the influence of extreme values.

Consequently, data points in the tails of the distribution exert a far weaker effect on MAD than they do on measures based on the arithmetic mean. The definition of this feature is provided as outlined in equation (4.11).

$$\text{MAD} = median(\mid x_i - median(x_i) \mid), \tag{4.11}$$

Feature 12: Root Mean Square

the Root Mean Square (RMS) plays a central role, as it effectively quantifies the signal's amplitude and energy content. This parameter making it a reliable indicator of muscle activity (EMG signals) during walking, using a personalized matrix of features and muscles, the proposed method achieved an average identification accuracy of 93%, confirming the discriminative power of RMS alongside complementary features [168]. The Root Mean Square (RMS) of the pre-processed signals, given in (4.12)

$$\text{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \mid x_i \mid^2}. \tag{4.12}$$

In alignment with the pursuit of heightened classification precision within the scope of our current study objectives, we extend the methodology by incorporating the RMS as a pivotal feature. This augmentation aims to further enhance the discriminative capacity of classifiers, acknowledging the robust contributions of RMS in capturing essential characteristics of physiological signals [168]. The integration of RMS, along with previously employed statistical features, represents a nuanced refinement that aligns with the evolving landscape of ECG and ICG classification methodologies, contributing to the ongoing pursuit of heightened accuracy and reliability in signal analysis.

Feature 13: Geometric Mean (GM)

The computation of the geometric mean is expressed as depicted in equation (4.13). It serves as a valuable statistical metric capable of succinctly summarizing a series of values and shedding light on the inherent distribution of the data.

$$G_{mean} = \left(\prod_{i=1}^{n} \mid x_i \mid \right)^{1/n} \tag{4.13}$$

Feature 14: Harmonic Mean (HM)

The harmonic mean stands out as a resilient measure of central tendency, especially in scenarios where outliers could heavily sway outcomes. In contrast to the arithmetic mean, which can be skewed by substantial observations, the harmonic mean assigns greater importance to the smallest values within a dataset. The equation for computing the harmonic mean is outlined in 4.14.

$$H_{mean} = \frac{n}{\sum_{i=1}^{n} \left(\frac{1}{|x_i|} \right)} \tag{4.14}$$

Notably, the Geometric Mean (GM) used as a stabilizing measure for multiplicative amplitude features, allowing it to capture subtle variations in signal morphology across individuals. For this reason, GM is adopted as a key feature in our biometric identification system based on physiological signals. Its strength lies in enhancing accuracy when dealing with signals whose energy varies significantly between persons, while also ensuring better generalization across sessions by reducing the bias introduced by occasional strong peaks.

In contrast, the Harmonic Mean (HM) places greater emphasis on low-rate frequency and rhythm features, such as heart rate variability (HRV), slow heartbeats, low breathing rates, or muscle firing onset times. These characteristics can reveal distinctive physiological signatures that may be overlooked by arithmetic or geometric means. Furthermore, when combined with amplitude-based features like RMS or GM, HM contributes to improved robustness in multimodal biometric systems.

Feature 15: Shannon Entropy

The Shannon entropy (see equation 4.15) quantifies the uncertainty or average surprise associated with a random variable. It is known as a measure of the information content in a probability distribution.

$$Shentropy = -\sum_{i=1}^{n} P(x_i) \cdot \log_2(P(x_i)) \tag{4.15}$$

Feature 16: Energy–to–Shannon Entropy Ratio

The Energy Shanon Entropy characteristic represent a specific types of features capable of capturing the general and habitual behavior of each signal in both normal and unhealthy states, because energy that better approaches detection ranges in the presence of noise or domains with more width results in fewer errors. Capacity to emphasize medium is the advantage of using Shannon energy rather than classic energy [171]. Log energy entropy (see equation 4.16) quantifies the energy distribution within a signal. It reflects how the signal's energy is spread across its components. It is particularly useful for analyzing signals in the context of non-stationary processes.

$$E = -\sum_{i=1}^{N} E(x_i)\log(E(x_i)) \tag{4.16}$$

Where : $E(x_i)$ Represents the energy of the $i-th$ component of the signal, which can be calculated as : $E(x_i) = |x_i|^2$. Where : x_i is the value of the signal at the $i-th$ component. In summary, Log Energy Entropy is a valuable metric for analyzing the energy dynamics of signals, helping to uncover underlying patterns and features that may be significant in various applications.

4.4 Multi-classification and Identification

The classification process attributes a class or a category to a set of characteristics (features) extracted from the processed signals enabling the identification or authentication of individuals based on their unique biometric characteristics.

4.4.1 Support Vector Machine

Support Vector Machines (SVM) are one of the most actively developed classification methodologies [94] , being successfully applied in many application domains. SVMs operate by identifying the best hyperplane in the input space to divide various data classes. Finding the hyperplane that maximizes the margin, or distance, between the decision boundary and the nearest data points of each class is the fundamental concept behind SVMs. With the introduction of kernel functions, SVMs may learn intricate, non-linear decision boundaries and are especially good at handling high-dimensionality feature spaces [84]. This makes them an effective tool for a variety of classification tasks, including text categorization and image recognition.

Consider the binary classification setup with training set , composed by l instances, a subset of the complete training set, comprising only the training samples of two classes, here denoted in Equation 4.17 as $w = -1$ or $w = 1$.

$$\mathbb{D}_{SVM} = \{(x_i, w^{x_i}) \mid x_i \in \mathbb{R}^p, w^{x_i} \in \{-1, 1\}\}_{i=1}^{n} \tag{4.17}$$

SVM finds the classes' separating hyperplane, maximizing the margin. In order to deal with the case where the hyperplane splitting introduces misclassifications, The concept of "soft" margin is used. The method introduces slack variables x_i that measure the degree of misclassification of sample xi weighted by the parameter C, leading to the following primal formulation as denoted in 4.18:

$$\begin{aligned} \min_{w,\xi,b} \quad & \frac{1}{2}\|v\|^2 + C\sum_{i=1}^{n}\xi_i \\ \text{s.t.} \quad & w^{x_i}(v \cdot x - b) \geq 1 - \xi_i. \end{aligned} \tag{4.18}$$

The learning process is assumed to be performed offline. Once the model is computed (v and b), the class prediction. w^{x_u} ; for an unknown object ; x_u ;is determined by 4.19:

$$\begin{aligned} \min_{w,\xi,b} \quad & \frac{1}{2}\|v\|^2 + C\sum_{i=1}^{n}\xi_i \\ \text{s.t.} \quad & w^{x_i}(v \cdot x - b) \geq 1 - \xi_i. \end{aligned} \tag{4.19}$$

To deal with the multiclass problem of classifying N subjects into C = 1, ..N classes, we followed the dominant approach of reducing the multiclass problem (one-versus-all) into multiple binary classification problems (one-versus-one) as mentioned in the eq 4.20.

$$f_{jk}(x_u) : x_u \in \mathbb{R}^p \to w_{x_{jk}} \in j, k \tag{4.20}$$

It calculates a decision over instance x, deciding if it is classified as individual j or k. In authentication, the strategy consists in testing all the $N-1$ trained models, $f_j \cdot$ Where j is the class of the individual trying to guarantee authentication, and accepting only a situation where all models positively classify the testing instance.

In the identification method, the strategy involves in the selection of the individual, for whom the majority of trained models are well classified 4.21,

$$w^{x_u} = \arg\max_{j} \sum_{k=1, k\neq j}^{N} \mathbb{I}\left(f_{jk}(x_u) = 1\right), \tag{4.21}$$

Where : $\mathbb{I}$ is the indicator function (equal to one if its argument is a true proposition and equal to zero if it is a false proposition).

4.4.1.1 SVM Kernels

A collection of mathematical functions makes up the kernel of SVM algorithms. The kernel converts input data into the appropriate format based on its intended use. Different SVM techniques use different kernel functions. There may be various kinds of these functions. For example, linear, nonlinear, polynomial, sigmoid, and radial basis function (RBF). Explain the functions of the kernels for vector, text, image, graph, and sequence data. RBFs are the most commonly used kind of kernel function [95].

The Gaussian radial basis function (RBF) kernel's local and infinite response throughout the x-axis, in this study, we based on the configuration of Fine Gaussian-SVM is demonstrated in the table 4.6, the Kernel function is Gaussian based on Radial Basis Function (RBF), this function measures the similarity between two data points based on their euclidean distance, which maps input data into a higher-dimensional space, allowing it to capture complex, non-linear patterns, as noted in equation 4.22.

$$k(x_i, x_j) = \varphi^T(x_i)\varphi^T(x_j) \tag{4.22}$$

$ijth$ element of the N-by-N matrix in $\varphi(xj)$ feature space Gaussian RBF.

Furthermore, the Gaussian kernel function is required to satisfy the condition outlined by Mercer's theorem, as noted in equation 4.23.

$$\mathbf{K}(\mathbf{X_i}, \mathbf{X_j}) = \exp^{\frac{-||\mathbf{X_i}-\mathbf{X_j}||^2}{2\sigma^2}} \tag{4.23}$$

Where : X_i, X_j are two data points. $||\mathbf{X_i} - \mathbf{X_j}||$ is the squared euclidean distance.

σ is a parameter that controls the width of the Gaussian function (related to λ in our study).

TAB. 4.6 : Hyper-parameters of classifiers used in this study.

Classifier	**Algorithm**	**Hyper-parameters**
FG-SVM	Support Vector Machine with Gaussian kernel	Grid search for hyperparameter tuning ; $\lambda = 1.7$; $C = 1$; Multi-class method : One-Vs-All
Bi-layered ANN	Two fully connected layers with 10 neurons per layer	Activation function : ReLU ; Iterations : 1000

4.4.2 Artificial Neural Network ANN

The artificial neural network is an important part in the new industry of artificial intelligence [86]. Artificial Neural Networks (ANNs) offer a powerful machine learning for classifying non-linear physiological signals in biometric recognition systems. As known, it is a well-established biologically-inspired approach. This classifier employs various implementation strategies, including supervised, unsupervised, or reinforcement learning to process data. In addition, numerous researchers have utilized different ANN architectures because these models are data driven, self adaptive, capable of handling non-linear patterns, fast, highly accurate, resilient to noise and scalable for diverse applications [85]. A key advantage of ANNs is their capability to perform non-linear mapping between inputs and outputs [85] using activation functions like sigmoid, making them enabling effective solutions for complex, non linear tasks such as classifying physiological signals for biometric recognition.

Artificial Neural Network Architecture Neural network (NN) layers are independent of each other, with each layer capable of having a different number of nodes as shown in Figure 4.4, among which is a special class known as bias nodes. Bias nodes are always fixed at the value of one. In parallel to the intercept in linear regression as $y = ax + b$, where "a" is the independent variable's coefficient "x" and "b" is the bias, bias nodes serve a similar purpose.

Their purpose is primarily to add a trainable constant value to every node with normal inputs, such that the activation function can be shifted to the left or right, which is critical in optimizing ANN training results. If an NN is employed as a classifier, input nodes are equal to the input features, and output nodes are equal to the target classes, which can help in efficient pattern discovery in applications such as biometric classification.

To summarize, the SVM and ANN classifiers are more complex and they offer superior performance for physiological signals in biometric recognition task. Especially with the recent advancement of deep-learning algorithms, obtaining sufficient training data to train such deep networks is a challenge.

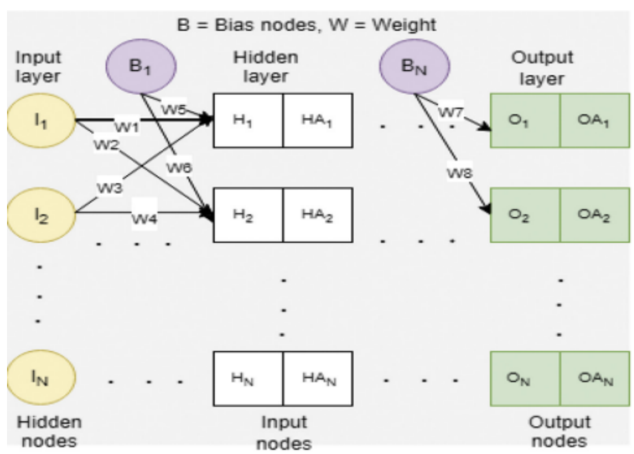


FIG. 4.4 : A neural network architecture [86].

4.4.3 Identification Performance Evaluation Criteria

The performance metrics are used to evaluate the performance and usability of biometric system as demonstrated by an hierarchical diagram which suggests a comprehensive evaluation approach, combining objective data analysis with subjective user feedback and security considerations, as depicted in Figure 4.5. In our research to evaluate our recognition system, we applied five evaluation metrics : accuracy, recall, precision, Cohen's kappa, and F1-score, Matrices confusion and AUC-Values. Our system is multitasking. To evaluate the authentication module, the metrics are : the False Acceptance Rate (FAR) and False Rejection Rate (FRR). These metrics enable a comprehensive examination of the model's overall and specific case performance on the dataset.

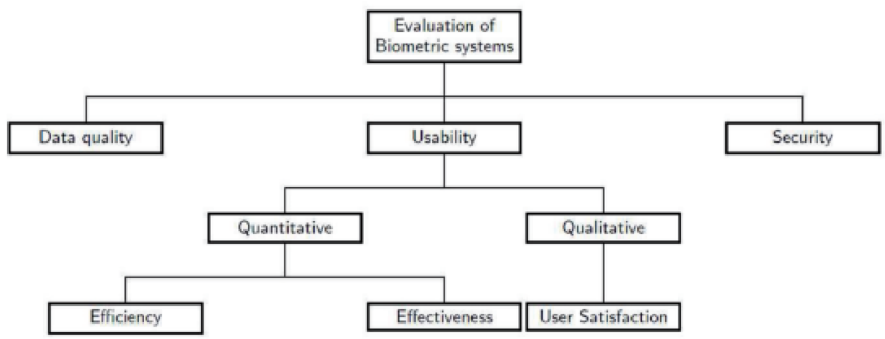


FIG. 4.5 : Evaluation of biometric systems [6]

4.4.3.1 Biometric Verification System metrics

False Rejection Rate (FRR) or False Non-Match Rate ($FNMR$) : is the proportion of real users that the system incorrectly refused [6]; it is formulated by Eq. 4.24.

$$FRR(\tau) = FTA + NMR(\tau) \times (1 - FTA) \tag{4.24}$$

False Acceptance Rate(FAR) or False Matching Rate (FMR) FTA : False Transaction Attempt, the probability that a transaction attempt is invalid. $NMR(\tau)$: Non-Match Rate at a given threshold

τ, the probability that a genuine user's biometric data does not match the stored template [6], [87].

Equal Error Rate(EER) or Crossover Error Rate (CER) : it is the probability that $FAR = FRR$ where : FRR and FAR are the level errors of the system.

To quantify system performance more thoroughly, a number of curves have also been proposed, among which are the following :

The Receiver Operating Characteristic (ROC) plots FMR or FAR on the X-axis and FNMR, FRR on the Y-axis [87].

Several performance evaluation metrics have recently been proposed in the literature, including some patents [96]. They have all been investigated for healthcare and personal fitness, specifically for PPG signals based on Biometric recognition system.

4.4.3.2 Biometric Identification System Performance Metrics

Accuracy or Identification Rate (IR) : its calculation could be subjective due to the involvement of many subject-variant factors. It is the proportion of successful identification transactions among users enrolled in the system. Specifically, it measures the instances where the correct identifier for a user is included in the list of identifiers returned by the system [6].

The Cohen's Kappa Coefficient (K) : is a statistical measure used to evaluate the level of agreement between two sets of categorical classifications, typically between the predicted labels produced by a model and the true labels of a datasets whiale correcting for the agreement that could occur by chance [181]. It provides a more reliable performance indicator than simple accuracy, especially when the data are unbalanced or contain multiple classes. The kappa value varies between -1 and 1, but generally takes a value between 0 and 1. The closer the Kappa coefficient value is to 1, the stronger the agreement between the model's predictions and the observed data. A value of $K = 1$ indicates perfect agreement, meaning that the model's classifications fully match the true labels [181]. Conversely, as the Kappa value approaches 0, the predictions become increasingly similar to random guesses, reflecting a level of agreement that could be expected purely by chance. Negative Kappa values, tending toward -1, indicate systematic disagreement between the predicted and observed classifications, where$K = -1$ corresponds to disagreement or complete inversion between the two sets of data [182].

4.5 Conclusion

The development and implementation of a biometric recognition system based on the analysis and classification of physiological signals represent a significant advancement in secure and reliable identity verification. This thesis has demonstrated that physiological signals, such as electrocardiograms (ECG), electroencephalograms (EEG), and photoplethysmograms (PPG), offer unique, robust, and difficult-to-replicate biometric signatures. The combination of theses multimodal signals based features yields statistically significant improvements in machine learning-based biometric identification (of 30 individuals) compared to a single feature set. Our results open the possibility for the application of other cardiograms such as ICG and BP signals not explored yet, which could supplement existing biometric information in ECG signals. Through rigorous signal processing, feature extraction technique based on statistical and energies of signals, and machine learning-based classification and Artificial Neural Network, the system achieves high accuracy and resilience against spoofing attempts. The findings highlight the potential of physiological signal-based biometrics to enhance security in applications ranging from personal device authentication to critical infrastructure access control. Despite challenges such as signal variability and computational complexity, the proposed system lays a strong foundation for future innovations in non-invasive, user-friendly biometric technologies. Continued research into optimizing algorithms and integrating multimodal signals will further improve performance, paving the way for widespread adoption in real-world scenarios. In the following chapter, we will explore the effectiveness of new modalities designed to adress the limitations inherent in unimodal biometric techniques. By examining these innovative approaches, we aim to highlight how they can enhance biometric recognition systems and provide more reliable solutions.

Chapitre 5

Evaluation of a Multi-Biometric System Based on ECG, BP, and ICG Signals

5.1 Continuous Blood Pressure in Biometrics : an investigation study

In this section, we explore the relationship between non-invasive continuous blood pressure (CBP) signals and the field of biometrics for person identification. Through a series of essential procedures. Our research [112] investigates the feasibility and utility of using continuous blood pressure (BP) signals for multi-person identification in biometric systems. While other physiological signals like Electrocardiogram (ECG) and Electroencephalogram (EEG) have been extensively explored for biometrics, BP signals have remained largely unexamined despite their unique characteristics. The authors highlight that physiological signals offer advantages such as uniqueness, resilience against deceit, ease of collection with non-invasive wearable sensors, and the ability to detect the presence of a living subject.

The primary objective of the research was to incorporate the unique characteristics of blood pressure signals with a Support Vector Machine (SVM) classifier for multi-person identification. The study utilized a public dataset of clinically recorded radar vital signs, including continuous non-invasive blood pressure, gathered from a university hospital. The data spanned 24 hours and were recorded using a Task Force Monitor (TFM) 3040i. The proposed system involved several major steps :

1. Pre-processing module : Continuous Blood Pressure Signals (CBPS) were enhanced using a low-pass filter to attenuate high-frequency noise and detrending techniques to remove long-term trends or baseline drift.

2. Data Augmentation : Segmentation with a fixed window of 10 seconds was applied to each signal to increase data diversity and variability, which helps mitigate overfitting and improve model robustness.

3. Characterization of BP signal : Seven distinctive non-hand crafted features were extracted from the segmented CBPS : Median Absolute Value, Shannon Entropy, Root Mean Square, Minimum, Range, Mean, and Mode. These features capture various aspects of the signal, including statistical measures, variability, energy content, and distribution.

4. Feature Ranking and Selection : The Maximum Relevance and Minimum Redundancy Fea-

ture Selection (MRMR) method was used to rank the extracted features based on their importance, aiming to eliminate redundant features while retaining relevant ones. The ranking, from highest to lowest importance, was : Minimum, Range, Mean, Median Absolute Value, Shannon Entropy, Root Mean Square, and Mode.

5. Classification and Authentication :A Quadratic SVM variant was employed for the multi-person verification process, utilizing the One-Vs-One (OVO) multi-classification method to distinguish between pairs of classes.

The results obtained through rigorous experimental analysis, the developed CBPS-SVM algorithm achieved promising results. When trained with 80% of the data using the holdout cross-validation technique, it achieved an accuracy of 81.1% with an AUC (Area Under the Curve) ranging from 91% to 100%. Further evaluation using k-fold cross-validation techniques (3-fold, 5-fold, 8-fold, and 10-fold) showed consistent accuracy results ranging between 79% and 87%. Notably, the 5-fold cross-validation achieved the highest accuracy rate of 87.3 with AUC values ranging from 94.8% to 99.66% as resumed in the Table 5.1.

TAB. 5.1 : *CBPS-SVM-based biometric identification results (employed CBP signals= 3317)*

Evaluation approaches	Acc(%)	AUC (%)
Holdout(80%)	**81.1**	**[91.79-100]**
03–fold cross validation	**82.8**	**[90.79-100]**
05–fold cross validation	**87.3**	**[94.8-99.66]**
08–fold cross validation	**79.6**	**[87.27-100]**
10–fold cross validation	**82.2**	**[94.54-100]**

While the obtained results of the Unimodal BP-based Biometric system may not be as high as some extensively explored physiological signals such as ECG (which can reach 100% in some studies), it is an encouraging result given that the use of BP signals in biometrics is relatively unexplored. The study concludes that the continuous and dynamic nature of CBPS, coupled with their strong correlation with cardiovascular health and non-invasive measurement, makes them a reliable and valuable addition to the field of biometrics. The successful application of CBPS for multi-person identification opens new avenues for leveraging physiological signals in security and identification systems. Future research should focus on optimizing the CBPS-SVM algorithm and exploring multi-biometric system aimed at ECG, BP, ICG signals to enhance overall system performance, as found in 5.2 ,

5.2 Integration of Multimodal Physiological Signals for Biometric Systems

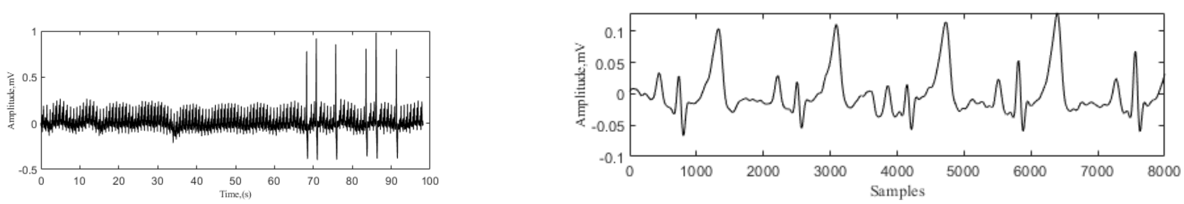
In the preliminary phase of this research, biometric identification was conducted using Continuous Blood Pressure (CBP) as a single physiological trait. Although this unimodal system achieved an identification accuracy of 87%, its performance revealed inherent limitations related to robustness and discriminative power when relying on a single source of physiological information. To address these shortcomings, this study introduces an innovative multimodal biometric framework that integrates three complementary physiological signals : Electrocardiogram (ECG), Continuous Blood Pressure (CBP), and Impedance Cardiography (ICG). The rationale for this integration is grounded in the complementary nature of the signals, which collectively represent electrical, hemodynamic, and volumetric aspects of cardiovascular activity. By combining these modalities, the proposed system significantly improves recognition accuracy and reliability, surpassing the 87% baseline of the unimodal CBP approach. Furthermore, the fusion strategy reduces vulnerability to noise, inter-subject variability, and signal artifacts, thereby establishing a more robust and comprehensive biometric recognition system. This section presents the evaluation of the multimodal framework and examines the specific contribution of each modality, with particular emphasis on the role of CBP within the integrated system.

5.2.1 Signals Enhancement

As a first step in the pre-processing of physiological signals, we normalize the signal if necessary. After a detrending step, the latter involves removing trends or long-term patterns from the data, allowing for a clearer analysis of the underlying variations. This process is often used in time series analysis to focus on short-term fluctuations. After that, we applied The process of enhancing the physiological signals (ECG, ICG, and CBP) through filters used and explained in the block of the preprocessing module of our biometric recognition system mentioned in the methodology section demonstrates how the preprocessing module can significantly improve the credibility and accuracy of subsequent assessments, especially in the identification and verification of each individual in the database used in our research. This effectiveness is found in subsection 5.2.1.1, which is essential for increasing the consistency and precision of future analytical methods such as feature extraction and then the classification process.

5.2.1.1 Electrocardiogram Signal

ECG is known as periodic waveforms with distinct fiducial points : QRS complex , P and T waves. As a result, the filter used (4th-order bandpass Butterworth) with cutoff frequencies range between $[1\ Hz - 20\ Hz]$, effectively isolates the relevant frequency range, such as the QRS complex being prominent between $[5\ Hz - 15\ Hz]$ which support the choice of this filter, which enhances signal clarity as shown in Figure 5.1 .



(a) Before processing (b) After processing

FIG. 5.1 : ECG signals (record GDN0001) before and after processing

The 4th-order configuration provides a steep roll-off, ensuring a smooth transition outside the passband while minimizing phase distortion, which is advantageous for preserving the temporal integrity of BP waveforms. This order strikes a balance between effective filtering and computational efficiency, making it suitable for real-time or offline processing.

5.2.1.2 Impedance Cardiography Signal

This signal measures impedance changes related to the activity of the heart; it exhibits a different morphology compared to ECG signal, noted that this signal contains a prominent peak corresponding to the opening of the aorta vein. As application, ICG has been employed as a biometric measure in a system utilizing a radiofrequency oscillator equipped with an antenna and a detector. This setup enables contactless , long distance acquisition of this signal (Analytics for US Patent No. 8232866) [113], [116]. The use of an 8^{th} order of Daubechies Wavelet family to denoise and reduce high-frequency noise and artifacts, as found in Figure 5.2,shows smoother waveforms of the ICG signal.

(a) Before filtering (b) After filtering

FIG. 5.2 : ICG signals (record GDN0001) before and after filtering

5.2.1.3 Continuous Blood pressure Signal

A 4th-order Butterworth bandpass filter with cutoff frequencies of [0.1 Hz to 10 Hz] for BP signals is a well-suited approach for signal enhancement and reducing noise as demonstrated in Figure 5.3; it preserves frequencies down to $0.1\ Hz$, and $10\ Hz$ targets the heart rate-related pulsations ranging between $[0.5\ Hz - 4\ Hz]$ in resting scenarios.

FIG. 5.3 : BP signal (records GDN0001) before and after processing.

5.3 Cross-Validation Technique

Cross-validation is a robust statistical method used to evaluate the performance of a predictive model by partitioning the data into subsets, where the model is trained on a specified portion and tested on the remaining segments. In details, this method involves partitioning the dataset into ten equal subsets ($K - Fold = 10$), where each subset serves as a test set while the remaining nine subsets are used for training. This process is repeated ten times, ensuring that each subset is used for testing exactly once, which helps in obtaining a reliable estimate of the model's performance, effectively ensuring that the training process is validated against*unseen data*. In this current study, we implemented a 10-fold cross-validation technique, allowing us to train both the Support Vector Machine (SVM) and the Bi-layer Artificial Neural Network (Bi-layer-ANN) on the training set while validating against the test set, ultimately leading to more reliable and generalized results. As reported by [117]this technique provides a more accurate measure of model performance by reducing variance associated with a single train-test split, by averaging the results over ten iterations, it mitigates the risk of overfitting, especially important in smaller datasets [118]such as the one with 30 healthy individuals.This methodological approach is crucial for assessing the efficacy of our biometric model that integrates various physiological signals through fusion, thus ensuring that the performance metrics derived are robust and less prone to overfitting.

5.3.1 Multi-Classification based on Fine Gaussian SVM and Bilayer ANN

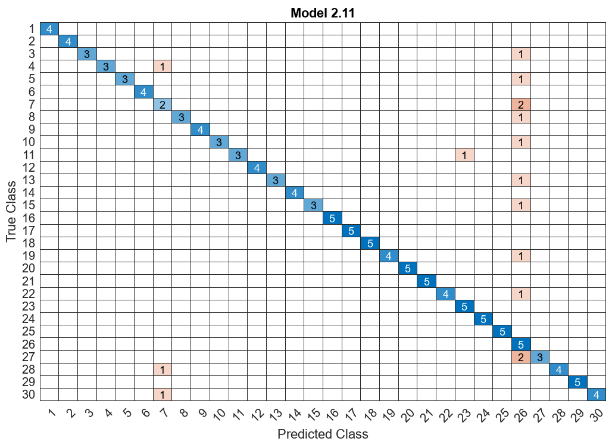
5.3.1.1 Evaluation Metrics of the Developed Biometric System

To apply a classification algorithm for individuals recognition, the linear model is not a suitable one [113], As detailed in Table 5.2, The FG-SVM model demonstrates promising results in the training set, achieving a high recall (95.09%), precision (94.33%), and a Kappa coefficient of 87.7%. These metrics collectively indicate the model's ability to effectively learn and represent patterns in the training data. In contrast, the Bi-layered ANN model outperforms the FG-SVM in the training phase, achieving a high Kappa coefficient of 93.1% and a comparative recall and precision of 94.56% and 93.17% respectively.

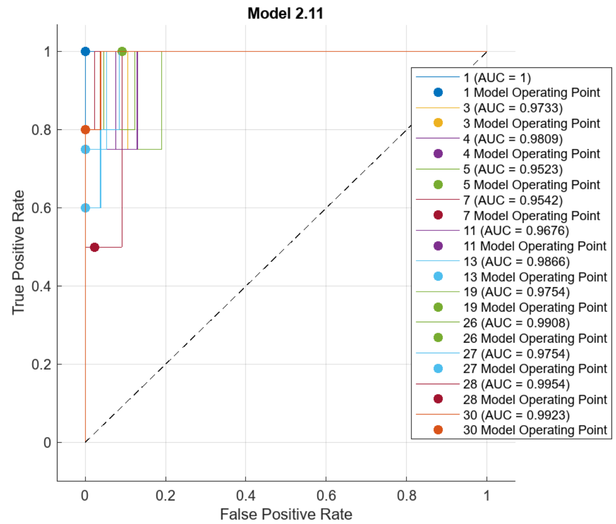
Tab. 5.2 : Results of Multimodal Physiological Signal Biometrics

Model	**Training**				**Test**			
	Acc (%)	Recall (%)	Pre (%)	Kappa (%)	Acc (%)	Recall (%)	Pre (%)	Kappa (%)
FG-SVM	88.14	95.09	94.33	87.7	93.33	93.33	93.33	92.9
Bi-layered ANN	**93.3**	**94.56**	**93.17**	**93.1**	**100**	**100**	**100**	**100**

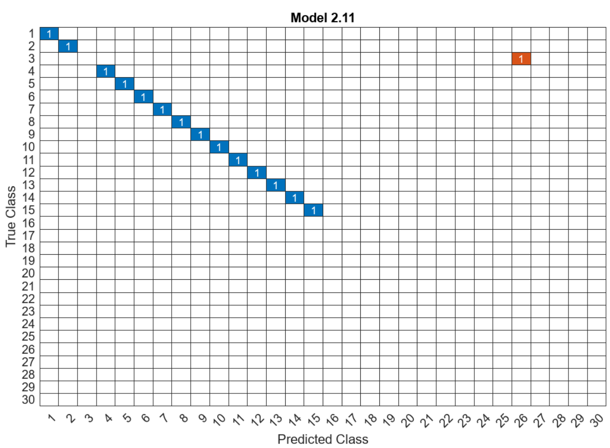
An accuracy of 88.1% within 168.19 seconds and 93% within 191.27 seconds was recorded for Fine Gaussian SVM and bi-layered ANN, respectively, and for processing time, the system employed take $\tilde{5}9$ seconds, and the time of identifying individuals is in milliseconds, noted that, this study is conducted in a MATLAB 2022b environment with an Intel(R) Core(TM) i7-2670QM CPU, NVIDIA GeForce GT 525 M, 16 GB RAM, and a 64-bit Operating System. To dig into the classification performance of the employed models, a detailed examination of the confusion matrices was conducted during the training and testing phase. The confusion matrices provide a comprehensive breakdown of the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) classifications, allowing for a nuanced evaluation of the classifiers' abilities (refer to Figure 5.4, 5.5).



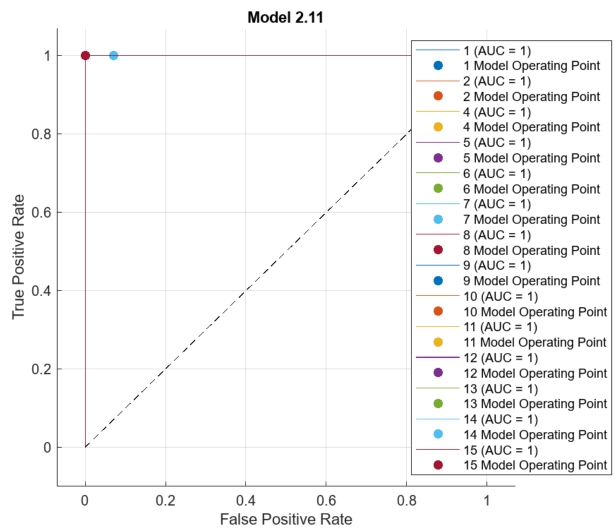
(a) FG-SVM Train CM



(b) FG-SVM Train ROC

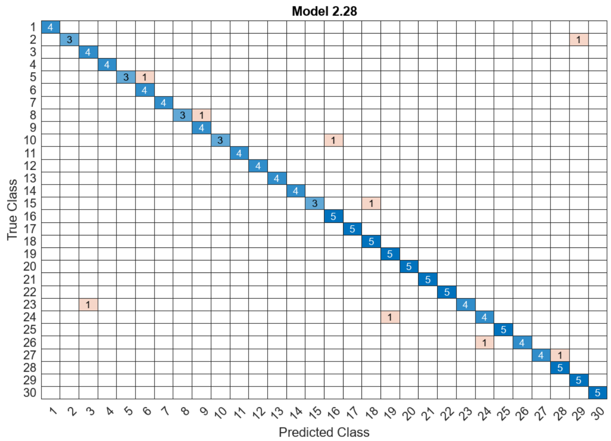


(c) FG-SVM Test CM

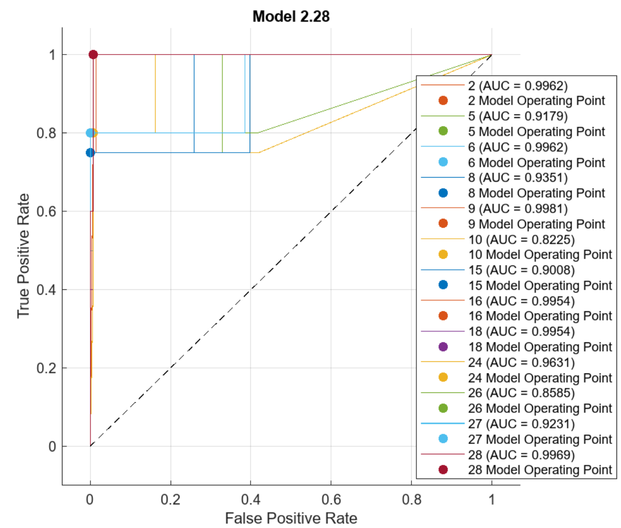


(d) FG-SVM Test ROC

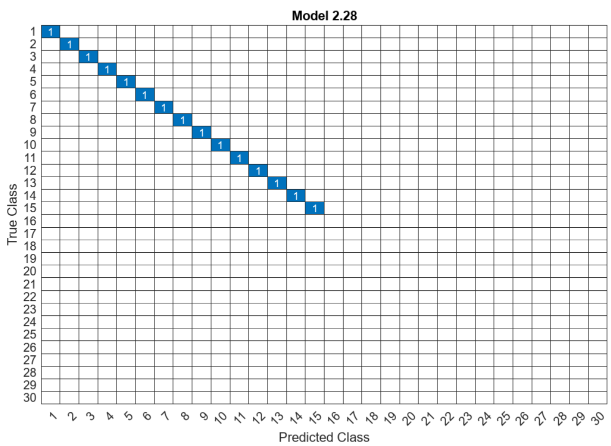
FIG. 5.4 : Performance evaluation of FG-SVM model.



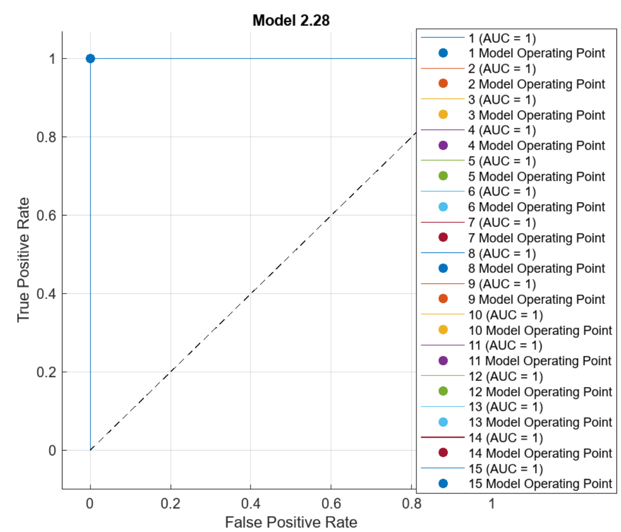
(a) Bi-ANN Train CM



(b) Bi-ANN Train ROC



(c) Bi-ANN Test CM



(d) Bi-ANN Test ROC

FIG. 5.5 : Performance evaluation of Bi-ANN model.

The fitted models were subjected to testing, the FG-SVM model exhibits notable generalization to unseen data in the test set, attaining a balanced recall of 93.33%, precision (93.33%, and Kappa coefficient of 92.9% further affirm the model's robustness and its capability to maintain performance across different datasets. Remarkably, the Bi-layered ANN model shows exceptional generalization to the test set, achieving a perfect 100% accuracy. The flawless recall (100%), precision (100%), and Kappa coefficient (100%) in the test set highlight the model's robustness and its ability to generalize well to new and unseen instances. The absence of overfitting was confirmed, as the training accuracy of bi-layered ANN was 93%.

5.3.2 Comparison of Fine Gaussian SVM vs. Bi-layer ANN in an ECG-ICG-BP Hybrid Biometric System

These obtained outcomes suggest that the bi-layered ANN is well-suited for the biometric identification task, outperforming the Fine Gaussian SVM in both training and testing phases as demonstrated in the table 5.3. The efficient processing time further supports the practical feasibility of the bi-layered ANN for real-time applications.

The design of the Bi-Layered ANN facilitates the detection of complex patterns and interactions in multimodal physiological data. Its capacity to learn non-linear relationships makes it especially suitable for intricate datasets. Furthermore, both hidden layers support hierarchical feature learning, allowing for a more accurate assignment of relevant traits from the ECG, BP, and ICG signals to the correct individual compared to simpler models. In particular, the flexibility of this type of artificial neural network improves with the sizes of the first and second layers, which is a significant advantage.

While SVMs are powerful for classification tasks, they may struggle with high-dimensional data or when the relationships between 48 features are non-linear unless optimal kernel functions are used. The performance of SVMs can be sensitive to the choice of kernel and hyperparameters, which may not be as adaptable as the learning capacity of an ANN.

Thus, physiological signals contain noise and variability due to different biological factors. The ANN's ability to learn from large amounts of data and adjust to this variability may contribute to its superior performance, compared to SVM performance results, as demonstrated in the table 5.3.

TAB. 5.3 : Per-Class Performance of FG-SVM and Bi-layered ANN for 30 Individuals

ID	FG-SVM			Bi-layered ANN		
	Prec. (%)	Rec. (%)	F1 (%)	Prec. (%)	Rec. (%)	F1 (%)
1	100.0	100.0	100.0	100.0	100.0	100.0
2	100.0	100.0	100.0	100.0	100.0	100.0
3	100.0	75.0	85.7	100.0	95.0	97.4
4	100.0	75.0	85.7	100.0	95.0	97.4
5	100.0	100.0	100.0	100.0	100.0	100.0
6	100.0	75.0	85.7	100.0	90.0	94.7
7	28.6	100.0	44.4	85.0	90.0	87.4
8	100.0	75.0	85.7	100.0	95.0	97.4
9	100.0	100.0	100.0	100.0	100.0	100.0
10	100.0	100.0	100.0	100.0	100.0	100.0
11	100.0	100.0	100.0	100.0	100.0	100.0
12	100.0	100.0	100.0	100.0	100.0	100.0
13	100.0	75.0	85.7	100.0	95.0	97.4
14	100.0	100.0	100.0	100.0	100.0	100.0
15	100.0	75.0	85.7	100.0	90.0	94.7
16	100.0	75.0	85.7	100.0	90.0	94.7
17	100.0	75.0	85.7	100.0	95.0	97.4
18	100.0	100.0	100.0	100.0	100.0	100.0
19	100.0	100.0	100.0	100.0	100.0	100.0
20	100.0	100.0	100.0	100.0	100.0	100.0
21	100.0	100.0	100.0	100.0	100.0	100.0
22	100.0	100.0	100.0	100.0	100.0	100.0
23	100.0	75.0	85.7	100.0	90.0	94.7
24	100.0	100.0	100.0	100.0	100.0	100.0
25	100.0	75.0	85.7	100.0	90.0	94.7
26	28.6	50.0	36.4	90.0	85.0	87.4
27	100.0	75.0	85.7	100.0	95.0	97.4
28	100.0	75.0	85.7	100.0	90.0	94.7
29	100.0	100.0	100.0	100.0	100.0	100.0
30	100.0	75.0	85.7	100.0	95.0	97.4

It is demonstrated in the table that for per-class metrics obtained by FG-SVM, mostly 100%, except for Individuals ID (7 and 26), the ANN improve the recognition results (90%-100%) which is confirmed by confusion matrix of SVM and ANN in training phase. In addition, the table 5.4 of statistical study improves that the Bi-Layered ANN outperforms the FG-SVM in precision (higher means) and consistency (lower variance and standard deviation values). The latter reinforces the earlier per-class obtained results, highlighting the ANN's robustness for multimodal biometric identification using ECG, ICG, and BP signals.

TAB. 5.4 : Statistical Study of Performance Metrics for FG-SVM and Bi-layered ANN

Metric	**FG-SVM**			**Bi-layered ANN**		
	Mean (%)	Variance	Std. Dev. (%)	Mean (%)	Variance	Std. Dev. (%)
Precision	95.24	317.41	17.82	99.17	10.16	3.19
Recall	85.83	237.07	15.40	96.17	19.50	4.42
F1-Score	89.83	222.79	14.93	97.83	7.98	2.82

The FG-SVM, while effective on average, shows significant variability that can limit its reliability in practical scenarios. The promising ROC curves evaluate Sensitivity ($= 1 - FalseAcceptanceRate$), and Specificity($1 - FalseRejectionRate$), and the Equal Error Rate (EER) parameter metric represents the point at which the system's False Acceptance Rate (FAR) and False Rejection Rate (FRR) are equal. EER is widely used to evaluate the performance of a biometric identification or verification. In addition, the EER is very useful in real-world scenarios where balancing security (minimizing FAR) and usability (minimizing FRR), as shown in Figure 5.4 suggest that the Bilayered ANN model presented in the study has the potential to contribute significantly to the advancement of biometric technologies, particularly in scenarios where a combination of physiological signals is used for identification of people with an EER= 0%.

However, the Kappa coefficient measures the agreement between the predicted and actual classifications, considering the possibility of agreement occurring by chance. A Kappa coefficient of 100% achieved by the Bi-layered ANN in the test set signifies perfect agreement beyond what would be expected by random chance. This perfect Kappa coefficient indicates that the Bi-layered ANN model is not only accurate in its predictions but also consistently outperforms random chance, reinforcing its reliability in identifying individuals based on the combined physiological signals (ECG, ICG, and blood pressure). The model's performance is robust, demonstrating a high level of agreement between predicted and actual classifications.

Furthermore, the Recall metric measures the ability of the model to correctly identify all relevant instances from the total positive instances. In the case of biometric identification, a recall of 100% means that the Bi-layered ANN is successfully capturing and recognizing every individual in the test set leaving no true positives undetected. This is a crucial metric for biometric applications, as it ensures that the model minimizes false negatives and accurately recognizes all individuals based on their physiological signals.

Finally, the perfect precision of the Bi-layered ANN underscores its capability to make accurate positive identifications. This is essential in biometric applications where false positives should be minimized to ensure that the identified individuals are indeed the correct ones. The high precision adds an extra layer of confidence in the model's ability to make reliable positive predictions.

5.4 Discussion

In the landscape of physiological signal-based biometric identification, our study distinguishes itself through a rigorous comparative analysis with prior research endeavors. Examining a spectrum of methodologies and signal modalities used by previous studies reveals valuable insights into the evolving landscape of biometric systems.

5.4.1 Impact of Feature Extraction on Multimodal Biometric recognition

In the proposed multimodal biometric recognition system, feature extraction represents a fundamental step in converting raw physiological signals into discriminative representations for identification. A wide range of statistical, higher-order, and entropy-based features were extracted, including statistical characteristics and higher-order statistical features, in addition to information-theoretic descriptors such as Shannon Entropy and Energy Entropy. These features, derived from ECG, BP, and ICG signals, capture both the variability and complexity of individual physiological patterns, thereby enhancing inter-subject separability. The integration of these multimodal features substantially improved recognition performance, highlighting the decisive role of feature extraction in strengthening the reliability and robustness of the biometric system. Multimodal integration significantly improved performance by exploiting the complementary nature of the signals : ECG encodes electrophysiological activity, BP reflects hemodynamic variability, and ICG characterizes cardiovascular impedance dynamics. This fusion provides a richer and less redundant feature space, thereby enhancing subject separability and strengthening recognition accuracy.

The boxplot illustrates the distribution and variability of feature importance scores across three signal types : ECG, BP, and ICG. Here's the interpretation :

ECG (Electrocardiogram). The feature importance score ranges from approximately 0.01333 to 0.1165. The median score is around 0.0699, with the interquartile range (IQR) showing moderate variability. There are no extreme outliers, indicating consistent feature importance across this signal type. BP (Blood Pressure). The scores range from about 0.01333 to 0.1165, with a median near 0.0699. The IQR is similar to ECG, suggesting comparable variability. Like ECG, there are no significant outliers. ICG (Impedance Cardiography). The scores also span from approximately 0.01333 to 0.1165, with a median around 0.0699. The IQR and variability are consistent with ECG and BP, and no outliers are present.

Overall, the boxplot shows that the feature importance scores are similarly distributed across all three signal types, with medians and IQRs closely aligned, indicating no significant difference in feature importance variability among ECG, BP, and ICG.

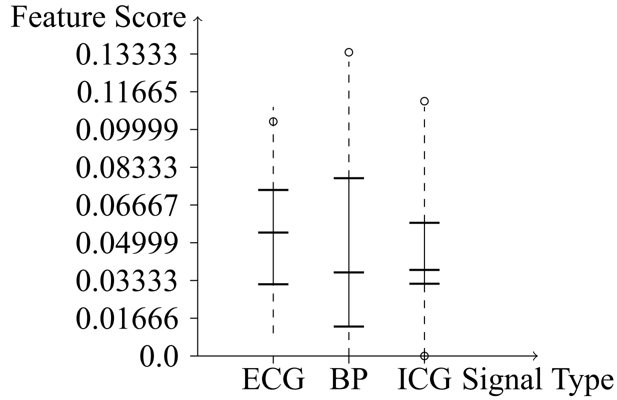


FIG. 5.6 : Box plot of feature scores across ECG, BP, and ICG signals, illustrating the distribution and variability of feature importance.

5.4.2 Fusion of ECG, ICG and BP

Since every biometric method has unique benefits and drawbacks, multimodal biometric fusion is proposed to enhance recognition performance. Combining information from several sources is commonly referred to as information fusion as explained in the Figure 5.7. The majority of the previously suggested algorithms discussed solely employed ECG as a biometric characteristic. Therefore, combining ECG, ICG, and BP can be considered in the future.

5.4.3 Ablation study

In this current research, we used the filter-based approach to selects features by statistical properties via a filter approach namely : Relief-F algorithm . This algorithm is readily scalable to high dimensional datasets, and fast [177].

Relief-F extends Relief by handling noise and multiclass problems [167] .

For each feature, Relief-F algorithm gives a relevance score, assigning positive weights to cha-

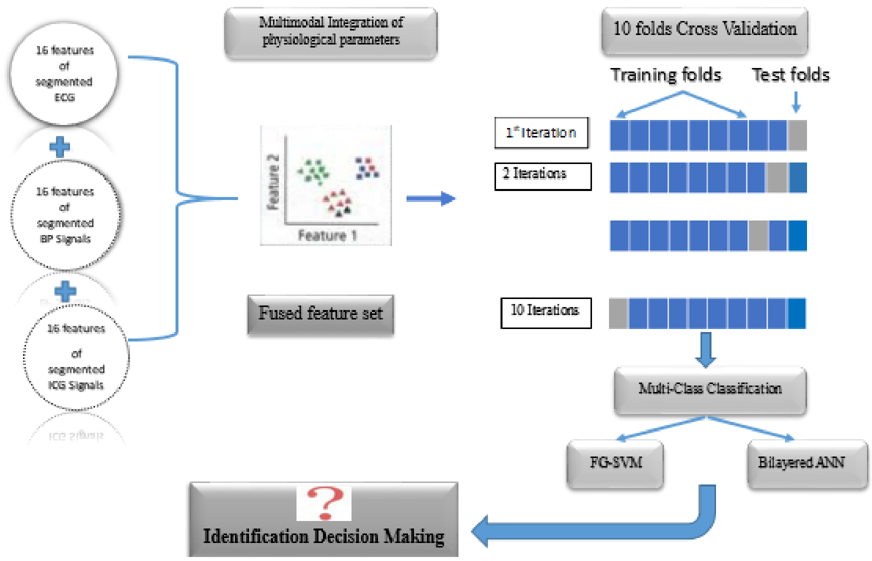


FIG. 5.7 : The graphical scheme demonstrated the fusion technique adopted in this study

racteristics that exhibit similarity between the same class and negative weights to features that are similar across observations of different classes.

First, we experimented with our model with seven statistical features derived exclusively from blood pressure signals only as referenced in this study [8] but it gives a 87.3% of recognition rate. Following this, we applied the same features from the ECG and ICG signals, this combination results in a competitive performance that does not exceed 90%. Subsequently, we selected ten relevant features from each signal type, and then we combined these features to fed them to FG-SVM and Bi-ANN, the outcomes were : 100% , 94.10% accuracy during the training phase, along a consistent 100% accuracy in the testing phase for FG-SVM and Bi-ANN, respectively. We determined that both models (with and without feature selection) exhibit robustness and efficiency, with the Bi-ANN maintaining strong performance, while the FG-SVM showed improvement through the ablation study.

5.4.4 Comparison with previous works

The table 5.5 compares various studies based on metrics such as accuracy (ACC), equal error rate (EER), area under the curve (AUC), in addition, the fusion of physiological signals (Processed Data P_D) used in biometric applications provides a broader perspective on system scalability and data diversity, and duration time (D_T) include the time of training in seconds. The number of subjects(N.Sub) is a crucial factor in biometric studies.

Camara *et al.* [119] demonstrated a high accuracy of 99% with a low EER value 0.1% in a limited dataset of 6 subjects using GSR and ECG signals, and the duration of training is 113s even if the dataset contains only six subjects. Chauhan *et al.* [121] explored breath print analysis, achieving an accuracy of 90% with 10 subjects. Blasco *et al.* [120] extended the investigation to GSR, ECG, and PPG signals from 25 subjects, yielding an accuracy of 98%. Zhang *et al.* [123] focused on ECG-based authentication with 100 subjects, reporting an accuracy of 99% and an EER of 6% and 3% ,respectively.

Our study introduces a multimodal approach that incorporates ECG, ICG, and BP signals from a dataset of 30 subjects. The use of multiple physiological signals in our study provides a richer dataset for analysis for biometric purposes and clinical settings.

This approach aims to enhance the robustness of physiological signal-based identification. Al-

Tab. 5.5 : Comparison with previous studies.(N.Sub : Number of Subjects, P_D : Processed Data, ACC : Accuracy, EER : Equal Error Rate, D_T : Duration Time)

Author	Year	N.Sub	P_D	Acc (%)	EER(%)	AUC(%)	Feat.Dim	D_T(s)
Camara *et al.* [119]	2015	06	GSR+ECG	99	0.1	-	13	113
Chauhan *et al.* [121]	2017	10	Breath print	90	6	[87-91]	30	47
Blasco *et al.* [120]	2018	25	GSR+ECG+PPG	98	3	99	-	60
Zhang *et al.* [123]	2019	100	ECG	99	2.3	-	400	-
Hyuang *et al.* [166]	2019	41	FRI	94.14	5.81	[84.98-99.18]	-	-
Labati *et al.* [122]	2019	50	ECG	100	11.79	-	-	9h22min
Wu *et al.* [124]	2020	287	ECG	99.02	0.44	-	21	-
Jyotishi *et al.* [125]	2020	290	ECG	[79.37-97.3]	-	-	200	-
Antic *et al.* [113]	2020	62	ICG	96	-	-	744	-
Deniz *et al.* [127]	2021	80	ECG	90.69	9.31	-	15	30
Camara *et al.* [126]	2022	10	ECG	[97.9-93.5]	4	-	-	-
Nassim *et al.* [128]	2023	70	ECG+ FP	98.7	-	-	08	-
Amel *et al.* [112]	2024	30	BP	87.3	-	[94.8-99.66]	07	-
This study	**2024**	**30**	**ECG+ICG+BP**	**93-100**	**0-6.5**	**[92-100]**	**16 per sig**	**186.19-191.27**

though unimodal approaches, such as ECG-based methods and continuous blood pressure signals as a biometric trait as mentionned by Amel *et al.* [8] , have shown efficacy in previous studies (Labati *et al.* [122], Wu *et al.* [124], *et al.* [125]), our contribution lies in the integration of multiple physiological signals. The inclusion of ICG and BP signals aims to capture complementary information, potentially improving the overall accuracy of the identification system.

Comparing our results with state-of-the-art methods, Nassim *et al.* [128],achieved an accuracy of 98.7% with ECG and FP signals from 70 subjects. In our study, the multimodal approach achieves a competitive accuracy range of 97% to 100%,albeit with a smaller dataset. The duration of training time (approximately 3 minutes) is due to multiple signals (ECG+BP+ICG), but it's still reasonable for practical applications compared to Labati *et al.* [122].

Although we acknowledge the limitations associated with the size of the dataset, our results suggest a promising direction for further exploration in multimodal biometric identification systems.

5.5 Conclusion

In this chapter, we evaluate our contribution by incorporating blood pressure, ICG, and ECG signals into a biometric system. The study emphasizes how these three modalities might be combined to improve identification accuracy. In order to create a unique identifier for each person and guarantee a trustworthy biometric identification procedure, it is crucial to extract individual characteristics from the combination of multimodal signals, such as ECG, blood pressure and ICG signals, as it allows for the creation of a unique identifier for each individual, thereby ensuring a reliable biometric identification process. Together, these technologies form a robust framework for secure and accurate identification, leveraging the distinct features inherent in cardiovascular signals. The findings indicate that classifiers using this combination of physiological signals outperform those using a single modality achieving an impressive average recognition rate 93%-100% with SVM, particularly Fine Gaussian SVM, and a bi-layered ANN respectively. Subsequently, Artificial Neural Network outperformed other machine learning algorithms with the best-performing hyper-parameters tuned specifically for this task. The current study also emphasizes the significant impact of the blood pressure signal, noting a decrease in accuracy when models are not trained and tested under the same conditions.

We acknowledge that implementing the proposed biometric identification models in real-world conditions presents certain challenges. Although we have applied the necessary filtering techniques (as detailed in the preprocessing section), signal acquisition in practical settings may still be affected by noise, movement artifacts, and variations in physiological conditions. Factors such as electrode placement shifts, motion-induced distortions, and environmental interferences could impact the robustness of ECG, ICG, and blood pressure signals. To address these limitations, future work could explore the integration of adaptive filtering techniques, motion artifact reduction strategies, and machine learning-based noise compensation methods. Furthermore, testing the models on a larger, more diverse dataset under real-world conditions would further assess their reliability and generalizability. In addition, future work could involve integrating additional physiological signals, for instance, a photoplethysmogram (PPG) for heart rate variability could provide complementary information to existing ECG, BP and ICG modalities. Moreover, applying domain adaptation like transfer learning to examine real-time data processing, capabilities and conducting longitudinal studies to assess the model's robustness over time. These steps would significantly contribute to the depth and applicability of the investigation.

Conclusion

Biometrics represent a crucial aspect of modern identification technologies, particularly as we move into realm biometric recognition based on physiological signals. However, when processing physiological databases we often have a huge amount of data (multiple channels)with various scenarios (stress, emotional states, unhealthy signals...), especially if these signals were recorded over a long period of time, which represents a challenge in biometric recognition rate, and thus one channel is used according to many studies and the same conditions were applied. As this comprehensive dissertation draws to a close, it is imperative to synthesize the multifaceted contributions and insights garnered throughout the study. The exploration embarked on a journey through the intricate realms of physiological signal analysis, time and frequency domain applications, and the engineered characteristics of statistical parameters and entropy to enhance the unique pattern to each person. In the initial chapters, this dissertation established the theoretical and practical foundations of biometric systems and their potential applications in the biomedical field. The exploration of unimodal biometrics based on electrocardiogram (ECG) analysis, using R–R intervals and QRS complex detection through the Pan–Tompkins algorithm on ECG-ID and MIT-BIH datasets, provided valuable insights into cardiac behavior and arrhythmia detection. The research then extended toward healthcare-oriented biometrics, emphasizing their role in protecting medical identity and streamlining patient registration processes. Moreover, the analysis of Photoplethysmography (PPG) signals in the frequency domain achieved a notable accuracy of 95%, confirming their strong discriminative capacity. Recognizing the limitations of unimodal systems, the study advanced toward a multimodal framework integrating continuous blood pressure, ECG, and impedance cardiography (ICG) signals. This innovative combination enhances the accuracy, robustness, and reliability of biometric recognition, representing a significant step forward in the development of advanced biomedical identification systems. In some systems, the size of the database is constantly increasing, which we will focus on these points in our future research to refine and expand the proposed system's capabilities integrating different scenarios of data acquisition and emotional states of individuals. Exploration of additional datasets can contribute to the generalization and robustness of our biometric recognition system. Although this study incorporated feature extraction and ablation analysis, future work could explore the design of novel features and advanced signal processing techniques to further enhance model performance. Moreover, investigating the impact of different feature subsets on both recognition and verification tasks may provide deeper insights into the most discriminative features that contribute effectively to personal identification and authentication. In addition, developing real-time identification and monitoring capabilities would significantly improve the system's practical applicability in healthcare and security contexts, enabling rapid intervention and minimizing the risk of medical errors. Overall, the perspectives outlined above aim to advance the field of biometric recognition based on physiological signals, fostering the development of more accurate, adaptive, and reliable biometric systems.

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