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Review Article

Review of Palm Vein Biometric Recognition Using Image Processing Techniques

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***Abstract* -** *The unique vascular patterns under the palm's surface have led to the emergence of palm vein biometrics as a reliable, contactless and secure biometric identification method. The strength of this technology over traditional biometrics is that it is immune to forgery, stable over time and can detect if a live user is present or not. Recent advances have improved Palm Vein Recognition (PVR) systems in imaging principles, preprocessing, feature extraction, and classification. This modality has high accuracy, robustness to environmental factors, and resistance to forgery. It thus offers an attractive alternative to conventional biometric systems, such as face or iris recognition and fingerprinting. Near-Infrared (NIR) imaging makes non-contact and hygienic data acquisition even more appropriate for use in high-security standards fields such as financial transactions, healthcare and border control. The review presents an in-depth state-of-the-art technique, including the use of Machine Learning (ML) algorithms, multi-spectral imaging, and feature extraction methods. It also addresses the challenges related to computational complexity and template security. Future directions highlight the potential of integrating advanced algorithms, 3D imaging, and privacy-preserving methods for different applications in diverse domains.*

***Keywords* -** *Palm vein recognition, Biometric authentication, Near-Infrared (NIR) imaging, Feature extraction, Deep Learning models.*

1. Introduction

Palm vein biometrics has recently been developed as a variable and reliable method of personal identification and security systems. Over conventional biometric procedures, this has several benefits, for example, high accuracy, robustness, and contactless operation, and, therefore, is suitable for clinical applications [1]. Compared to other readily accessible vein networks in the body, the vascular patterns beneath the palm surface are more intricate and rich in features [1]. Because this biometrics can get around some of the drawbacks of other frequently utilized biometric techniques, it is also of interest. For instance, the palm vein pattern is not forgeable. It has an individual's pattern throughout a lifetime, which is more secure and reliable than extrinsic methods like fingerprint, face and palm print recognition [3]. Furthermore, PVR offers liveness detection, which is very robust to forgery attempts [2, 4]. PVR systems are impressive and have improved recently. Palm vein biometrics has been shown to be secure, accurate and user-acceptable [3, 5]. However, several research gaps exist in this field: 1. Detection accuracy and translation and rotation invariance are improved by improvements in preprocessing and feature representation techniques [6]. Although methods like Gabor wavelet features are effective, more robust approaches are needed. The utilization of Deep Learning (DL) algorithms in PVR has been an emerging area requiring further study. As demonstrated by finger vein authentication, DL models have the potential for better feature extraction as well as categorization [7], but their use in PVR remains limited. More efficient and faster acquisition methods are also needed. Despite proposals for 3D palm vein imaging techniques, acquisition time poses a challenge for practical applications [8].

1.1. Advantages of Palm Vein Recognition

Compared to conventional biometric methods that include face and fingerprint, along with iris recognition, palm vein biometrics has a number of advantages. The primary benefits include low-risk forgery, non-invasiveness, and non-contact nature [9]. These patterns are distinct to everyone and remain stable over time, making them a reliable biometric trait [10]. The subcutaneous nature of palm veins makes them extremely difficult to forge or replicate, enhancing security against spoofing attacks [6]. Additionally, PVR systems can incorporate liveness detection features, further improving their anti-spoofing capabilities [6, 11]. Interestingly, while palm vein biometrics is gaining attention, some researchers are exploring other vein-based modalities. For instance, finger vein recognition has been proposed as an alternative, offering similar advantages to palm vein biometrics [9, 12]. However, the effectiveness of any biometric system, including PVR, is based upon factors, for example, preprocessing techniques, image quality, and feature extraction methods [13, 14]. Palm Vein Authentication (PVA) offers several significant advantages over other biometric techniques, for example, fingerprints or facial recognition.

The most compelling reason for the adoption of palm vein technology is its resistance to forgery. Under normal circumstances, it is challenging to duplicate or steal the vein patterns because they are internal beneath the skin’s surface. Additionally, unlike other parts of the hand (e.g., fingers or else back of the hand), the palm is typically hairless, which reduces the chances of interference during vein capture [15].

This renders PVA a non-contact and non-invasive method, enhancing its suitability for security applications. High accuracy levels have been achieved with the technology. To test the consistency and accuracy of palm vein patterns, In a large-scale investigation conducted in 2005, Fujitsu gathered 140,000 palm vein images from 70,000 individuals. Results showed that PVA is both a stable and consistent means of personal identification and, thus, suitable for long-term deployment [15]. Furthermore, it is demonstrated that palm vein patterns remain consistent throughout time, which is essential for accurate identification.

1.2. Historical Development

Vascular patterns have long been utilized for personal identification. In 1543, the great anatomist Andreas Vesalius described the great variability in the structure and position of blood vessels in the extremities of the human body [15]. It served as a basis for modern vascular biometric understanding. Professor of forensic medicine at Padua University, Arrigo Tamassia, corroborated this theory in the 19th century, saying that no two patterns of blood vessels on the hand’s dorsal were alike [15].

These early insights further demonstrated that vascular patterns can act as an unconventional biometric in which they could serve as a unique identifier, akin to other well-known biometric modalities, such as fingerprints. Vascular patterns have been utilized in personal identification since the 1980s. Joseph Rice filed a patent application for hand vein authentication in the US in 1985 [15]. However, the practical application of PVA did not materialize until the late 1990s. The first PVA device was introduced by Advanced Biometrics, Inc. in the US in 1997 [16].

This initial effort laid the foundation for further advancements in the field. The remainder of the paper is organized as subsequent. The overall approach utilized for PVR has been explained in Section 2. Section 3 explains state-of-the-art related to palm vein biometrics. Section 4 explains challenges and limitations and provides a roadmap for future work directions.

2. Palm Vein Recognition: Basic Steps

The section describes steps utilized in palm vein-based biometrics recognition.

2.1. Imaging Principle

The effectiveness of this imaging method stems from haemoglobin’s ability to absorb Near-Infrared (NIR) light. Haemoglobin, the iron-containing pigment in blood that transports oxygen, absorbs NIR light, causing blood vessels to appear dark when illuminated by NIR, while the surrounding tissues, which absorb less light, appear bright. Veins, which contain more deoxygenated haemoglobin than arteries, exhibit different NIR light absorption patterns. As a consequence, the vascular pattern of the hand can be seen by employing NIR light and an NIR-sensitive image sensor. The light source’s positioning in relation to the camera along with the hand of the subject distinguishes between two imaging techniques: reflected light imaging, where the camera and the light source are on the same side, and transillumination imaging, where they are on opposite sides, allowing light travel through the tissue and skin of hand before it reaches the camera [15]. Figure 1 represents an interaction of blood vessels with IR Light. Figure 2 represents components of the palm vein capturing setup. In the case of a controlled environment, an enclosure is used that mostly has a black coating inside to reduce the reflection of IR light. Infrared (IR) Light Source Setup: A Near-Infrared (NIR) light source in the 700–1000 nm range is used to penetrate the skin and illuminate veins effectively. Haemoglobin absorbs NIR light, making veins appear as dark lines against a bright background.

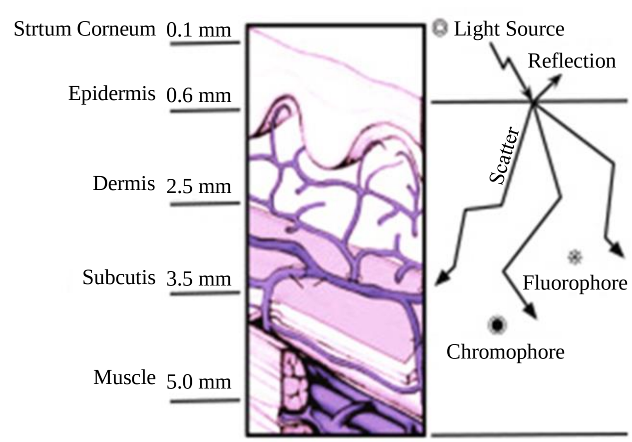


Fig. 1 Interaction of blood vessels with infrared light [17]

2.1.1. Hand Positioning

A guiding mechanism (e.g., pegs or outlines) ensures consistent hand positioning for optimal imaging. To minimize variations in size and angle, the hand must be at a constant distance from the camera. Some systems use contactless imaging to enhance hygiene and usability. It can include a sensor to tell the user where to place the hand at a certain distance from the camera.

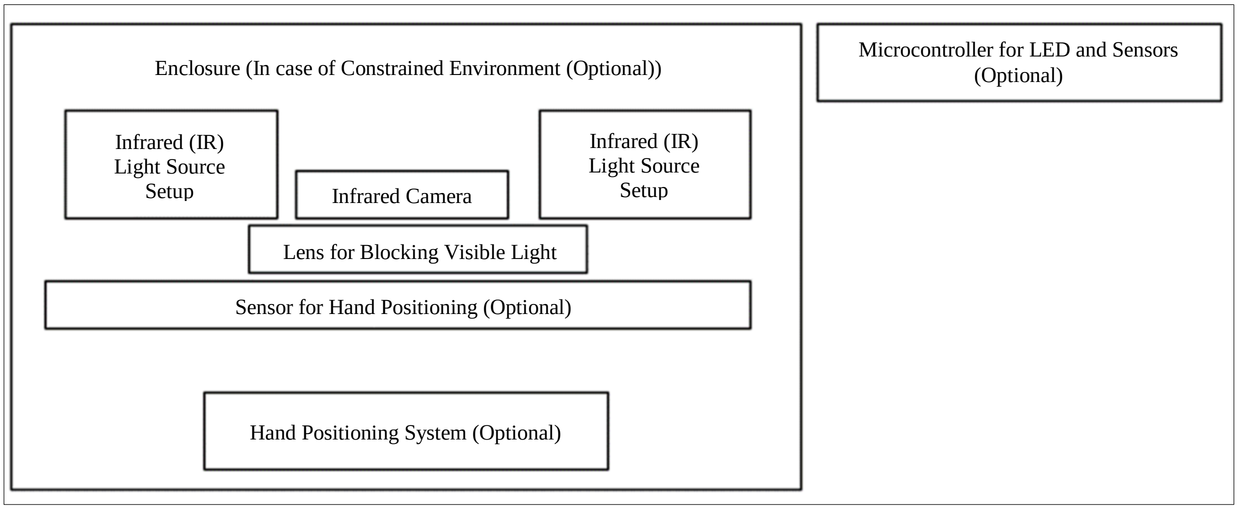


Fig. 2 Palm vein image capturing setup

2.1.2. Infrared Camera

This pattern is captured with a specialized infrared-sensitive camera and requires sufficient resolution for accurate feature extraction.

2.1.3. Illumination Optimization

It is important to avoid shadows or overexposure because that could overshadow the vein patterns. Diffusing sheets are often used to spread NIR light evenly over the palm.

2.1.4. Real-time Feedback

Modern systems provide real-time feedback, such as visual or auditory signals, guiding users to adjust their hand position and ensuring the palm is fully captured and centered.

2.1.5. Image Quality Check

Automated algorithms assess image quality, checking for overexposure, underexposure, blurriness due to hand movement, and misalignment or partial capture. If the image fails, the system prompts the user to retry. A typical palm vein image is illustrated in Figure 3.

Fig. 3 Typical palm vein image [15]

2.2. Preprocessing

Preprocessing steps for palm vein biometrics involve 1) noise reduction, 2) Region of Interest (ROI) localization, and 3) ROI Enhancement. Based on the imaging conditions, i.e. either the image is captured in a constrained environment like an enclosed box or an open environment, noise is introduced in the palm vein images. Noise reduction is important to locate Region of Interest (ROI), which contains maximum palm vein information.

2.2.1. Noise Reduction

For noise reduction, averaging filters or similar filters are used in the spatial domain. This works by replacing the pixels with the average of the neighborhood defined based on filter size.

2.2.2. Region of Interest Localization

In PVR, the ROI is the specific area of the palm that has the most useful vein pattern data. The following steps are deployed to locate the ROI.

- Grayscale Conversion: If the captured image is not already in grayscale, it is converted to a grayscale format for simplicity in further processing. Infrared images are often grayscale by default.
- Thresholding: Utilizing thresholding techniques, the palm area is distinguished from the background. Pixels corresponding to the palm are highlighted, while non-palm regions are suppressed.
- Edge Detection: Algorithms like Canny or Sobel edge detection are used to outline the palm’s boundaries. This ensures the palm contour is clearly defined.
- Contour Analysis: The palm boundary is the greatest closed contour in the thresholded image.
- Key Landmark Detection Finger Base Points: Locate the bases of the fingers using curvature analysis of the palm contour. These points are where the fingers meet the palm.

- Finger base points are often used to define the top boundary of the ROI.
- Palm Center Detection: The palm's center is identified as a reference point. This can be done by finding the centroid of the largest contour.
- ROI Definition Geometric Anchors: Using the finger base points and the palm center, a rectangular or circular region is defined.
- Example: A rectangle is drawn starting from a point slightly below the finger bases to the center of the palm, covering a portion of the palm rich in blood vein patterns.
- Fixed Proportion: Some systems use a fixed-size window to ensure consistency across images based on the average palm size.
- Alignment and Cropping Rotation Correction: The palm's orientation is corrected if it is tilted. The angle of tilt is calculated using the alignment of key landmarks (e.g., the line between the finger base points).
- Cropping: From the original image, defined ROI has been extracted, leaving out unnecessary parts like the fingers, wrist, or background.
- Normalization: Rescale the ROI to a standard size (e.g., 128 × 128 pixels) to ensure uniformity in subsequent processing. Figure 4 is a typical palm vein ROI Image.

2.2.3. ROI Enhancement

ROI Enhancement consists of,

- Noise Reduction: To minimize noise while preserving vein patterns, methods that include median filtering, Gaussian filtering, or else bilateral filtering are employed.
- Contrast Enhancement: Approaches like CLAHE (contrast-limited adaptive histogram equalization) or histogram equalization are applied to improve the visibility of vein patterns.
- Normalization: Image intensity normalization ensures uniform brightness and contrast across the dataset.

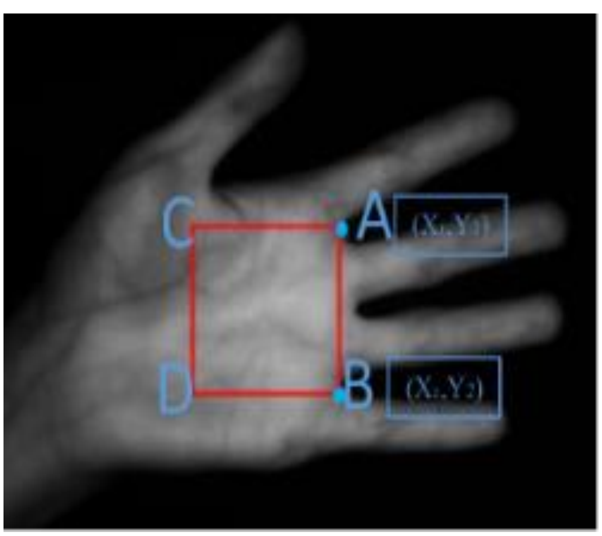
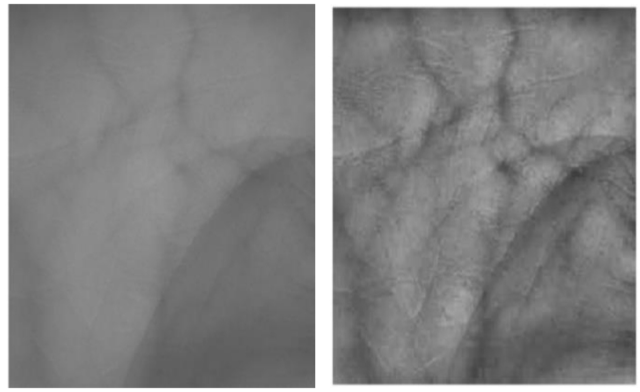


Fig. 4 Palm vein ROI localization [18]



(a) **(b)**

Fig. 5(a) Extracted ROI, and (b) Enhanced ROI using CLAHE.

2.3. Feature Extraction

For feature extraction, several approaches are employed for feature extraction. These are listed below.

2.3.1. Local Binary Pattern-Based Methods

- Local Binary Patterns (LBP): Encodes the texture of palm vein images by comparing pixel intensities with neighbouring pixels.
- Modified LBPs: Variants like uniform LBP, multiscale LBP, or directional LBP are used to capture more discriminative features.

2.3.2. Gabor and Wavelet Transform Methods

- Gabor Filters: Extract directional features by convolving images with multiscale as well as multi-orientation filters.
- Discrete Wavelet Transform (DWT): The palm vein image has been decomposed into sub-bands to analyze features at different resolutions.
- Curvelet Transform: Enhances vein detection in curved structures.

2.3.3. Gradient-Based Methods

- Sobel/Laplacian Operators: Detect vein edges by analyzing image gradients. Histogram of Oriented Gradients (HOG): Analyze the distribution of edge orientations to capture vein patterns.

2.3.4. Key Point Detection Methods

- Scale-Invariant Feature Transform (SIFT): Detects and describes key points in the palm vein region.
- Speeded-Up Robust Features (SURF): A quicker alternative to SIFT for key point-based feature extraction.

2.3.5. Morphological and Vesselness-Based Methods

- Morphological Operations: Enhance and isolate vein structures using dilation, erosion, and skeletonization.
- Frangi Vesselness Filter: Detects vein-like tubular structures based on Hessian matrix analysis. Matched Filters: Matches a predefined template of vein structures for enhancement.

2.3.6. Local Phase and Frequency-Based Methods

- Phase-Only Correlation (POC): Extracts phase information to match vein patterns effectively. Fourier Transform: Captures frequency domain features that represent vein textures.

2.3.7. Feature Transformation and Reduction

- Principal Component Analysis (PCA): Reduces dimensionality while preserving essential vein patterns.
- Linear Discriminant Analysis (LDA): Enhances class separability in the feature space.

2.3.8. Deep Learning-Based Methods

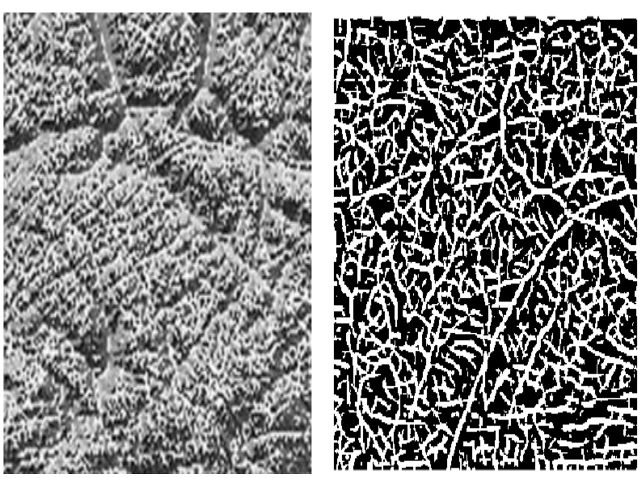
- Convolutional Neural Networks (CNNs): Without requiring manual feature engineering, learn hierarchical features straight from vein images. Pretrained models, for example, ResNet, VGG, or else Inception, are often fine-tuned for palm vein biometrics.
- Autoencoders: Extract compact and robust feature representations in an unsupervised manner.
- Region-Based CNNs (R-CNN): Combine feature extraction and ROI selection for adaptive feature learning.

2.3.9. Localized and Hybrid Methods

- Fuzzy-Based Feature Extraction: Models uncertainty in palm vein patterns for robust extraction.
- Hybrid Methods: Combine multiple techniques, such as LBP with wavelets or Gabor filters with CNNs, to improve feature extraction.

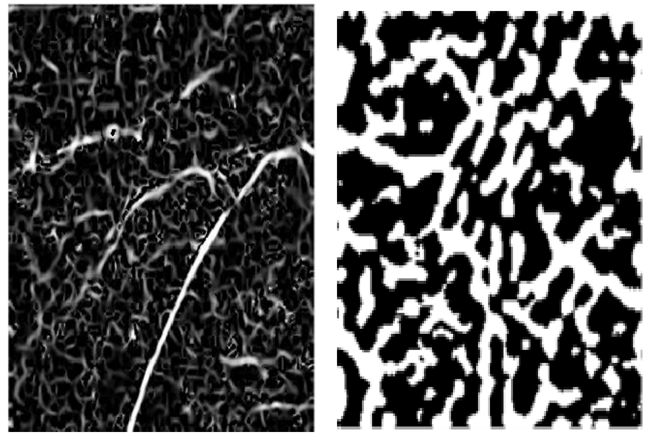
2.3.10. Coding and Quantization Techniques

- Vein Code and Binary Pattern Techniques: Encode vein patterns into compact binary features (e.g., vein binary code, competitive code).
- Hashing-Based Methods: Generate hash codes for fast and memory-efficient matching.



(a) **(b)**

Fig. 6(a) ROI applied with LBP [19], and (b) ROI applied with kumar gabor.



(a) **(b)**

Fig. 7(a) ROI applied with jerman filter, and (b) ROI hessian phase [20].

Figures 6 and 7 show the region of interest applied with respective feature extraction methods.

2.4. Classification and Matching

Classification and matching techniques are integral to palm vein biometrics, responsible for comparing extracted features to those in a database for identification or verification. Below are commonly used classification and matching techniques, along with their descriptions:

2.4.1. Distance-Based Matching

- Euclidean Distance: Measures similarity between feature vectors using the Euclidean metric. Manhattan Distance: Uses absolute differences for feature comparison.
- Cosine Similarity: Determines the angle's cosine between 2 feature vectors in order to match them. Hamming Distance: Used for binary-coded features like vein codes.

2.4.2. Correlation-Based Matching

- Cross-Correlation: Evaluate the similarity of palm vein templates by shifting one image relative to another and computing correlation.
- Phase-Only Correlation (POC): Robust matching using only the phase information of the Fourier transform.

2.4.3. Statistical Classifiers

- Support Vector Machine (SVM): The best hyperplane for categorization is found by this supervised learning algorithm.
- K-Nearest Neighbors (KNN): According to KNN with the majority class.
- Naïve Bayes Classifier: For classification, Bayes' theorem is assumed, but feature independence is assumed.

2.4.4. Template Matching

Templates are compared directly by similarity or dissimilarity metrics like normalized correlation coefficients.

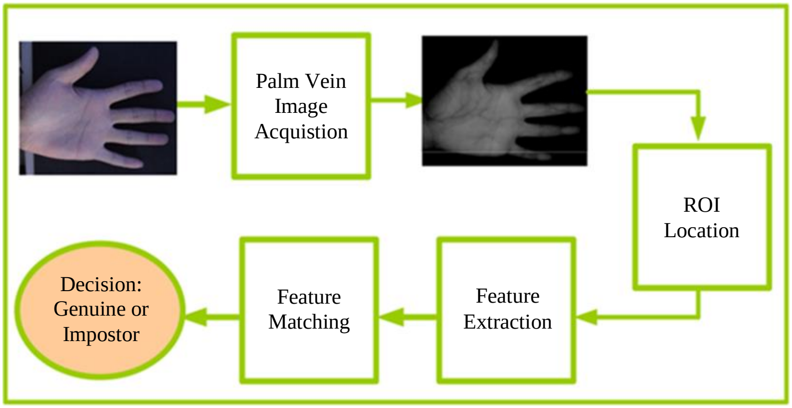


Fig. 8 Workflow of palm vein recognition system [5]

2.4.5. Neural Network-Based Techniques

- Artificial Neural Networks (ANN): Learns relationships between input features and output classes.
- Convolutional Neural Networks (CNN): Automatically extract hierarchical features for robust classification and matching.

2.4.6. Feature Fusion and Ensemble Techniques

It combines features of multiple methods (e.g. static texture, dynamic geometry information) and uses ensemble classifiers such as Random Forest or Gradient Boosting for classification.

2.4.7. Probabilistic Models

- Hidden Markov Models (HMM): Models spatial and sequential relationships in palm vein patterns. Gaussian.
- Mixture Models (GMM): Models feature distributions probabilistically.

2.4.8. Hashing and Indexing Methods

- Locality Sensitive Hashing (LSH): Reduces computational complexity by mapping feature vectors similar to those in the same hash bucket.
- Min-Hashing: Computes compact signatures for matching. The following figure summarizes the process of palm vein biometrics-based recognition.

2.4.9. Deep Learning-Based Classification

- Softmax Classifier: Often utilized as an output layer in DL architectures like CNNs for multi-class classification.
- Siamese Networks: Measures similarity between palm vein images by learning a feature embedding.
- Triplet Loss Networks: Ensures that images of the same person are closer in feature space compared to those of different people.

2.5. Evaluation Metrics

Evaluation of palm vein biometric systems involves several performance metrics to assess their accuracy, reliability, and efficiency. These metrics ensure the robustness and usability of the systems in real-world applications. Below are key evaluation metrics commonly used.

2.5.1. Accuracy Metrics

- False Acceptance Rate (FAR): The proportion of unauthorized users that the system has incorrectly accepted.

FAR = (Number of false acceptances/ Total number of impostor attempts) ×100 (1)

- False Rejection Rate (FRR): The percentage of authorized users that the system incorrectly rejects.

FRR = (Number of false rejections/ Total number of genuine attempts) ×100 (2)

- Equal Error Rate (EER): A single value that may be utilized to evaluate system accuracy is the rate at which FAR equals FRR. Lower EER denotes better performance.

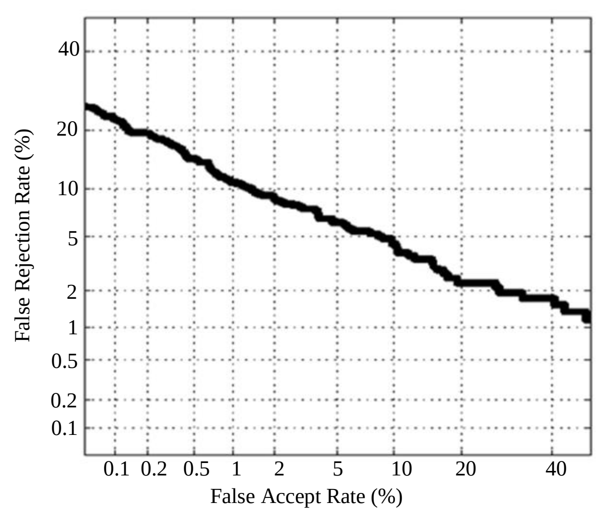


Fig. 9 DET curve that plots FRR against FAR in the normal deviate scale [22]

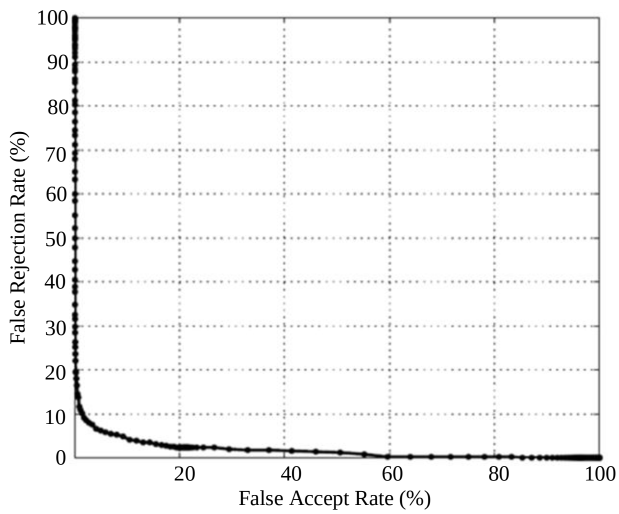


Fig. 10 ROC curve plots FRR against FAR in the linear scale [22]

2.5.2. Receiver Operating Characteristic (ROC) Curve

The trade-off between the Genuine Acceptance Rate and the FAR is represented graphically

$$GAR = 1 - FRR \quad (3)$$

at various thresholds. The Area Under the Curve (AUC) is often utilized as a performance indicator.

2.5.3. Genuine Acceptance Rate (GAR)

The proportion of genuine attempts correctly identified through the system.

2.5.4. Detection Error Tradeoff (DET) Curve

A plot of FAR versus FRR on a logarithmic scale, providing a more detailed evaluation of system performance across different operating points.

2.5.5. Processing Time

Time required for image acquisition, feature extraction, preprocessing, and matching. Lower processing time indicates better system efficiency.

2.5.6. Template Matching Accuracy

- True Positive Rate (TPR): Percentage of genuine matches correctly identified.
- False Negative Rate (FNR): Percentage of genuine matches missed by the system.

2.5.7. Robustness Metrics

Evaluates system performance under diverse conditions, for example, lighting, hand positioning, or environmental changes.

2.5.8. Computational Complexity

Measures the time and resource requirements for preprocessing, feature extraction, and matching algorithms.

3. State of the Art in Palm Vein Biometrics

This section describes the investigation done by various researchers, explaining the main highlights of their work. The method employs a recursive algorithm as per a positive linear dynamical system to compare vein patterns, demonstrating strong noise-rejection and authentication capabilities even with corrupted images. Experiments on the PolyU and CASIA multi-spectral palmprint databases yielded very low EER: 2.341×10^{-5} for PolyU and 1.081×10^{-3} for CASIA [23]. A 2-D Gabor filter is utilized to extract local features from the palm vein patterns, and a new directional coding technique encodes these features as bit strings called Vein Codes. Vein codes are compared for similarity utilizing normalized Hamming distance. The suggested approach was evaluated on a database of 4140 palm vein images from 207 people and compared to other recognition approaches, for example, minutiae feature points, Hessian phase, and Laplacian palm, based on Recognition Rate (RR) as well as ERR. With total execution time under 0.6 seconds, it achieved a 99.18% RR and a 0.46% ERR and is suitable for real-time applications [24]. A Modified Opposition-based Discrete Artificial Bee Colony (MODABC) algorithm is proposed for novel feature selection in PVA. The selected Gabor features improve authentication accuracy and reduce the feature vector size. It incorporates a variant of Opposition Based Learning (OBL) to enhance diversity along with search space exploration. CLAHE and ROI extraction are included in preprocessing. Gabor filters have been employed for feature extraction, with 32 filters at four scales and eight orientations. The MODABC algorithm optimizes feature selection through a multi-objective function balancing accuracy and feature vector size. Normalized Cross-Correlation (NCC) is employed in the matching stage for template comparison. The approach was tested on the CASIA Multi-Spectral Palmprint Images Database. Consequences indicate that MODABC surpasses other methods like DPSO, GA, DABC, GDABC, and ODABC in authentication accuracy and feature vector size reduction, achieving a top authentication rate of 97.61% [20].

The Adversarial Masking Contrastive Learning (AMCL) method for vein recognition addresses limited training data by combining a Generative Adversarial Network (GAN) with contrastive learning to produce challenging samples and enhance model robustness. The GAN generator is integrated into a contrastive learning framework, where the model minimizes contrastive loss while generating difficult samples that increase loss. For vein recognition, the encoder is combined with a classification layer after training. Investigation of 3 public palm vein datasets demonstrates AMCL's superior performance over traditional deep learning and other contrastive learning methods, achieving state-of-the-art recognition due to its ability to generate challenging and representative samples during training [24]. The authors present a cost-effective, embedded standalone PVA system using a Raspberry Pi 3, featuring a contactless acquisition system with a novel ROI-locating algorithm. The system reports a FAR of 0.32 percent, False Rejection Rate (FRR) of 1.58 percent as well as EER of 1.45%. Image acquisition uses an NIR camera, LEDs, and a proximity sensor. Preprocessing includes CLAHE, Gaussian filtering, and median filtering, with template matching employing Hellinger distance for histogram comparison. On a database of 21 individuals with three samples each, the system achieves 99.59% accuracy [25]. Utilizing a Deep Belief Network (DBN) to extract vein features from automatically generated as well as repeatedly corrected label data, the authors present an iterative DNN (deep neural network) approach for hand-vein verification. This method addresses challenges in palm vein segmentation, such as limited and inaccurate labelled data. Experiments on the PolyU Multi-spectral Palmprint Database along with the CASIA Multi-Spectral Palmprint Image Database exhibited significant accuracy improvements over baseline methods, achieving EERs of 0.33% on CASIA and 0.015% on PolyU. Iterative training allows the DBN to correct label errors and learn robust vein features, proving effective in both contact and contactless imaging environments [21].

The study investigates LBP and LBPU for palm vein biometric verification, evaluating the effect of wavelengths and parameters on performance. CASIA Multi-Spectral Palmprint Image Database V1.0 has been employed, with preprocessing involving hand segmentation, key point detection, and ROI extraction. LBP and LBPU describe palm vein texture, and $\chi 2$ distance compares features. The evaluation follows ISO/IDE 19795 guidelines. LBP slightly outperforms LBPU, with 940 nm and 630 nm wavelengths yielding the best results [26]. A multimodal biometric identification system combining palm and dorsal hand vein patterns is introduced, leveraging their uniqueness, stability, and forgery resistance. A JAI AD-080GE camera with NIR sensors captures vein patterns. Pre-processing extracts ROIs and enhances image quality. 2D Gabor filters extract features, converting vein patterns into binary matrices. Matching uses normalized Hamming distance between matrices. The multimodal system combines palm and dorsal vein scores using a SUM-rule classifier. Experiments show the multimodal system outperforms unimodal systems in EER, FAR, and FRR, achieving a 0% EER compared to 1.39% for palm veins and 1.43% for dorsal veins [27].

A novel contactless device for capturing finger and hand vein images uses NIR laser modules, LEDs, and a specialized NIR-enhanced industrial camera, creating the PLUSVein-Contactless dataset with images from 42 subjects. The dataset is challenging due to unrestricted finger/hand movement during acquisition. Image quality assessment confirmed acceptability. Baseline recognition performance, evaluated with established vein recognition schemes, showed hand veins with a 0.35% EER and finger veins with a 3.66% EER, both competitive with other technologies. Biometric fusion of finger and hand vein data improved performance to a 0.03% EER. The dataset is publicly available for research, promoting reproducibility and advancements in the field [28]. The work evaluates four local invariant feature algorithms for palm vein recognition: Harris-Laplace, ASIFT, SIFT, and MSER. PVR faces challenges from affine transformations (rotation, translation, scaling, tilting) during capture. Experiments using the CASIA-MS-PalmprintV1 database and the authors' database (350 images from 70 samples) measured performance by matching feature points and features from original and transformed images. Results indicated SIFT, ASIFT, along with Harris-Laplace extracted sufficient invariant characteristics from vein images. ASIFT, as well as Harris-Laplace, outperformed SIFT with large angle changes. MSER underperformed, often failing to extract matching points in transformed images. The study concludes that ASIFT, along with Harris-Laplace, are more effective for PVR under affine transformations, enhancing accuracy and reliability in real-world applications with variable hand positioning [29].

A novel PVR approach utilizing competitive coding with 2D log Gabor filters is introduced, involving feature extraction with four scales and six orientations and matching using Jaccard distance. Experiments on the MS-PolyU database showed a 99.50% recognition accuracy, surpassing current methods [30]. Employing palm veins along with DNN, a contact-free multi-spectral identification verification system in which utilizes ultraviolet (UV) and NIR lights are demonstrated. A dataset of 10,160 images from 1030 hands was used, achieving a TPR of 99.5 percent at the EER threshold [31]. Three prototypes for costless palm and finger vein biometric recognition using Near-Infrared (NIR) imaging are introduced, highlighting vein recognition as a promising authentication method. The prototypes include two palm vein systems and one finger vein system optimized for mobile applications. Three publicly available databases were created, including images from European subjects [32].

The authors utilize Bayesian optimization along with CNN to present a PVA model. Palm vein photos are pre-processed to draw attention to vein patterns utilizing a Jerman enhancement filter. Bayesian optimization automates CNN hyperparameter selection, including network structure and training options. CNN model, adaptable in convolutional layers, achieved 99.4 percent average identification accuracy and a 0.0683 percent EER, outperforming existing methods. Optimized CNN has three main parts with variable convolutional layers determined by Bayesian optimization. The method is robust against hand pose variations and computationally efficient, identifying an image in about 0.0076 seconds. CASIA Multi-Spectral Palmprint Image Database has been employed in experiments with 1200 left-palm vein images from 100 volunteers [33]. This study also introduces a PVR system using an attention-gated residual U-Net for segmentation as well as an ECA-ResNet for recognition. The segmentation model enhances feature learning and accuracy with attention gates and residual blocks.

The recognition model uses Efficient Channel Attention (ECA) with ResNet-50 for improved feature extraction without extra computational cost. A combined loss function, including ArcFace, focal loss, and triplet loss, is suggested to enhance inter-class diversity and intra-class compactness. The method achieves 100% recognition accuracy and a 0.018 EER for verification. The segmentation model outperforms baselines with a 96.24 IoU coefficient and a 98.09 Dice coefficient. An ablation study confirms the combined loss function's effectiveness in enhancing recognition performance. Experiments utilize the CASIA Multi-Spectral Palmprint Image Database with 1920 training along with 480 testing samples. The method addresses contactless PVR challenges, such as low contrast, optical blurring, and image rotation, offering security, reliability, and hygiene advantages over other biometrics [1].

While addressing issues that include inadequate data and the requirement for lightweight networks, a contactless multi-spectral palm-vein identification system employing a lightweight CNN with an adaptive Gabor filter along with a triplet loss function achieves a low recognition error rate of 0.0556 percent. [34]. Incorporating Multi-frame Super-Resolution (MSR) algorithms into PVR systems enhances performance and reduces costs by reconstructing high-resolution images from multiple low-quality images. A novel diffusion-driven regularization functional for MSR improves image quality, resulting in an MSR-PVR integrated system that surpasses traditional PVR systems in accuracy (99.33%), FAR (0.67%), and FRR (1.00%). This approach enables the use of lower-cost infrared cameras while maintaining high recognition performance, promoting accessibility and flexibility in PVR system design [35].

Utilizing palm-vein as well as palmprint characteristics from RGB and NIR images, this research introduces a new cross-spectral matching approach for identity verification. It extracts features from both RGB and NIR palm images, enabling verification through fusion. A Local Directional Binary Code (LDBC) improves palmprint feature discrimination. The system matches NIR probe images with RGB gallery images. Experiments on PolyU-M and CASIA-M databases show superior verification performance, excelling in EER and computational efficiency. Score-level fusion with the TERRM classifier enhances accuracy, addresses cross-spectral matching challenges, and performs well in both contact-based and contactless environments, facilitating practical applications by matching NIR probe images with existing RGB databases [36]. Utilizing the VERA, UTFVP, and R3VEIN databases, the investigation examines the implications of gender on hand vein patterns for biometric recognition. Gender recognition accuracies were high: VERA: 93.55%, UTFVP: 95.83%, R3VEIN: 89.47%. Males typically have larger vein diameters, while females have paler vein patterns due to lower haemoglobin levels. Gender-aware biometric systems improved recognition performance: VERA's EER improved from 4.37% to 4.08%, UTFVP's from 0.42% to 0.30%, and R3VEIN's from 0.64% to 0.55%. Incorporating gender-specific characteristics enhances hand vein-based biometric systems [37]. The paper also introduces Neighbourhood Matching Radon Transform (NMRT) as well as Hessian-Phase-Based Feature Extraction to enhance palm-vein identification. NMRT surpasses existing methods in contactless and constrained imaging, delivering superior performance with minimal training samples. For palm-vein template representation along with matching, the Hessian-phase-based method provides a computationally effective solution. Experiments on CASIA (contactless) and PolyU (constrained) databases showed NMRT achieving the highest rank-1 identification rates of 99%, 99.33%, and 100% with EERs of 0.32%, 0.66%, 0.002%, and 0.001%. Increasing training samples generally improved performance. The proposed methods show robustness to image deformations and rotational and translational variations, making them suitable for both contactless and constrained imaging environments [38].

We provide a multi-spectral palm vein image collection system for safe and easy biometric identification in public spaces. The SDSPCA-NPE algorithm tackles issues that include light scattering, rotation, translation, and scale variation, along with illumination variations, by combining label information, sparse constraints, and local information. Experiments on various databases resulted in low ERR [39]. The proposed method integrates the DAISY descriptor as well as the CPM algorithm in parallel matching, using sparse matching for improved efficiency. A low-cost PVR system utilizing a CMOS camera and the HDPLS feature extraction method achieves competitive EERs on self-built and CASIA databases [40]. The authors examine NIR palm vein pattern recognition using 850nm wavelength imagery, integrating ROI extraction, LBP feature extraction, and CNNs. The approach addresses limited data and image displacement issues, demonstrating satisfactory performance with low hardware requirements and minimal memory and computational costs [41].

This work introduces a wavelet denoising ResNet for contactless PVR that consists of a Squeeze-and-Excitation ResNet18 (SER) model to handle rotation and position translation, along with scale transformation difficulties and a Wavelet Denoising (WD) model to enhance low-frequency features and preserve high-frequency information. The suggested approach outperformed state-of-the-art techniques for accuracy and EER, according to experiments conducted on three databases [18]. The VERA Palm Vein database, as well as an experimental framework for PVR research, have been presented, including 2,200 images from 110 volunteers captured using a contactless infrared sensor. The database is categorized into RAW and ROI-1 datasets, and PalmveinRecLib, an open-source framework, supports reproducible benchmarks. Three experimental protocols are defined, and baseline results indicate that automatically segmented ROI-2 images outperform sensor-generated ROI-1 images [42]. The authors present a PVR algorithm utilizing Multilobe Differential Filters (MLDF) that includes ROI extraction, feature vector extraction, and image matching. ROI extraction uses Gaussian blur, the OTSU algorithm, and the radial distance function to locate palm key points. Image preprocessing enhances vein visibility with CLAHE and NLM algorithms. Principal curvature analysis is applied for vein structure extraction, treating the image as a 3D surface. Feature extraction employs MLDF with Gaussian kernels to highlight vein branch points, and NRMSE aids in feature matching, providing some translation and rotation invariance. Tested on the CASIA Multi-Spectral Palmprint Image Database, it achieved an EER of 0.01693, outperforming other methods. Future improvements could involve machine learning for MLDF selection [43].

Another enhanced Palm Vein Identification (PVI) system uses texture-based feature extraction. It extracts the ROI from palm vein images, applies Gabor filters for local feature extraction, and reduces features sequentially. An artificial neural network classifies the condensed feature vectors. PVA's high accuracy, with a FAR below 0.00008%, is due to unique vein patterns. ROI extraction involves Otsu's thresholding, inner border tracing, and key data point identification for consistent placement. Feature extraction employs 2D Gabor filters for effective texture analysis. Experimental results show a 97.5% similarity in the output confusion matrix and high regression analysis accuracy. Tested on 100 individuals, it accurately identified 92 [44]. Three phases are involved in a PVR system that utilizes an adaptive 2D Gabor filter: adaptive Gabor filtering, template matching, and ROI extraction. A new approach to ROI extraction avoids palm position errors while optimizing ROI size. The adaptive Gabor filter optimizes parameters (orientation, standard deviation, center frequency) for each sub-region of the palm vein image. Template matching employs an Minimum Normalized Hamming Distance (MNHD) algorithm to correct displacement errors. This method achieved an EER of 0.12% on the CASIA-MS-PalmprintV1 database, outperforming existing techniques in accuracy and computational efficiency. The optimal ROI size of 256x256 pixels, divided into 8x8 sub-regions, was used for adaptive Gabor filtering. The investigation underscores the value of ROI selection as well as adaptive parameter optimization in rising PVR performance [45].

A PVR system combining Binarized Statistical Image Features (BSIF) on sub-regions and a CNN on whole images utilizing decision-level fusion is presented. BSIF extracts texture features from sub-regions, with scores fused through score-level fusion. CNN model is based on AlexNet architecture. The final decision merges BSIF and CNN results using a weighted OR rule. Tests on multiple databases showed high accuracy, surpassing several state-of-the-art techniques and demonstrating comparable performance to some multimodal systems [46]. A new PVR method using HDR (high dynamic range) imaging has been introduced. Multiple-exposure vein images are combined to create an HDR vein pattern representation. Tone-mapped HDR, raw HDR, and single-exposure images are employed to extract LBP as well as Local Derivative Pattern (LDP) features. The study utilized a dataset of 86 subjects, each contributing 12 palm samples captured at five different exposures. Various Tone Mapping Operators (TMOs) were tested, with Chiu and Shibata TMOs yielding the best results. The HDR approach outperformed single-exposure imaging, score-level fusion of multiple exposures, and various image enhancement techniques applied to single-exposure images [47].

A new PVR approach utilizing the curvelet transform is proposed to extract curve-like features and offer sparse representations. The system includes preprocessing, feature extraction via discrete curvelet transform, and matching using Scale 1 coefficients for low-level matching and Thresholded Scale 2 and 3 coefficients with Hamming distance. Experiments on the Hong Kong PolyU multi-spectral palmprint database show an EER of 0.66% using 40% of curvelet coefficients, achieving competitive results with a template size of around 900 bytes [48]. Enhanced Center-Symmetric Local Binary Pattern (ECS-LBP) and SIFT are combined in a new palm vein feature extraction technique called EL-SIFT. The technique entails obtaining SIFT features after utilizing ECS-LBP to identify stable palm vein lines. Vein texture detection is improved by ECS-LBP, a modified CS-LBP that calculates feature values from blocks rather than isolated spots. Tested on CASIA Multi-spectral Palm vein Image Database V1.0, EL-SIFT showed improved accuracy over LBP, CS-LBP-SIFT, and Gabor-SIFT. For the left-hand database, EL-SIFT achieved a 3.12% EER as well as a 96.33% RR, outperforming other methods. For the right-hand database, it achieved a 3.25% EER and a 95% RR [49].

The work explores PVR using LBP along with LDP with optimized parameters. Applying uniform LBP (16,7) to 16 59x59 pixel sub-images was the optimal LBP, and applying third-order LDP at scale 6 in the 0°, 45°, 90°, as well as 135° directions to 16 sub-images was the optimal LDP. Custom mapping reduced the dimensionality of LBP and LDP descriptors with minimal performance loss. LDP outperformed LBP in identification and verification tasks on the CASIA palm vein database. Fusion of LBP and LDP scores did not significantly enhance performance over LDP alone. The minimum Half Total Error Rate (HTER) was 3.24% for LDP and 6.67% for LBP [50]. The work proposes Wavelet Locality-Preserving Projections (WLPP) for global features and Local Binary Pattern Variance-Locality Preserving Projections (LBPV-LPP) for local features in PVR. The system enhances images using a matching filter, extracts feature using Wavelet, LBPV, and LPP and perform verification using nearest neighbor matching with Euclidean distance and a weighted sum fusion rule. Experiments on the PolyU multi-spectral palmprint database attain an EER of 0.1378% [51]. Palm RCNN, a Deep Convolutional Neural Network (DCNN) as per a modified Inception_ResNet_v1 architecture, is suggested for palmprint and PVR. A new contactless palm vein image acquisition device was developed, producing a dataset of 12,000 images. PalmRCNN uses an SVM classifier for identification and Euclidean distance for verification, demonstrating superior performance on benchmark datasets [52]. Using RGB images, the method emphasizes vein information in the red channel. Techniques for improving images encompass image differencing, gamma correction, as well as Red-Stretched-RGB (RSRGB). Vein line detection employs a Simplified Gabor Filter (SGF), binarization, and noise removal. Feature matching is performed using Hamming distance between binary vein templates. The possibility of employing RGB images for PVR was demonstrated by experiments conducted on the PolyU-M database, which produced an EER of 0.87% [53].

The work proposes using Gabor-Positional Weber's Law Descriptor (GPWLD) and a DNN optimized via Bayesian methods. GPWLD integrates Gabor filters with Weber's Law Descriptor to capture rotation and spatial data from palm vein images. A Stacked Autoencoder (SAE) with Bayesian optimization refines the DNN's structure and hyperparameters. Tests on the PolyU and CASIA palm vein databases showed high RRs: PolyU achieved 99.73% CRR and 0.0029 EER, while CASIA reached 98.67% CRR and 0.24 EER. GPWLD outperformed WLD, Gabor+WLD, and PWLD in recognition. Bayesian optimization effectively identified the best DNN structures and hyperparameters, surpassing manual selection. The method proved robust against illumination, hand pose, and scale variations, especially for contactless PVR. Combining manually crafted features (GPWLD) with deep learning (optimized SAE) enhanced recognition [54].

The paper suggests a new approach for palm-vein verification using RGB images, specifically red and blue channels, differing from conventional Near-Infrared (NIR) methods. It uses a difference image projection technique to extract multi-direction along with multiscale palm-vein line characteristics, with feature matching via a fast-hamming distance implementation as per vector product operations. The proposed method shows superior performance compared to both NIR-based and RGB-based competing methods in terms of EER. Investigation on PolyU-M (contact-based) as well as CASIA-M (contact-free) databases showed an EER of 0.54% on PolyU-M and 8.35% on CASIA-M, outperforming other methods [55]. The work presents a pose-invariant contactless PVI system utilizing CNNs, addressing challenges such as pose variations and matching speed. Key components include data augmentation to simulate hand rotation, a new fast ROI extraction algorithm, and a specific CNN structure for feature extraction and classification. Tested on the PolyU and CASIA databases, synthetic datasets simulated out-of-plane rotations. The system achieved high accuracy: 99.73% ± 0.27 on PolyU and 98% ± 1 on CASIA, demonstrating robustness to translation, scaling, and out-of-plane rotation variations. Identification is rapid, taking about 0.01 seconds per palm. This approach, combining a fast ROI algorithm with CNN, is reported as the first use of CNN for contactless PVR and the first synthetic simulation for such scenarios [56].

The reliability of palm security biometric systems in challenging industrial conditions was investigated using a Fujitsu PalmSecure reader and a Fujitsu Lifebook laptop with an integrated palm scanner. Fifty participants were tested in both office and outdoor settings, with hands contaminated by water, dust, oil, and writing materials. Viscous fluids and dust significantly impaired system reliability, with clay and oil reducing reliability by nearly 30% and 26%, respectively. Other adverse conditions decreased reliability by up to 10%. The system performed better indoors than outdoors, with normal conditions reducing reliability by 2.12% indoors and 1.52% outdoors. Alternative biometric methods and enhancements for non-standard and outdoor environments are recommended [57].

A single-sensor multimodal hand-vein biometric detection technique that extracts four finger-vein along with palm-vein ROIs from a single hand-vein image is presented in this paper. The ROIs are converted into feature representations via CS-LBP, and a hierarchical non-rigid method modelled after DCNN has been employed to match the feature representations. Score-level fusion depends on the weighted sum rule that integrates finger-vein and palm-vein scores. Experiments on an in-house database and the CASIA dataset demonstrated the method's superiority over existing techniques, with a fusion of palm-vein along with finger-vein information enhancing performance compared to using palm-vein alone, surpassing approaches using features from palm-vein images [19].

The paper proposes a hybrid algorithm combining CNN and principal curvatures for palm vein image segmentation. Preprocessing involves ROI extraction along with enhancement. Vein structure extraction utilizes principal curvatures and an unsupervised W-Net CNN autoencoder.

Final segmentation results from intersecting both approaches were assessed using MLDF for feature extraction and normalized root-mean-square error for feature map matching. Experiments with the CASIA Multi-Spectral Palmprint Image Database demonstrate superior performance compared to using principal curvatures or CNN alone, evaluated using FAR, FRR, and EER metrics. This method tackles challenges in unsupervised image segmentation for PVR [58]. The state of the art in terms of databases, techniques, and outcomes is compiled in Table 1.

Table 1. State of the art of palm vein recognition

No.	Algorithm / Method	Database Used	Results
1	Recursive Algorithm based on Positive Linear Dynamical System	PolyU and CASIA	EER: 2.341×10^{-5} (PolyU), 1.081×10^{-3} (CASIA)
2	2-D Gabor Filter + Vein Codes	Database of 4140 images from 207 people	Recognition Rate: 99.18%, EER: 0.46%, Execution Time: <0.6 seconds
3	MODABC Algorithm	CASIA Multi-Spectral Palmprint Database	Authentication Rate: 97.61%; Outperformed DPSO, GA, DABC, and others
4	Adversarial Masking Contrastive Learning (AMCL)	Three Public Palm Vein Datasets	State-of-the-art recognition performance
5	Iterative Deep Neural Network (DBN)	CASIA and PolyU Multi-Spectral Databases	EER: 0.33% (CASIA), 0.015% (PolyU)
6	LBP and LBPU	CASIA Multi-Spectral Database V1.0	Optimal Wavelengths: 940 nm, 630 nm
7	Multimodal System (Palm + Dorsal Vein Patterns)	Custom Dataset	EER: 0% (Multimodal), 1.39% (Palm Vein), 1.43% (Dorsal Vein)
8	Contactless Device + PLUSVein Dataset	PLUSVein Dataset (42 subjects)	EER: 0.35% (Hand Vein), 3.66% (Finger Vein), 0.03% (Fusion)
9	Competitive Coding + 2D Log Gabor Filters	MS-PolyU	Accuracy: 99.5%
10	Contact-Free Multi-spectral System	A dataset of 10,160 images	TPR: 99.5% at EER Threshold
11	Attention-Gated U-Net + ECA-ResNet	CASIA Multi-Spectral Database	Accuracy: 100%, EER: 0.018%
12	CNN with Bayesian Optimization	CASIA Multi-Spectral Database	Identification Accuracy: 99.4%, EER: 0.0683%, Avg. Time: 0.0076 seconds per image
13	Wavelet Denoising ResNet	Three Public Databases	Superior accuracy and EER performance
14	Adaptive 2D Gabor Filter	CASIA-MS-PalmprintV1	EER: 0.12%, Enhanced accuracy and computational efficiency
15	High Dynamic Range (HDR) Imaging	A dataset of 86 subjects	Superior to single-exposure imaging and other enhancement techniques
16	EL-SIFT (Enhanced LBP + SIFT)	CASIA Multi-Spectral Database	EER: 3.12% (Left-Hand), 3.25% (Right-Hand), Recognition Rate: >95%
17	Wavelet Locality Preserving Projections	PolyU	EER: 0.1378%
18	PalmRCNN (Modified Inception_ResNet_v1)	Custom Dataset (12,000 images)	Superior performance on benchmark datasets
19	Hybrid Algorithm (CNN + Principal Curvatures)	CASIA Multi-Spectral Database	Outperformed individual approaches, tackling segmentation challenges

4. Discussion

Palm vein biometrics is an emerging field of biometric authentication that leverages the new vascular patterns beneath the surface of the skin. The utilization of NIR imaging provides a contactless and hygienic approach, making it particularly appealing for applications requiring high security and user comfort. This modality offers distinct advantages, including stability of vein patterns over time, resistance to forgery, and non-invasiveness.

4.1. Challenges and Limitations

Palm vein biometrics shows promise but faces practical challenges: significant computational complexity and storage requirements for templates necessitate efficient processing, especially in resource-limited systems [59]. Privacy and security of sensitive biometric data are critical [3, 59]. Despite high security and liveness detection, image acquisition issues like uneven illumination and difficulty in extracting regions of interest in contact-free imaging can impair accuracy [60]. Variability in hand positioning during capture requires robust feature extraction and matching techniques [61, 62]. Thus, while palm vein biometrics is promising in accuracy and security, addressing computational efficiency, privacy, and image quality is essential for broader adoption. Future research should focus on effective algorithms for feature extraction as well as matching improving image acquisition methods to enhance reliability [59, 5]. Infrared imaging in PVR is sensitive to ambient light, requiring controlled environments. Proper hand positioning is crucial, as misalignments or rotations can degrade accuracy. Variations in palm vein visibility due to temperature, hydration, health conditions, or occlusions like jewellery or scars may affect performance. Large-scale deployment can be computationally intensive, particularly for high-dimensional vein templates, and ensuring fast, accurate matching in real-time systems is challenging. Different skin tones and textures can affect infrared absorption and reflection, impacting image quality. Humidity and temperature also impact vein visibility and imaging quality. Vein patterns may change over time due to ageing, health, or injuries, leading to template mismatches.

Although difficult, creating a fake palm vein image or template is not impossible, making the security of stored biometric templates a significant challenge. Infrared imaging devices are more expensive than cameras used in other biometrics, requiring regular calibration and maintenance for consistent performance.

Public and healthcare settings may be deterred, and some users may be unwilling to use biometric systems by virtue of physical contact with scanners or due to privacy, cultural, moral or religious concerns. With suboptimal imaging conditions, feature extraction from infrared images can be difficult because of low contrast. The extracted vein pattern's accuracy has been impacted by noise in infrared imaging. Computational demands of accurate vein pattern extraction are prohibitive and require robust algorithms. Recognition errors can also be produced from intraclass variations and interclass similarities.

4.2. Ethical Considerations

Like all biometric technologies, it elevates several ethical consequences that must be fixed for the technology to be used fairly, transparently, and responsibly. Key ethical aspects include:

4.2.1. Privacy Concerns

- Data Collection and Consent: However, palm vein data collection requires explicit and informed consent from users. The data is very sensitive because it uniquely identifies individuals.
- Data Minimization: The data required for their intended purpose should be collected by systems, and over-collection should be avoided.
- Surveillance Risks: The widespread adoption of biometrics could lead to misuse in mass surveillance, undermining individual privacy [62].

4.2.2. Data Security

- Storage and Encryption: Palm vein patterns must be stored securely using encryption to prevent unauthorized access or breaches.
- Template Security: Techniques like cancelable biometrics or homomorphic encryption can help ensure that stolen templates cannot be reversed to reconstruct the original data.
- Data Sharing: Ethical concerns arise if biometric data is shared across organizations without user consent [63].

4.2.3. Bias and Fairness

- Algorithmic Bias: Recognition systems may perform differently across demographic groups (e.g., age, gender, or ethnicity). Developers must test for and mitigate such biases to ensure fairness.
- Inclusivity: Palm vein biometrics should be designed to accommodate individuals with varying physiological conditions, such as poor vein visibility [64].

4.2.4. Autonomy and Consent

- User Control: Individuals should have control over how their biometric data is used, including the ability to withdraw consent and delete their data.
- Transparency: Users need to be aware of the ways in which their data is processed, stored, and shared [65].

4.2.5. Misuse and Abuse

- Identity Theft: Although difficult to forge, stolen templates could potentially be used for identity theft if not properly secured.
- Coercion: Individuals could be forced to offer their biometric data under duress, particularly in sensitive applications like financial transactions [66].
- Function Creep: Biometric data gathered for one purpose (e.g., workplace attendance) might be repurposed for another without consent.

4.2.6. Legal and Regulatory Compliance

- Data Protection Laws: Systems must comply with data protection laws such as General Data Protection Regulation (GDPR) or California Consumer Privacy Act (CCPA).
- Auditability: Systems should be auditable to assure compliance with ethical standards along with regulations [67].

4.2.7. Accessibility and Equity

- Cost Barriers: The high cost of PVR systems could limit access, creating inequity between organizations or regions with varying resources.
- Technological Access: Ensuring widespread availability of the technology is necessary to prevent systemic exclusion.

4.2.8. Psychological and Social Implications

- User Acceptance: Some individuals may feel uneasy about the use of biometrics due to a perceived invasion of bodily autonomy.
- Social Trust: Over-reliance on biometrics could lead to reduced trust if systems fail or are misused [68].

Addressing these ethical considerations requires a collaborative effort from policymakers, researchers, and developers. Transparency, user education, robust legal frameworks, and technological safeguards are essential for building trust and ensuring the responsible deployment of palm vein biometrics.

4.3. Future Trends

The development of palm vein biometrics is driven by advancements in hardware, algorithms, and application demands. Below are key future directions:

4.2.1. Improving Image Acquisition

- Non-Contact Systems: Transition to contactless imaging for hygienic, user-friendly, and robust acquisition systems.
- Miniaturized Sensors: Development of compact, portable infrared sensors for widespread use in mobile and wearable devices.
- Enhanced Infrared Imaging: Incorporating adaptive techniques for high-quality vein imaging under varying environmental conditions.

4.2.2. Advanced Feature Extraction Techniques

- Deep Learning Models: Leveraging CNNs and transformer-based models to extract robust and discriminative features.
- 3D Vein Imaging: Developing three-dimensional PVR systems to capture richer spatial vein data for improved accuracy.
- Multimodal Feature Fusion: Combining vein features with other biometric modalities like fingerprints or palm prints to enhance recognition performance.

4.2.3. Enhanced Matching Algorithms

- Siamese and Triplet Networks: Improved matching using deep neural networks that learn feature similarity directly.
- Explainable AI (XAI): Integrating interpretable AI techniques to increase transparency and trust in PVR systems.

4.2.4. Template Security and Privacy

- Cancelable Biometrics: Developing methods to create non-invertible templates to prevent template misuse.
- Homomorphic Encryption: Implementing encrypted operations for secure template storage and matching without decryption.
- Federated Learning: Enabling decentralized learning systems to train models on private data without sharing sensitive information.

4.2.5. Scalability and Real-Time Systems

- Edge Computing: Using lightweight algorithms optimized for real-time recognition on edge devices like smartphones.
- Cloud Integration: Developing scalable, cloud-based systems to handle large-scale deployments with high-speed processing.

4.2.6. Multi-Spectral and Multimodal Biometrics

- Multi-Spectral Imaging: Combining near-infrared with visible and thermal imaging for more robust vein pattern recognition.
- Multimodal Systems: Combining palm vein biometrics with other modalities, for example, iris, face, or gait, to improve accuracy and reduce spoofing risks.

4.2.7. Application-Specific Innovations

- Mobile Integration: Adapting PVR for mobile platforms for payments, authentication, and personal identification.
- Healthcare Applications: Extending its use for medical purposes, such as detecting vascular diseases or verifying patient identities.
- Blockchain for Biometric Data: Leveraging blockchain to ensure secure, decentralized storage of biometric templates.

4.2.8. Standardization and Interoperability

- Open Standards: Developing international standards for data formats, acquisition protocols, and evaluation metrics to enhance interoperability.
- Benchmark Datasets: Creating large, publicly available datasets for benchmarking and fostering innovation.

5. Conclusion

The development of palm vein biometrics as an extremely reliable, secure, personal authentication technology has arisen from the use of the surface. This modality has high accuracy, robustness to environmental factors, and resistance to forgery and thus offers an attractive alternative to conventional biometric systems, for example, fingerprint, face or iris recognition. Near-Infrared (NIR) imaging makes non-contact and hygienic data acquisition even more appropriate in fields with high-security standards, such as financial transactions, healthcare, and border control. In this review, the PVR systems have been explored in relation to key components such as imaging techniques, preprocessing methods, and feature extraction algorithms. Robust and discriminative features from palm vein patterns have been extracted using techniques such as adaptive Gabor philtres, LBP and DL-based models. Further, we have improved system accuracy and speed by adding classification and matching algorithms such as CNNs, Siamese networks, and statistical methods. In addition, multimodal biometrics and multi-spectral imaging have shown promise in combining palm vein data with other biometric traits to yield superior performance.

Palm vein biometrics has its challenges, however. To obtain robust and consistent performance, issues of variability in hand positioning, environmental sensitivity and ageing effect on vein patterns need to be addressed. However, there still exist problems of computational complexity, especially in large-scale deployments and secure template storage. Furthermore, in resource-limited environments, specialized

NIR imaging hardware may be prohibitively expensive. These challenges have future research directions that offer promising solutions. They also outline how deep learning models, such as transformers and attention-based mechanisms, can be integrated to further improve the feature extraction and recognition accuracy. Scalability and real-time application opportunities are available through contactless, mobile-compatible systems with edge computing and cloud integration. Security concerns, as well as the need to protect sensitive data, require privacy-preserving techniques such as homomorphic encryption, federated learning, and cancellable biometrics. Palm vein biometrics concludes as a revolutionary biometric authentication modality with a high degree of technology and real-world applicability. PVR systems can overcome current limitations and converge to innovative strategies to realize a future of secure, efficient and user-friendly biometric solutions.

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