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A Review on Vein Biometric Recognition: Techniques, Datasets, and Models

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Abstract. Vein biometric recognition has emerged as a promising and, above all, reliable security solution, thanks to its resistance to tampering and the physiological stability of vein patterns, even over time. Among the various modalities, hand and finger veins offer a rich source of information and relevant data for reliable individual identification and authentication. To enhance the performance of this recognition modality, a lot of image processing, machine learning techniques and methods have been developed.

This paper provides a comprehensive review of the main approaches and recent techniques used for vein feature extraction, focusing on traditional methods such as Gabor filters and local binary patterns (LBP), as well as more recent and revolutionary techniques based on convolutional neural networks (CNNs). Some of the most commonly used databases in this field are also presented, as well as the various recognition models and methods that exploit these features. This study aims to better understand current advances, performance levels, and remaining challenges in vein-based biometric recognition.

Keywords.Vein Biometrics, Feature Extraction, Finger Vein, Deep Learning, Convolutional Neural Networks, Support Vector Machines, Biometric Datasets.

INTRODUCTION

In recent years, in the domain of security and authentication, biometric systems have emerged as a crucial component across various applications, from access control to financial transactions. Among these, vein biometric recognition stands out due to its inherent advantages, such as difficulty to replicate, low susceptibility to external injuries, and high accuracy. The uniqueness of the unique patterns of blood vascular structure beneath the skin

makes them less vulnerable to spoofing compared to other traditional biometric recognition such as fingerprints or facial features (Wang et al.,2024; Yang et al., 2019;2023). As a result, vein recognition has gained traction in both academic research and commercial deployment.
In this paper, we aim to present an overview of vein biometric recognition techniques, from the traditional handcrafted feature-based methods to the modern deep learning approaches. Fig. 1 illustrates the general pipeline of a biometric recognition system, highlighting the main processing stages involved. It also surveys the most used datasets and furnishes a comparative analysis of recent models. This review is structured as follows. In Section II we introduce a hierarchical classification of vein recognition techniques, combining feature extraction and recognition models. In Section III, we provide an overview of publicly available vein biometric datasets. Section IV discusses major open issues in the field and outlines promising research directions. Finally, in Section V, we conclude the paper by summarizing key insights and perspectives for future work.

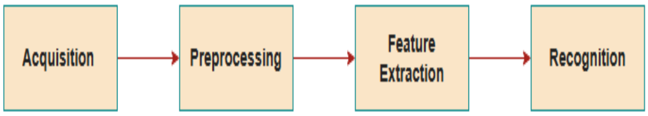

Fig. 1.General pipeline of a recognition system.

HIERARCHICAL CLASSIFICATION OF VEIN RECOGNITION TECHNIQUES

In this section we merged the techniques of vein feature extraction and recognition models to provide a comprehensive review through a two-level hierarchical classification. The first level categorizes approaches by the method of feature extraction, while the second subcategorizes them by the classification or recognition model used.

Gabor Filter-Based Methods

The Gabor filter is a common image processing method. It is inspired by the way simple cells in the human visual cortex react. This technique combines a complex sine wave with a Gaussian envelope, allowing it to detect patterns of specific orientations and frequencies. This makes it very effective for capturing detailed textures, such as vein patterns (Ma et al., 2016).

1) Gabor Filter → Template Matching :X. Ma et al. (2016) developed an adaptive 2D Gabor filter that was used for palm vein recognition. The palm image was divided into fixed subregions, and the features were then encoded in a binary format called VeinCode. This study demonstrated excellent performance by achieving an equal error rate (EER) of only 0.12%.

M. H. Abed(2012), used a Gabor filter to extract features from palmar and wrist vein images. The author applied a combination of principal component analysis (PCA) and linear discriminant analysis (LDA) to reduce the dimensionality of the features extracted, and the recognition phase was calculated using Euclidean distance. The approach achieved an average accuracy of 94% on palmar vein data.

J. C. Lee. (2012), applied a 2D Gabor filter with a novel directional coding strategy to convert vein features into binary strings. This enriches the identification and authentication process, making it both faster and more reliable.

2) Gabor Filter→ Support Vector Machine (SVM): S. Khellat-Kihel et al. (2014),developed a finger vein recognition system that first uses Gabor filters for feature extraction and then an SVM for data classification. This method demonstrates a significant improvement in the recognition rate of 98.75%.
3) Gabor Filter →Artificial Neural Networks (ANNs): N. Devkota and B. W. Kim. (2024), Proposed a method that uses principal component analysis (PCA) to extract features, followed by classification using an ANN. This approach successfully

increased recognition performance with an EER of 1%, and in some datasets, it even fell below this threshold.

Table 1.Summary Table: Gabor Filter-Based Methods.

Feature Extraction	Classification Method	Key Studies	EER / Accuracy	Dataset	Notes
Gabor Filter	Template Matching	Ma et al., 2016; Abed, 2012 ; Lee, 2012	0.12%, 94%	Palm, Wrist	Binary encoding (VeinCode), PCA+LDA strategy
	SVM	Khellat-Kihel et al., 2014	98.75%	Finger Vein	Robust classification
	ANN	Devkota and Kim, 2024	≤ 1%	Multiple	PCA for dimension reduction

Gabor filters remain highly effective in vein feature extraction due to their sensitivity to orientation and frequency. Template matching methods are often used with binary encoding strategies like VeinCode. SVM and ANN classifiers improve significantly the performance, especially when combined with dimensionality reduction techniques.

Local Binary Pattern (LBP)-Based Methods

Local binary pattern (LBP) is a feature extraction method widely used in biometric recognition, particularly for finger vein identification. This method compares each pixel in an image with its neighboring pixels, generating a binary pattern that effectively captures local textures. LBP is primarily valued for its simplicity, computational efficiency, and, most importantly, its robustness to varying light conditions (Sidiropoulos et al., 2021).

1) LBP →SVM: H. C. Lee et al.(2010), proposed a method combining weighted LBP with a Support Vector Machine (SVM) classifier. They successfully classified local image regions based on vein pattern density and assigned a specific weight to each region, all using holistic LBP codes without explicitly detecting vein patterns. This method allowed them to reduce processing time and improve recognition accuracy.
2) LBP + Gabor → SVM : K. R. Park et al. (2011), developed a method combining LBP with Gabor wavelets to extract local and global features from finger vein images. This combination had improved the system's robustness to local shadows and light variations and reduced the equal error rate (EER) to 0.011%.
3) LBP → Template Matching: B. A. Rosdi et al. (2011), They presented a new variant of LBP specifically, the Local Line Binary Pattern (LLBP). This new approach is designed to detect linear patterns in finger veins by using a linear structure instead of square windows, which allows a better extraction of vein patterns. The results showed that the new variant (LLBP) outperformed the original technique (LBP) in terms of EER and processing time.

Table 2.Summary Table: LBP-Based Methods.

Feature Extraction	Classification Method	Key Studies	EER / Accuracy	Dataset	Notes
LBP	SVM	Lee et al., 2010	Not specified	Finger Vein	Weighted codes, no explicit vein detection
LBP + Gabor		Park et al., 2011	0.011%	Finger Vein	Global + local features

LLBP	Template Matching	Rosdi et al., 2011	Improved over LBP	Finger Vein	Linear structure for better pattern detection

LBP-based methods are computationally lightweight and suitable for real-time applications. Due to their performance are improved when combined with Gabor filters. Variants like the LBP demonstrate superior structure detection, leading to improved accuracy and processing time. However, LBP may lack robustness for more complex global patterns.

Convolutional Neural Networks (CNNs)
Convolutional neural networks (CNNs) have taken biometric recognition to the next level, particularly for vein identification, thanks to their ability to automatically extract discriminatory features from images, including their ability to recognize complex and subtle patterns, such as subcutaneous veins (Hemis et al., 2024) (Fig. 2).

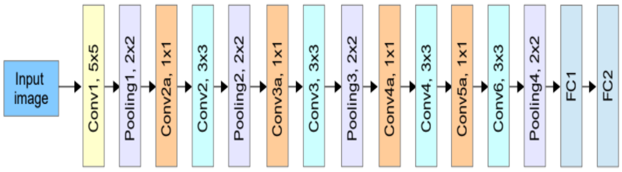

Fig. 2.A simple architecture of a CNN mode used (Hemis et al., 2024).

1) CNN (End-to-End): M. Hemis et al. (2023) presented an improved lightweight CNN (ILCNN) for extracting finger vein features. This model was highly optimized to make it as simple as possible, allowing them to achieve an accuracy of 99.82% on the FV-USM database and 95.90% on PLUSVein-FV3, with only 1.23 million parameters.

Z. Zhang and M. Wang (2022)proposed a CNN integrated with a Convolution Block Attention Module (CBAM) for finger vein recognition. This approach uses an attention mechanism to be more accurate in capturing visual structures and also reduces the computational effort.

2) CNN → Cancellable Template*:* Y. Wang et al. (2024)developedCFVNet, Which is an end-to-end cancellable digital vein network. This new system integrates preprocessing and model protection using a deep learning model to ensure the security and confidentiality of biometric data. CFVNet demonstrated an average accuracy of 99.82% across four public databases.

Table 3.Summary Table: CNN-Based Methods.

Feature Extraction	**Classification Method**	**Key Studies**	**EER / Accuracy**	**Dataset**	**Notes**
CNN (End-to-End)	N/A	Hemis et al., 2023 Zhang and Wang, 2022	99.82%, 95.90%	FV-USM, FV3	Lightweight, CBAM module
CNN	Cancellable Template	Wang et al., 2024	99.82%	Multiple	Integrated privacy protection

CNNs enable automated and highly accurate recognition pipelines. Lightweight and attention modules improve the efficiency without compromising performance. Their integration with cancellable biometrics like CFVNet highlights growing attention to privacy and data protection.

Template Matching -Based Methods

Template matching is a classic technique that is widely used for vein recognition. It implies comparing an input image with a pre-recorded template by measuring their similarity score. This method is highly used in this field because of its simplicity and effectiveness, although it can be sensitive to variations in the alignment, the rotation, or the distortion of the image (Mahalakshmi et al., 2012).

Several studies have demonstrated the effectiveness of template matching in vein recognition. Y. Matsuda et al. (2015) proposed a template-based method for finger vein recognition by comparing the curvatures and nonlinear shapes of the veins. Their approach demonstrated remarkable robustness to lighting variations and vein pattern deformations. They also successfully introduced new techniques that increase the template matching tolerance to vein shape deformations caused by finger flexion or rotation.

A. Banerjee et al. (2018) developed a system called ARTeM that uses template matching for finger vein recognition. Their system follows some preprocessing steps such as extraction of the region of interest (ROI), normalization of the intensity, enhancement of the blur contrast, equalization of the CLAHE histogram, and directional dilation. These innovations enabled ARTeM to achieve 100% accuracy using two-finger consensus.

X. Meng et al. (2021) proposed an innovative approach that combines template matching with dense SIFT descriptors for finger vein recognition. This combination allows for the calculation of a matching score between two finger vein images by fusing multiple feature types. The results obtained using this approach showed that it outperformed other similar methods.

Table 4.Summary Table: Template Matchin -Based Methods.

Feature Extraction	**Classification Method**	**Key Studies**	**EER / Accuracy**	**Dataset**	**Notes**
Vein Template	Template Matching	Matsuda et al., 2015 Banerjee et al., 2018 Meng et al., 2021	Up to 100% acc	Finger Vein	ARTeM system, SIFT fusion

Despite being an older method, template matching is still achieving excellent results, especially with preprocessing (ROI extraction, histogram equalization). Modern enhancements like dense SIFT fusion improve resilience to variation. However, performance heavily relies on alignment and image quality.

SVM-Based Recognition in Other Feature Domains

The support vector machine (SVM) is a supervised learning algorithm that is widely used in biometric recognition, particularly for vein recognition. This method involves finding an optimal hyperplane that separates data into different classes in a multidimensional space, thus maximizing the margin between data groups. SVM is a preferred choice for biometric recognition systems due to its ability to process complex multidimensional data (NalavadeandMeshram, 2012).

K. Nalavade and B. B. Meshram2012) proposed a method for detecting spoofing attacks in finger vein recognition systems. Their approach decomposes vein images into 3D shape representations, then extracts texture descriptors and performs a classification of the features using the SVM algorithm. This method is highly robust against spoof detection; she achieved a Bona Fide Presentation Classification Error Rate (BPCER) of 0%.

Table5.Summary Table: SVM-Based Methods.

Feature Extraction	**Classification Method**	**Key Studies**	**EER / Accuracy**	**Dataset**	**Notes**
3D Shape + Texture	SVM	Singh et al., 2019	0% BPCER	Finger Vein	Anti-spoofing (presentation attacks)

SVM remains highly effective in diverse applications, including spoof detection when combined with complex image decomposition (e.g., 3D modeling). It provides a reliable classification boundary even with relatively small datasets.

ANN-Based Recognition in Other Feature Domains

Artificial neural networks (ANNs) play an important role in biometric vein recognition, as they enable the modeling of complex relationships between extracted features and individual identities thanks to their adaptive learning capabilities. Unlike traditional methods, ANNs can learn directly from raw data, thus eliminating the need for manual feature engineering (Yin et al., 2022).

Several studies have demonstrated the effectiveness of ANNs in this field. Y. Yin et al. (2022) collected and summarized 149 relevant articles on advances in the field of finger vein recognition using ANNs. This study covers the various tasks and steps for vein recognition, such as verification, image enhancement, segmentation, attack detection, multimodal recognition, and pattern protection. This review highlights and emphasizes the current challenges and highlights the future prospects and developments of ANN-based digital vein recognition.

Table 6.Summary Table: ANN-Based Methods.

Feature Extraction	Classification Method	Key Studies	EER / Accuracy	Dataset	Notes
PCA / Raw Input	ANN	Yin et al., 2022 Devkotaand Kim, 2024	≤ 1%	Multiple	Covers all steps: enhancement, segmentation, spoof detection

ANN-based systems are covering a wide range of biometric tasks. They offer flexibility and learning capacity across the multiple stages of the recognition pipeline. However, training stability and the risk of overfitting remain concerns, especially with limited or unbalanced data.

Vein Biometric Datasets

Several datasets have been developed to support research and advancements in the field of venous biometrics. We are going to explore and compare the more common and used datasets.

FYO Multimodal Vein Database

This is a multimodal dataset that includes vein images from the dorsal hand, palm, and wrist. It was collected from 160 people, and in total there are 1,920 images. The acquisition was done with a medical vein detector that uses an infrared CMOS camera (Toygar et al., 2020) (Fig.3).

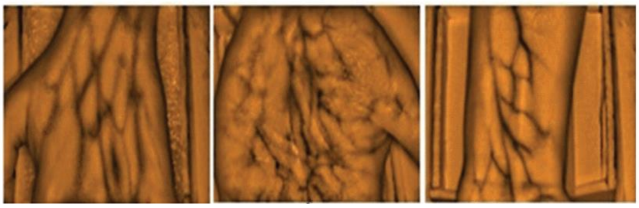

Fig. 3.Sample Images from the FYO Multimodal Vein Database (Toygar et al., 2020).

UTFVP (University of Twente Finger Vascular Pattern)

This dataset has 1,440 finger vein images, collected from 60 volunteers. The images were taken during two sessions that were around 15 days apart. Each finger was scanned four times (Ton and Veldhuis, 2013) (Fig.4).

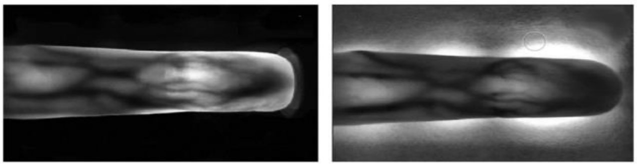

Fig. 4.Sample Images from the UTFVP Database (Ton andVeldhuis, 2013).

FV-USM Finger Vein Database

This dataset comes from Universiti Sains Malaysia, where 123 volunteers participated. It contains finger vein images from four fingers per subject, and six images were taken for each finger. So it has 492 classes with six images in each (Asaari et al., 2014) (Fig.5).

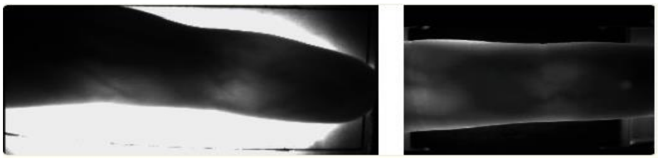

Fig. 5.Sample Images from the FV-USM Database(Asaari et al., 2014).

HKPU Finger Vein Database

Gathered from 156 individuals, this dataset includes finger vein images from the left index and middle fingers. Each finger was captured six times, which makes 312 finger classes, each with six images (Zhang et al., 2025) (Fig.6).

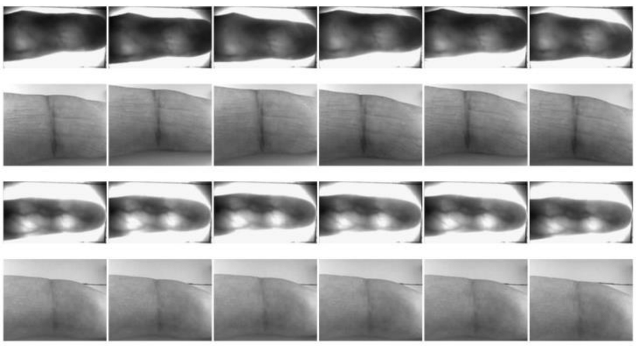

Fig. 6.Sample Images from the HKPU Database (Zhang et al., 2025).

CASIA Multi-Spectral Palmprint Database (CASIA-MS-Palmprint)

This database contains palmprint and palm vein images taken under different spectral bands, including near-infrared. It allows multimodal biometric analysis. It includes data from more than 100 subjects (Hou and Yan, 2018) (Fig. 7).

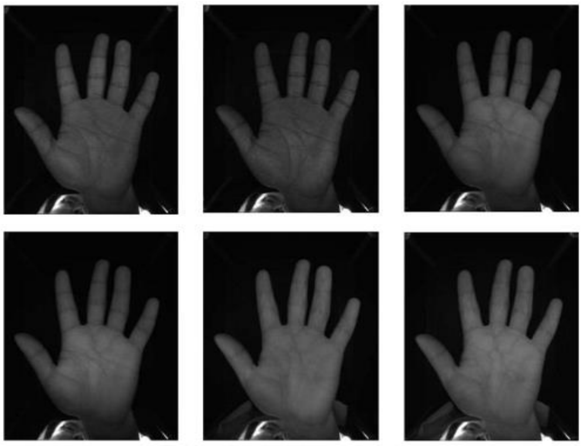

Fig. 7.Sample Images from the CASIA-MS Database(Hou and Yan, 2018).

PUT Vein Database

This dataset was created by Poznan University of Technology. It includes dorsal hand vein images from both hands of 100 people. The images were taken in different lighting and hand positions to see how robust the recognition can be (Kumar and Zhou, 2012) (Fig. 8).

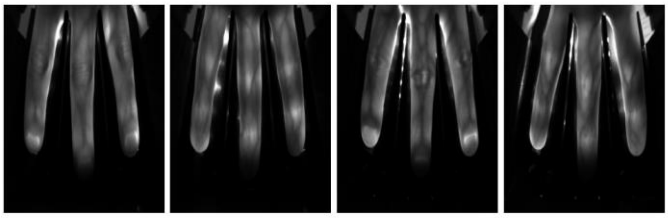

Fig. 8.Sample Images from the PUT Database (Kumar and Zhou, 2012).

JLU Wrist Vein Database

This one includes wrist vein images collected with near-infrared imaging. It was taken from 120 participants, with multiple images for both left and right wrist. It’s a good dataset for testing wrist-based biometric techniques (Qin and Wang, 2019) (Fig. 9).

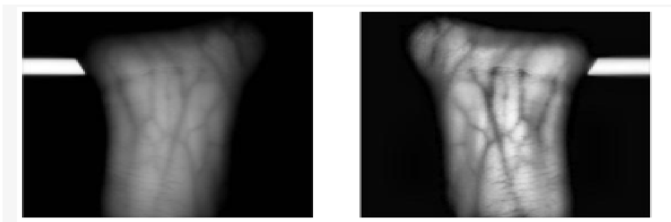

Fig. 9.Sample Images from the JLU Database (Qin and Wang, 2019).

SCUT-3DFV Database

This dataset is about 3D finger vein recognition. It was collected from 100 people using the SCUT-3DFV-V1 system, which captures the finger from three angles to make a 3D model of the vein structure. It’s really useful to study 3D vein recognition (Hong et al., 2024) (Fig. 10).

Fig. 10.Sample Images from the SCUT-3DFV Database (Hong et al., 2024).

Bosphorus Hand Vein Database
Developed by Boğaziçi University in Turkey, this dataset contains dorsal hand vein images under NIR light. What is special is that subjects had to do actions like holding a bag, squeezing a rubber ball, or cooling their hand with ice. These actions changed the vein patterns and made the dataset more realistic and challenging (Yuksel et al., 2011) (Fig. 11).

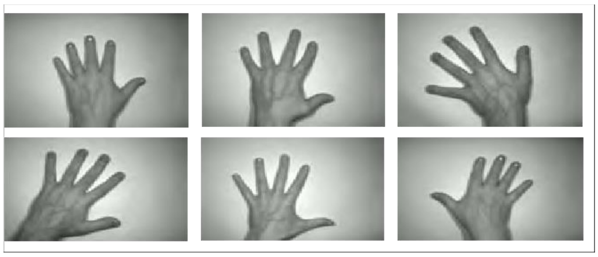

Fig. 11.Sample Images from the Bosphorus Hand Vein Database (Yuksel et al., 2011).

Table 7.Comparative Overview of Vein Biometric Datasets.

Dataset	Vein Type(s)	Subjects	Images	Acquisition Type	Notes
FYO	Dorsal, Palm, Wrist	160	1920	Infrared, CMOS	Multimodal; medical imaging setup
UTFVP	Finger	60	1440	Custom IR device	Captured over two sessions
FV-USM	Finger (4 fingers)	123	2952	Near-infrared	Six images per finger
HKPU	Finger (Left index and middle)	156	1872	NIR	Six images per finger
CASIA-MS-Palmprint	Palm and Vein (Multispectral)	100+	N/A	NIR and visible bands	Multimodal analysis supported
PUT	Dorsal Hand	100	N/A	Varying lighting and positions	Designed for robustness testing
JLU Wrist Vein	Wrist	120	N/A	NIR	Both wrists were imaged multiple times
SCUT-3DFV	Finger (3D from multiple angles)	100	N/A	Mirror-based 3D capture	Useful for 3D vein recognition studies
Bosphorus Hand Vein	Dorsal Hand	N/A	N/A	NIR with interaction scenarios	Includes tasks to simulate realistic hand states (e.g., stress, cold)

OPEN CHALLENGES AND FUTURE RESEARCH DIRECTIONS

In this section, we bring together key unresolved issues and promising future directions in the field of vein recognition, including challenges related to acquisition conditions, dataset diversity, data augmentation, cross-database evaluation, and biometric data protection. These factors represent the essential research frontiers that must be addressed to achieve robust and secure systems.

Acquisition Challenges On Datasets

The performance and accuracy of biometric systems can be affected simply by variability in acquisition conditions. For example, a little variation in the lighting intensity can alter the features extracted from a vein image, while a simple movement of the hand or a slightly cold temperature can affect pattern acquisition. Therefore, it is very essential and important to have datasets that contain a large dataset captured under varied conditions (images from different angles and lighting) to improve the performance of the biometric (Geissbühler et al., 2024).

Data Augmentation and Cross-Dataset Evaluations

Data augmentation is a technique that improves the robustness and the efficiency of biometric systems, especially those that use a limited or imbalanced training dataset. To vary and enrich the data bank, some techniques like cropping, rotating, or changing the intensity of the lighting of images are used to generate and produce artificial variations on the dataset. This will allow the models to learn with a more general and variable dataset (Shorten and Khoshgoftaar, 2019). For example, in study (Haider et al., 2023), the researchers modified the light intensity of finger images and rotated them to enrich their training dataset. With this variation, they successfully raise the accuracy of their system.

Cross-database evaluation is a technique that involves training a recognition system on one dataset and then evaluating it on another. This strategy allows measuring the detection capacity and robustness of the system against environmental conditions variation in real life (Vanoni et al., 2014).

Protection of Biometric Data

Protecting biometric data is essential to maintaining the confidentiality and security of systems against attacks. Several techniques and approaches are available to achieve this:

1) Cancellable biometrics :Cancellable biometrics use an irreversible function to transform an individual's features into a modifiable template before storing it in the database. Unlike traditional approaches, these templates can be canceled and regenerated in the case of a compromised event, just like we do with a password. This transformation will help to improve the security and flexibility of the biometric systems (Patel et al., 2015).
2) Biometric cryptosystems :Bio-cryptosystems combine the benefits of biometrics and cryptography techniques to improve the security of personal data. By using biometric characteristics not only for identification but also to protect or generate cryptographic keys. Methods such as ”fuzzy commitment” or ”fuzzy vault” allow a biometric identity to be securely linked to a key used to encrypt or decrypt data, which will increase the security and the confidentiality of the biometric system against attacks (Uludag et al., 2004).
3) HomomorphicEncryption :Homomorphic encryption is an advanced cryptographic technique that permits performing computations on encrypted data without ever decrypting it. This will improve the protection of privacy issues inside the system, because the data remains encrypted and can only be decrypted by the data owners(Yang et al., 2023).

CONCLUSION

Vein-based biometrics have shown important progress in the last few years, evolving from classical methods toward more modern and new approaches like deep learning. While performance has improved, several challenges remain, particularly regarding image acquisition conditions, privacy preservation, and ethical considerations in biometric systems. Future work could focus on integrating vein data with other biometric traits, improving the protection and security of biometric information, and optimizing these systems for faster, real-time applications.

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