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AI-Enhanced Vein Biometrics: A Comprehensive Survey

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Abstract

Vein biometrics has emerged as a promising biometric modality for personal identity authentication, benefiting from its intrinsic properties such as high discriminative capability, resistance to forgery, and contactless acquisition. Recent advances in artificial intelligence, particularly deep learning, have significantly accelerated its development. This paper presents a comprehensive and systematic survey of AI-enhanced vein biometrics. We review fundamental principles, publicly available datasets, and evaluation protocols, and systematically analyze existing methods across the entire vein biometric pipeline, including acquisition, preprocessing, feature extraction, recognition and verification, security and privacy protection, and multimodal fusion. Furthermore, we summarize representative application scenarios, identify key challenges, and highlight promising directions for future research. To facilitate reproducible research and long-term development of the field, we release an open, evolving research resource *Awesome-Vein-Biometrics* that systematically summarizes and tracks recent advances in vein biometrics.

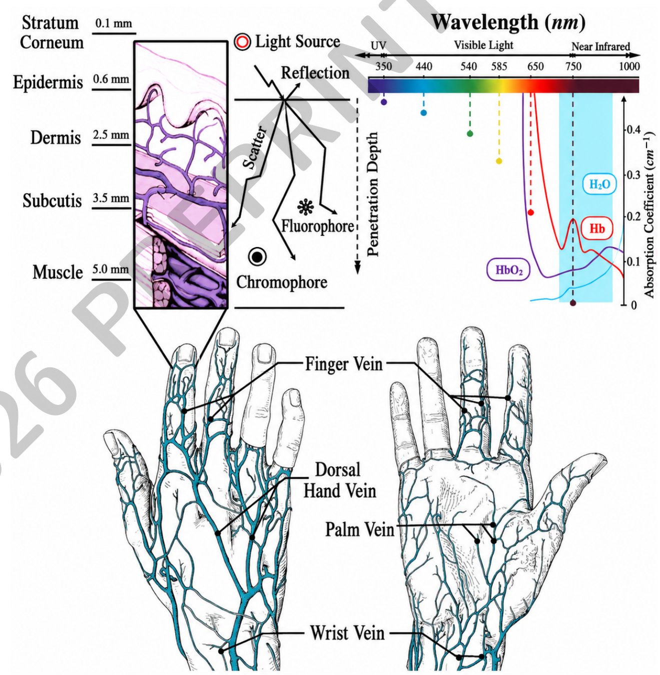

Figure 1: Vein Biometrics. Top: Penetration depth and path of the light into the skin, for different wavelengths and the corresponding absorption coefficients of oxidized hemoglobin (HbO2), deoxidized hemoglobin (Hb), and water (H2O) [Salazar-Jurado *et al.*, 2023]. Bottom: Vein biometrics in different areas of the hand [Grant, 1972].

1 Introduction

Biometrics refers to the automatic capture, processing, analysis and recognition of human digital physiological or behavioral characteristic signals by intelligent machines, which is a typical pattern recognition task and has been at the forefront of artificial intelligence development [Jain *et al.*, 2016]. Biometric characteristics play a crucial role in authentication, as humans have been using facial features, fingerprints, and voices for mutual recognition throughout thousands of years. They cannot be lost and are difficult to forge, unlike token-based methods (Keys, ID cards, etc.). Moreover, they cannot be forgotten, unlike knowledge-based methods (passwords, security questions, etc.) [Kumar and Zhou, 2011]. The main biometric characteristics include face [Liu *et al.*, 2023], fingerprint [Yang *et al.*, 2022] and iris. Each has advantages, but also challenges: face recognition raises privacy concerns; fingerprints can degrade; iris acquisition is costly and has low user acceptance.

Joseph Rice [9] first attempted to use the dorsal hand vein pattern as a biometric characteristic for authentication in 1983, followed by palm veins (1991), finger veins (1997), and wrist veins (2010). After over three decades, vein biometrics has become a representative of the second generation of biometrics due to its uniqueness (individual variability in vein patterns, even in twins), stability (unchanged vein patterns after adulthood), and high security and privacy (strong liveness detection and difficulty in forgery as veins are hidden beneath the skin). Traditional vein biometrics techniques

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mainly rely on hand-crafted image processing and feature extraction methods, such as extracting vein pattern features using Gabor filters, SIFT, etc., and using geometric features such as maximum curvature points and intersection points for matching. However, hand-crafted features cannot adequately capture the complexity of the data and especially when dealing with high-dimensional data, they may not be able to distinguish the samples effectively. Traditional methods are often sensitive to noise and variations in the data (e.g., light, angle, background interference), this results in a significant decrease in robustness and accuracy in complex scenarios [10], thus limiting the vein authentication system's performance, until the emergence of deep learning techniques.

Since the 1960s, advancements in pattern recognition and machine learning have been driven by fundamental problems in biometrics. New theories and methods, including Principal Component Analysis (PCA), Boosting, and Deep Learning, often benchmark biometric capabilities against human recognition abilities. The biometrics paradigm shifted in 2012 with the introduction of AlexNet. Vein biometrics has similarly benefited from new deep learning techniques, as early as 2005 neural networks were used to process vein images. Techniques such as representation learning, adversarial learning, multi-task learning, and reinforcement learning have since been widely adopted in various vein biometric subtasks.

Existing survey works typically focus on specific vein modalities or isolated technical aspects. In contrast, this paper presents a comprehensive survey of AI-based vein biometrics, covering all major vein modalities (palm, finger, dorsal hand, and wrist) and the entire recognition pipeline, including acquisition, preprocessing, feature extraction, recognition and verification, template protection, privacy and security, and multimodal fusion. We further summarize representative applications, open challenges, and future research directions, aiming to provide a systematic reference and promote research engagement in this rapidly evolving field.

2 Background

2.1 Principles of Vein Imaging

Vascular Network. The vascular network of the hand consists of veins and arteries. This network includes both deep and superficial branches, with superficial veins located just beneath the epidermis. The complexity of the vascular structure supports its application in biometric authentication.

Vein Imaging. Currently, vein pattern imaging can be achieved using infrared, laser, and ultrasound technologies. However, near-infrared (NIR) equipment is the most common method. NIR interacts with oxyhemoglobin (HbO2) and deoxyhemoglobin (Hb) within the vascular network. Figure 1 illustrates the penetration depth and path of light entering the skin, along with the corresponding absorption coefficients of HbO2, Hb, and water. The optical window for image acquisition, ranging from 720 nm to 950 nm, is highlighted. When the wavelength of light is between 720 nm and 760 nm, radiation is strongly absorbed by Hb, creating shadows that correspond to the vein patterns.

Properties of vein biometrics. The uniqueness of vascular network patterns forms the basis for vein biometric applications. Medical research has confirmed this distinctiveness through anatomical studies and reflection-based analysis of cutaneous vascular systems. Statistical analyses of large vein image databases within the biometric community have further validated this uniqueness property. Vein patterns offer advantages: they remain stable, are protected from damage and forgery due to their subcutaneous nature, require living tissue for detection, and enable contactless authentication.

2.2 Publicly Available Vein Datasets

Currently, most publicly available vein datasets consist of 2D grayscale images. Notable exceptions include the SCUT-3D dataset of 3D finger veins from South China University of Technology, a 3D dataset with 141 objects from IDIAP Research Institute in Switzerland, Tsinghua University released THUMVFV-3V, a publicly available multi-view finger vein dataset, Shenzhen University releases a full-view finger vein dataset with multiple deformations and a 360-degree 2D grayscale finger vein dataset from the University of Salzburg, which includes one image per degree. Table 1 summarises all publicly available vein datasets and details[1].

2.3 Evaluation Metrics and Protocols

Different tasks require specific evaluation metrics.[2].

Image Preprocessing: The metrics of the image preprocessing stage are mainly image quality assessment, typically assessed using Peak Signal to Noise Ratio (PSNR) or Structure Similarity Index (SSIM).

Feature Extraction: Feature extraction refers to obtaining the binarized vein patterns. Commonly used metrics for image segmentation include: F_1 Score, Dice similarity coefficient (DSC), Jaccard Index (JI), Precision and Recall.

Recognition/Verification:

- Accuracy: Proportion of correctly identified samples.
- False Non-Match Rate (FNMR)/False Match Rate (FMR): Proportion of mated/non-mated comparison trials resulting in non-match/match decisions.
- False Reject Rate (FRR)/False Accept Rate (FAR): The proportion of a specified set of true/false biometric claims that are erroneously rejected/accepted.
- Equal Error Rate (EER): The threshold when FNMR $=$ FMR or FAR $=$ FRR.
- Receiver Operating Characteristic (ROC): Curve plotting FNMR/FRR/TAR (Y-axis) vs. FMR/FAR (X-axis).
- Detection Error Tradeoff (DET): Curve using nonlinear axes to show regions of error rates.

Template Protection/Security/Privacy:

- *Global Linkability* $\boldsymbol{D_{\leftrightarrow}^{sys}}$: A small $D_{\leftrightarrow}^{sys}$ indicates weak linking, and vice versa, where $D_{\leftrightarrow}^{sys} = \int p(s|H_m)[p(H_m|s) - p(H_{nm}|s)]ds$.
- *Decidability Index* $\boldsymbol{d'}$: A higher value of d' indicates good separation between the two distributions, and vice versa, where $d' = |\mu_1 - \mu_2| / \sqrt{\frac{1}{2}(\sigma_1^2 + \sigma_2^2)}$.

[1] All dataset application links: *Awesome-Vein-Biometrics*
[2] More detail: *Awesome-Vein-Biometrics*

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Dataset	Institution	Year	Subjects	Fingers/Hands	Capture times	Total images	Size	Illumination type
Finger Vein								
SDUMLA-FV	Shandong University (CN)	2011	106	6	6	3816	320×240	Top-Transmission
HKPU-FV	PolyU (HK)	2012	156	3	12/6	3132	513×256	Top-Transmission
MMCBNU_6000	Seoul National University (KR)	2013	100	6	10	6000	480×640	Top-Transmission
UTFVP	University of Twente (NL)	2013	60	6	4	1440	672×380	Top-Transmission
THU-FV	Tsinghua University (CN)	2014	610	2	16	9760	720×576	Top-Transmission
FV-USM	Malaysia Polytechnic University (MY)	2014	123	4	6	5904	640×480	Top-Transmission
VERA-FV	IDIAP (CH)	2014	110	2	2	440	665×250	Top-Transmission
PLUSVein	University of Salzburg (AT)	2019	63	6	5	454860	1280×1024	Top-Transmission
SCUT-FV	South China University of Technology (CN)	2021	174	4	42	8526	400×400 640×480	Top-Transmission
NUPT-FV	Nanjing University of Posts and Telecommunications (CN)	2022	140	6	20	16800	300×400	Top-Transmission
MIFVD	Anhui University (CN)	2025	-	-	330	10560	200×400	-
FingerVeinSyn-5M	Southeast University (CN)	2025	50000	-	100	5000000	300×600	Synthetic
Palm Vien								
CASIA-MS	CASIA (CN)	2008	100	2	36	7200	768×576	Reflection
HKPU-PV	PolyU (HK)	2010	255	2	12	6000	352×288	Reflection
PUT-PV	Eastern Mediterranean University (TR)	2011	50	2	12	1200	1280×960	Reflection
VERA-PV	IDIAP (CH)	2012	110	2	10	2200	480×640	Reflection
Tecnocampus-PV	Tecnocampus Mataró-Maresme (ES)	2014	100	2	15	3000	640×480	Reflection
TongjiPV	Tongji University (CN)	2018	300	2	10	6000	640×480	Reflection
FYO-PV	University of Salzburg (AT)	2020	160	2	2	640	800×600	Reflection
Dorsal Hand Vein								
GPDS	University of Las Palmas de Gran Canaria (ES)	2009	100	1	10	1000	1392×1040	Reflection
NCUT	North China University of Science and Technology (CN)	2009	102	2	10	2024	640×480	Reflection
Bosphorus	Bozok University (TR)	2011	100	1	12	1575	300×240	Reflection
Tecnocampus-DHV	Tecnocampus Mataró-Maresme (ES)	2014	100	2	15	3000	640×480	Reflection
DHVI	Pontificia Universidad Javeriana (CO)	2020	138	2	4	1104	752×560	Reflection
FYO-DHV	University of Salzburg (AT)	2020	160	2	2	640	800×600	Reflection
JLU	Jilin University (CN)	2020	736	1	5	3680	320×240	Reflection
Wrist Vein								
PUT-WV	Eastern Mediterranean University (TR)	2011	50	2	12	1200	300×240	Reflection
FYO-WV	University of Salzburg (AT)	2020	160	2	2	640	800×600	Reflection

Table 1: Publicly available vein biometric datasets. All datasets presented are the latest versions.

– Privacy Leakage Rate: It is in the range $[0, 1]$ and should be close to 1, indicating that knowledge of the protected template Y does not reveal information about the original biometric X, where $H(X|Y)/H(X) = 1 - I(X;Y)/H(X)$.

– Successful Attack Rate (SAR): The probability of successfully bypassing an authentication system through security attacks, such as brute force attacks, false acceptance attacks, or dictionary attacks, etc.

3 Traditional Methods in Vein Biometrics

Traditional vein biometric systems typically consist of three main stages: preprocessing, feature extraction, and matching.

Preprocessing focuses on image enhancement and region-of-interest (ROI) extraction. Image enhancement methods can be broadly categorized into frequency-domain approaches, such as Gabor filtering and Retinex-based methods, and spatial-domain approaches, including adaptive histogram equalization, often combined with denoising operations. In addition, some studies introduce image degradation restoration models to further improve vein visibility. ROI extraction strategies vary across vein modalities. For finger vein images, edge detection and finger joint characteristics are commonly used to locate rectangular ROIs. For dorsal hand and palm vein images, finger valley points are typically employed to establish a coordinate system for ROI extraction, while some methods adopt maximum inscribed circles as ROIs. Wrist vein images often rely on binarized representations, where stable rectangular ROIs are extracted based on centroid localization or morphological features. **Feature extraction** methods can be broadly divided into four categories. Minutiae-based methods extract vein endpoints or bifurcation points, often using techniques such as SIFT. Dimensionality reduction-based methods, including PCA and its variants, project 2D vein images into low-dimensional feature spaces. Local descriptor-based methods, such as LBP and its extensions, encode local pixel intensity variations within neighborhood windows. Vein pattern-based methods aim to capture the global vascular structure by extracting vein skeletons using techniques such as curvature analysis, Gabor filtering, repeated line tracking, and wide line detection. During the **matching** stage, various similarity or distance measures are employed, including Euclidean distance, Hausdorff distance, Hamming distance, and cosine similarity. In addition, several studies have explored **template protection** techniques for vein biometrics, such as feature transformation methods for generating cancelable templates, as well as key generation and key binding schemes to enhance security and privacy.

Traditional methods often struggle with substantial image quality variations and complex vein patterns, especially under non-ideal acquisition conditions. Their reliance on handcrafted features and predefined rules limits their robustness and generalization capability.

4 AI-Enhanced Vein Biometrics

Similar to other biometric modalities, vein biometrics has increasingly adopted deep learning techniques, resulting in notable improvements in recognition performance, robustness,

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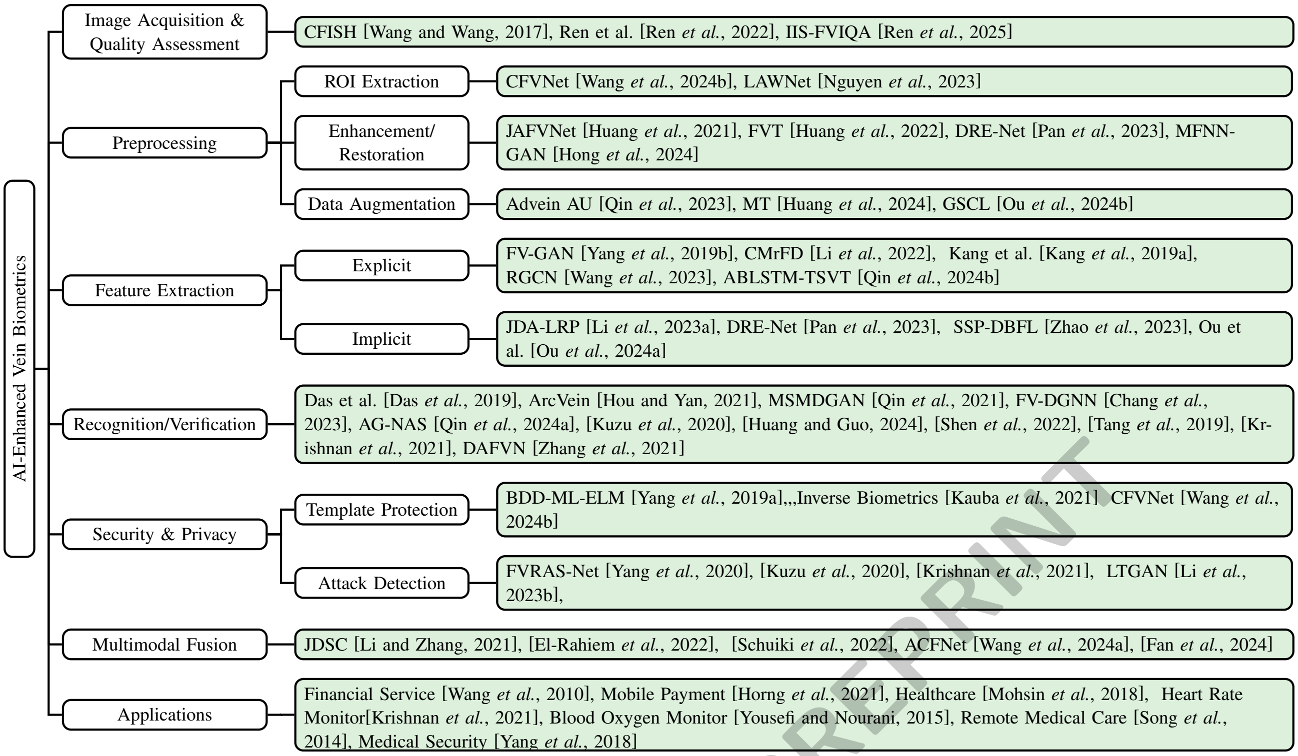

Figure 2: A taxonomy of AI-enhanced vein biometrics.

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and overall reliability.

4.1 Image Acquisition and Quality Assessment

Image quality significantly impacts recognition performance. Traditional fixed near-infrared acquisition devices are susceptible to environmental and individual variations. While quality assessment research has lagged behind recognition algorithms, its importance is increasingly recognized.

Early quality assessment research in an indirect manner. For example, early work employed deep neural networks for classification, where incorrectly rejected samples were implicitly regarded as low-quality images. While such strategies provided a coarse indication of quality, they lacked explicit quality modeling and interpretability. Subsequent research shifted toward more systematic and explicit quality assessment frameworks. Ren *et al.* [2022] constructed quality-aware datasets by screening low-quality samples through one-to-one matching and trained deep convolutional neural networks to learn common characteristics associated with image quality. To further overcome the limitations of indirect evaluation, several studies manually annotated vein images with quality scores and employed supervised learning to directly predict image quality [Wang and Wang, 2017; Ren *et al.*, 2025]. These approaches enabled finer-grained quality estimation but heavily relied on the availability and consistency of human-labeled quality annotations. However, the absence of standardized quality labels across datasets hinders supervised quality assessment, prompting a shift toward unsupervised and weakly supervised methods. In parallel, intelligent acquisition strategies based on deep reinforcement learning have been proposed to address quality issues during image acquisition.

4.2 Preprocessing

Image preprocessing is a fundamental stage in vein biometrics, aiming to enhance image quality, suppress unstable noise, and facilitate subsequent processing and analysis.

ROI Extraction aims to reduce inter-class variations caused by hand pose changes during acquisition while suppressing unstable background noise. Traditional approaches rely on geometric constraints and morphological operations, which are effective under controlled conditions but lack adaptability to complex imaging environments. In contrast, deep learning-based methods learn implicit spatial and structural cues from data, providing improved robustness and flexibility.

For finger veins, DNN learn finger edge contours and joint cavity distributions for ROI extraction, overcoming the limited applicability of traditional methods [Wang *et al.*, 2024b]. For palm and dorsal hand veins, ROI extraction resembles gesture recognition, starting with accurate hand segmentation followed by ROI delineation of fixed shapes (circles or rectangles) based on finger valley localization. For wrist veins [Nguyen *et al.*, 2023], the localization of wrist joint markers determines the optimal feature extraction region.

With the rapid advancement of contactless vein recognition, ROI extraction is increasingly required to operate automatically and adapt to varying environmental conditions. Consequently, robust and precision ROI extraction methods are expected to play a critical role in enabling large-scale and real-world deployment of vein biometric systems.

Restoration. In vein imaging, image quality is often degraded by factors such as skin scattering blur, optical blur, motion blur, and over- or underexposure [Yang *et al.*, 2019b]. Mild degradations mainly reduce the contrast between vein patterns and surrounding tissues, whereas severe degradations may disrupt vascular continuity and introduce missing segments. Traditional deblurring approaches typically formulate restoration as a linear inverse filtering problem, which limits their ability to recover discontinuous or severely corrupted vein structures.

By contrast, DNNs are suited for modeling nonlinear degradation processes in blind deblurring tasks. They reformulate vein restoration as an end-to-end learning problem, enabling the reconstruction of clear images while implicitly preserving vascular connectivity through supervised training. Existing vein restoration methods can be broadly categorized into two groups. Model optimization-based approaches focus on designing tailored network architectures and loss functions to learn the mapping from degraded to clean vein images [Hong *et al.*, 2024]. Discriminative learning-based approaches introduce adversarial training mechanisms, where generator–discriminator interactions enhance the realism and structural details of restored vein patterns.

Enhancement. This task aims to enhance the distinguishability of vascular structures and minutiae features from surrounding tissues. From a visual perception perspective, several studies have introduced learnable filtering mechanisms in either the frequency or spatial domain to adaptively enhance low-level vein characteristics, including vessel points, patterns, and orientations. For example, Pan et al. [2023] proposed an adaptive decoupling strategy that separates vein morphological and pattern features to guide the enhancement process, while Wang et al. [2023] employed learnable Gabor convolutions to explicitly strengthen vein patterns and orientation responses.

Beyond low-level feature enhancement, recent works have increasingly focused on improving higher-level semantic representations. Joint attention mechanisms have been explored to dynamically reweight feature channels and spatial regions, thereby facilitating effective feature fusion and enhancing discriminative representations [Huang *et al.*, 2021]. Moreover, considering that vein patterns exhibit strong global structural coherence, modeling long-range dependencies has become an important direction. Self-attention mechanisms have therefore been introduced to capture global spatial relationships, further improving the integrity and quality of reconstructed vein patterns [Huang *et al.*, 2022].

Data Augmentation Techniques Currently, generative adversarial networks [Qin *et al.*, 2023] constitute the dominant framework for vein biometric data augmentation, supporting both intra-class and inter-class generation [Wang *et al.*, 2025]. Intra-class augmentation aims to synthesize diverse samples of the same vein identity, whereas inter-class augmentation seeks to generate entirely new vein identities, which is considerably more challenging due to the need for identity-level structural diversity.

To enhance the diversity and realism of GAN-generated vein images, recent studies have explored advanced strategies such as pose-shifting to model acquisition variations [Huang *et al.*, 2024] and self-supervised learning to improve representation consistency and generalization [Ou *et al.*, 2024b]. A comprehensive review of vein biometric data augmentation techniques can be found in [Salazar-Jurado *et al.*, 2023].

4.3 Feature Extraction

Feature extraction is a core component of vein biometric systems, aiming to learn discriminative representations that effectively characterize vascular structures for recognition and verification.

Explicit Extraction follows the traditional vein representation paradigm, leveraging a priori domain knowledge to explicitly model structured vein characteristics, such as vein patterns [Yang *et al.*, 2019b], minutiae, and orientations [Wang *et al.*, 2023]. These approaches typically adopt encoder–decoder architectures to directly extract vein patterns or salient detail points, producing interpretable feature representations. For example, Lu *et al.* [Lu *et al.*, 2025] constructed a pattern-annotated dorsal hand vein dataset and proposed DSHR-Net, a high-resolution segmentation network based on snake convolutions. Alternatively, some studies focus on learning explicit basic features through learnable feature descriptors, enabling adaptive extraction of vein primitives [Li *et al.*, 2022].

Implicit Extraction exploits the strong representational capacity of deep learning to learn compact and highly discriminative features without explicitly enforcing vein structure constraints. This line of research emphasizes advanced network architectures, loss function design, and attention mechanisms to capture rich semantic information [Huang *et al.*, 2021]. For low-quality or noisy vein images, sparse and low-rank representation learning has been shown to effectively suppress noise and enhance feature robustness [Li *et al.*, 2023a]. Pan *et al.* [2023] decoupled vein patterns from finger shape and positional information to obtain more discriminative representations. Kang *et al.* [2023] further enriched vein representations by incorporating background intensity variations and semantic similarity constraints for binary feature learning. Moreover, recent studies have demonstrated that combining explicit shallow vein patterns with implicit deep semantic features can provide complementary information and lead to more comprehensive vein representations [Ou *et al.*, 2024a].

3D Representation. With the increasing adoption of contactless vein authentication, the limitations of single-view 2D vein representations have become evident, including insufficient structural information, sensitivity to pose variations, and feature degradation caused by projection effects. To address these challenges, researchers have explored 3D vein representation and reconstruction techniques [Kang *et al.*, 2019a]. These include stereo vision and binocular imaging approaches to reconstruct 3D vein point clouds, as well as methods that exploit multi-view or global contextual cues to infer 3D vascular structures [Qin *et al.*, 2024b; Huang *et al.*, 2025]. In addition, advanced vision techniques such as reinforcement learning [Li *et al.*, 2024b], multi-scale learning [Pan *et al.*, 2020], and generative adversarial networks [Yang *et al.*, 2019b] have been incorporated to enhance the robustness and completeness of 3D vein representations.

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4.4 Recognition/Verification

Vein biometric authentication systems fundamentally address pattern recognition problems, where *recognition* corresponds to $1 : N$ multi-class identification and *verification* to $1 : 1$ authentication [Hou and Yan, 2021]. Unlike explicit feature extraction methods, modern recognition systems adopt a data-driven paradigm, learning discriminative feature representations and decision boundaries jointly through end-to-end deep models. Although the learned features may lack direct physical interpretability, they enable superior discrimination by leveraging multi-level and hierarchical representations.

Recent advances in vein recognition have been driven by the development of powerful model architectures, including deep neural networks (DNNs) [Das *et al.*, 2019; Qin *et al.*, 2025], generative adversarial networks [Qin *et al.*, 2021], Transformers [Huang *et al.*, 2022], and graph neural networks (GNNs) [Chang *et al.*, 2023]. These models are often combined with attention mechanisms to emphasize discriminative vascular regions [Qin *et al.*, 2024a] and with optimized objective functions to enhance inter-class separability and intra-class compactness [Hou and Yan, 2021].

In practical deployment, vein recognition systems must operate under diverse constraints and challenging conditions. For **real-time authentication**, system-level designs that combine multi-view acquisition with efficient deep models have been proposed to balance accuracy and latency [Kuzu *et al.*, 2020]. **Cross-device authentication** addresses the performance degradation caused by sensor and device heterogeneity, where data normalization and feature alignment strategies are commonly adopted to reduce domain discrepancies [Huang and Guo, 2024]. To meet the requirements of **edge devices**, lightweight network architectures, knowledge distillation, and efficient convolutional designs have been explored to reduce computational and memory overhead [Shen *et al.*, 2022; Tang *et al.*, 2019].

Beyond recognition accuracy, robustness and security are also critical considerations. Some studies have integrated physiological cues, such as vein vessel pulsation, into the recognition pipeline to simultaneously support **liveness detection** [Krishnan *et al.*, 2021]. In addition, **3D vein representations** [Kang *et al.*, 2019a] offer richer geometric and depth information, which enhances discriminative capability, improves inter-class separability, and increases robustness to noise and pose variations. For **unconstrained scenarios**, learning illumination-invariant representations and aligning features across lighting domains have been shown to mitigate domain shifts and improve generalization under complex illumination conditions [Zhang *et al.*, 2021; Wang *et al.*, 2025].

To further reduce intra-class variations, Wang *et al.* [2024b] proposed a stable ROI-based alignment strategy that performs soft feature alignment during recognition. Moreover, auxiliary cues such as background textures and finger shape have been explored as **soft biometric** information to complement vein features and further enhance identification performance [Kang *et al.*, 2019b]. Issues related to data security and privacy protection in recognition and verification are discussed in Section 4.5.

4.5 Security and Privacy Protection

Biometric authentication inherently involves a trade-off between strong authentication guarantees and security and privacy protection. Although biometric traits are immutable and uniquely linked to individuals, which enables reliable identity verification, this tight binding also raises significant privacy and security concerns. Once biometric references are associated with identity information, they are regarded as Personally Identifiable Information (PII) and require strict protection mechanisms. The ISO/IEC 24745 standard systematically analyzes potential security threats in biometric systems, including presentation attacks, replay attacks, hill-climbing attacks, decision threshold manipulation, template reconstruction attacks, and dictionary attacks, and highlights two major defense directions: presentation attack detection and biometric template protection.

Template Protection is the most actively studied area in biometric information security. Existing approaches mainly include cancelable biometrics (CB), biometric cryptosystems (BCs), and biometrics in encrypted domains. These methods are commonly evaluated based on revocability, unlinkability, irreversibility, and the preservation of recognition performance. BCs primarily focus on biometric key generation and key binding, while encrypted-domain biometrics employ symmetric or homomorphic encryption to protect templates. In the context of artificial intelligence, most studies emphasize **irreversible and cancelable** biometric representations. Yang *et al.* [2019a] proposed a Binary Decision Diagram (BDD)-based template protection scheme for deep learning–based finger vein recognition. Kauba *et al.* [2021] investigated the reversibility risk by reconstructing grayscale hand vein images from binary templates, highlighting potential privacy leakage. Wang *et al.* [2024b] introduced a BWR-ROIAlign module incorporating localization, compression, and transformation, where block warping remapping explicitly enforces unlinkability, irreversibility, and cancellability.

Presentation Attack Detection (PAD) aims to identify and reject non-authentic biometric samples, such as spoofed or artificial vein images. Yang *et al.* [2020] proposed FVRAS-Net, which integrates vein recognition and anti-spoofing through multi-task learning with an auxiliary PAD branch. Since vein patterns inherently exist only in living tissue, video-based vein acquisition has been widely exploited to capture physiological cues, such as vessel pulsation, for liveness detection and presentation attack defense [Kuzu *et al.*, 2020; Krishnan *et al.*, 2021]. Moreover, given the vulnerability of deep learning models to **adversarial attacks**, recent studies have investigated robust defense strategies to improve the reliability and security of vein biometric authentication systems [Li *et al.*, 2023b].

4.6 Multimodal Fusion

Beyond vein patterns, human hands provide a rich set of complementary biometric traits, including fingerprints [Wang *et al.*, 2024a], palm prints [Fan *et al.*, 2024], finger knuckle prints [Li and Zhang, 2021], hand geometry, and electrocardiograms (ECGs) [El-Rahiem *et al.*, 2022]. In addition, vein biometrics are often fused with other commonly used modalities such as face, iris, and gait to further enhance recognition

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performance. Depending on the fusion stage, multimodal biometric systems can be broadly categorized into sensor-level, feature-level, score-level, and decision-level fusion.

ompared with single-modality vein-based authentication, multimodal fusion systems generally achieve superior performance, particularly in reducing false acceptance rates (FAR) and false rejection rates (FRR). More importantly, multimodal biometrics offer enhanced security and robustness, as successful spoofing becomes more difficult when attackers are required to bypass multiple heterogeneous biometric channels simultaneously [Schuiki *et al.*, 2022]. For a comprehensive overview of multimodal hand biometric fusion techniques, readers are referred to the systematic survey by Li *et al.* [Li *et al.*, 2024a], which provides an in-depth analysis of existing methods and discusses future research directions.

5 Applications

Vein biometrics have been increasingly adopted in a wide range of real-world authentication scenarios due to their high security and contactless acquisition capability. In **financial services** [Wang *et al.*, 2010], vein recognition is applied to bank transaction authentication, mobile payment verification [Horng *et al.*, 2021], and ATM access control. In **smart terminals**, it has been integrated into access control systems for smartphones, intelligent vehicles, and other consumer devices. In **enterprise security**, vein-based authentication is widely used for access control, attendance management, and restricted-area authorization, while in the **judicial domain**, vein characteristics provide an additional biometric evidence source for identity verification. Notably, in the post-pandemic era, the contactless nature of vein biometrics offers distinct advantages for identity authentication in public environments.

Beyond security-oriented applications, vein biometrics have also shown growing potential in **smart healthcare** [Mohsin *et al.*, 2018]. For **health monitoring**, contactless or wearable vein imaging devices enable continuous acquisition of vascular and blood-flow information, supporting real-time estimation of physiological indicators such as heart rate [Krishnan *et al.*, 2021] and blood oxygen saturation [Yousefi and Nourani, 2015]. In **remote medical care** [Song *et al.*, 2014], vein biometrics can be combined with Internet-of-Things (IoT) technologies to facilitate remote monitoring and diagnosis of patients' vital signs. Furthermore, in **medical data security** [Yang *et al.*, 2018], vein-based authentication has been integrated with medical information systems to enhance patient privacy protection and secure access to electronic health records.

6 Challenges and Future Directions

Despite the substantial progress achieved in AI-enhanced vein biometrics, several critical challenges remain unresolved. This section discusses key limitations of current systems and outlines promising directions for future research.

Lack of Large-Scale Datasets and Benchmarks. While biometric modalities such as face and fingerprint recognition have benefited from large-scale datasets and standardized benchmarks, vein biometrics is still limited to relatively small user populations, typically at the scale of hundreds of identities. This limitation severely restricts the evaluation of scalability, generalization, and open-set recognition performance. The absence of standardized large-scale datasets and benchmark protocols remains a major obstacle to advancing vein biometrics toward real-world, large-population deployment.

Data Security, Privacy, and Trustworthiness. Although vein biometrics is often considered inherently secure, emerging AI technologies introduce new security and privacy risks. For example, generative models may be exploited to reconstruct vein features from protected templates, leading to potential privacy leakage or identity misuse, or to synthesize realistic vein patterns for spoofing attacks. In addition, the limited interpretability of AI-driven vein recognition models poses challenges for security auditing, risk assessment, and trustworthy deployment, highlighting the need for explainable and privacy-preserving learning frameworks.

Cross-Device and Cross-Scenario Authentication. Maintaining robust performance across heterogeneous devices and acquisition scenarios remains a significant challenge. Variations in sensor characteristics, imaging geometry, illumination conditions, and user positioning can introduce severe domain shifts. With the growing demand for unconstrained and contactless vein recognition in post-pandemic applications, future research should focus on cross-device generalization, domain adaptation, and self-calibration techniques that enable reliable authentication across diverse environments.

Multimodal and Beyond-2D Vein Biometrics. Current vein biometric systems predominantly rely on single-view 2D grayscale images. Future research may explore richer vein representations acquired through multimodal sensing technologies, such as ultrasound, multispectral imaging, laser-based acquisition, and 3D reconstruction. While acquisition cost and system complexity remain practical concerns, combining vein information with other hand-based biometrics in multimodal frameworks offers a promising direction for improving robustness, accuracy, and security.

7 Conclusions

This paper presents a comprehensive survey of AI-enhanced vein biometrics, systematically reviewing existing methodologies, application scenarios, and open challenges, as well as outlining future research directions. To facilitate further research and reproducibility, we summarize representative approaches and release a publicly accessible repository accompanying this survey. We hope this work will serve as a useful reference and encourage broader engagement in the study and deployment of vein biometric authentication systems.

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