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Project Report

Secure Identification Through Vein Recognition: A Study of Biometric Advancements

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Abstract

This paper explores the use of vein recognition as a secure biometric method for personal identification. A vein pattern is the network of blood vessels under the skin; the shape of vascular patterns in the same part of the body is believed to be distinct from one individual to another and remains very stable over a long period of time. Additionally, vein patterns are significantly more difficult for intruders to copy compared to other biometric features. These properties of uniqueness, stability, and strong immunity to forgery make vein recognition a promising and reliable method for identity verification. This paper discusses the different types of vein recognition systems, including palm vein, finger vein, and retina vein pattern recognition. It explains how vein recognition functions generally, the technologies used in the system, and briefly outlines how each type operates.

Moreover, the paper highlights the key advantages of vein recognition, such as high accuracy, high privacy, reliability, and its contactless and Hygienic nature, which enhances user comfort. However, like any biometric system it also faces challenges including high costs due to advanced technology and hardware required, environmental factors, and user acceptance. Various real-world applications of vein recognition are also presented. Furthermore, the paper compares vein recognition to other biometric techniques like fingerprint and facial recognition, emphasizing where it performs better in terms of security and privacy.

Recent developments in finger vein recognition have focused on improving both accuracy and security through the use of deep learning methods, detecting spoof attacks, and integration of finger vein recognition with other biometric systems. Studies have explored how to enhance image quality, extract features more effectively, and protect against fake inputs using both software and hardware solutions. These advancements significantly increase the reliability and adaptability of the technology in real-world scenarios.

Finally, the paper explores future trends and potential opportunities for expanding the use of vein recognition technology in both public and private sectors. The report concludes with an overview of the current state of vein recognition technology, its strength in biometric security, the challenges it continues to face, and its potential future applications in real-world authentication systems.

Chapter 1: Introduction

The ability of an individual to identify himself is very important in our lives. Humans often use body features such as face, voice and even smell, along with other contextual information such as location and clothing. These features associated with a person form his personal identity. In the past, this was not considered highly important, as individuals typically lived in small communities where they could easily recognize one another. However, due to population growth and continuous development, it became necessary to develop identity management systems that record and preserve the identity of individuals.[1]

The need to verify the identity of individuals is increasing in our current digital world. Biometric technologies have emerged as one of the most reliable solutions for identity verification. These systems are automated technologies used to verify or identify an individual based on their unique physiological or behavioral characteristics, such as fingerprints, iris patterns, or vein structures. Unlike traditional identity verification methods, such as passwords or ID cards, biometrics offer a more secure and reliable approach by identifying individuals based on who they are, rather than what they possess or what they remember. Biometric systems play a crucial role in modern identity management, especially in high-security applications like online banking, airport security, and restricted area access. Additionally, biometrics can enhance security through dual-factor authentication, where biometrics supplement other methods like passwords or ID cards to provide an extra layer of protection.[2]

Vein recognition, also known as vascular biometry, is a technique for measuring parts of a person's circulatory system that are unique to the individual. This technique uses scanning to capture images of the veins in the palm of the hand, finger, or eyeball.[3]

We chose the topic of vein recognition because it is one of the newest and least common biometric methods, so we wanted to explore this unique technology to increase knowledge about security technologies. This topic aligned with our research focus on advanced authentication systems, providing a novel and academically pertinent perspective within the course framework.

Real-world adoption of vein recognition technology spans various fields. This report presents brief examples of its use in key sectors such as banking and finance, healthcare, and government and public services, which are outlined in the relevant section.

Chapter 2: Research plan

2.1 Exploring vein recognition technology.

Vein recognition is an emerging biometric technology that uses the distinct vascular patterns located beneath the skin for the purpose of identification and authentication. This method is gaining attention due to its high accuracy, security, and resistance to forgery. Unlike external biometrics such as fingerprints or facial features, vein patterns are internal and thus much harder to steal or replicate. According to Wang, Zhang, and Yang (2018), vein structures remain stable over time and are largely unaffected by surface-level injuries, making them a reliable biometric trait. The principle behind vein recognition lies in near-infrared (NIR) imaging. When NIR light is applied to the skin, the hemoglobin in the blood absorbs the light, making veins appear as dark patterns that can be captured by specialized sensors. Miura, Nagasaka, and Miyatake (2007) demonstrated the effectiveness of this technique in palm vein recognition, achieving high accuracy and robustness against spoofing attacks. Moreover, since veins are not visible to the human eye, vein recognition offers improved privacy and protection against data theft compared to visible biometrics. This technology has become even more relevant in the context of contactless biometric systems, especially after the COVID-19 pandemic, where hygiene and non-contact solutions are prioritized. Palm and finger vein recognition have already been implemented in banking systems, hospital access control, and personal device authentication in countries like Japan and South Korea (Kim et al., 2020).

The objective of this research is to explore the underlying scientific principles of vein recognition technology, its implementation, and its growing role in security applications. This foundational understanding will set the stage for further analysis of system design, comparative advantages, and potential challenges facing vein-based biometrics. [4,5,6]

2.2 Previous studies on vein recognition

This research will begin by reviewing previous studies on vein recognition in order to understand the current state of the field, identify existing challenges, and highlight areas for future development. Vein recognition, as a biometric technique, has attracted growing interest due to its high security, non-invasiveness, and resistance to forgery. Previous works, such as the comprehensive survey conducted by Wang and Liu (2019), have categorized various methods based on vein image acquisition, preprocessing, feature extraction, and matching techniques. These studies provide a foundation for evaluating the strengths and limitations of current systems and for exploring how modern technologies—such as deep learning—can enhance recognition accuracy and robustness. Through this literature review, the study aims to build a clear understanding of how vein recognition compares to other biometric methods and what improvements can be made using emerging tools like artificial intelligence.[7]

2.3 How vein recognition works

Vein recognition is a biometric authentication method that relies on the unique patterns of blood vessels (veins) beneath the skin surface, typically in the finger or palm. The uniqueness, stability, and internal location of vein patterns make them highly secure and difficult to forge.

1. **Imaging and Acquisition:**
   Vein recognition systems use near-infrared (NIR) light to capture subcutaneous vein patterns. Hemoglobin in the blood absorbs NIR, causing veins to appear darker than surrounding tissues. Devices include contact-based or contactless sensors, often using LEDs and CCD/CMOS cameras. According to Zhang & Lu (2020), NIR imaging is widely adopted due to its efficiency in visualizing finger-vein patterns in a non-invasive way.[8]

2. **Preprocessing**
   Steps include image enhancement, ROI (Region of Interest) extraction, normalization, and noise reduction. These steps ensure consistent and high-quality input for feature extraction, regardless of variations in finger position or lighting.[8]

3. **Feature Extraction**
   Traditional methods use texture-based, line-based, or statistical features. Recent advances adopt deep learning, especially CNNs (Convolutional Neural Networks), to automatically learn high-level vein features from raw or preprocessed images.[8]

4. **Matching and Classification**
   Extracted features are compared to stored templates using distance metrics (e.g., Euclidean distance) or similarity functions. A match score is calculated; if it exceeds a threshold, the identity is confirmed.

5. **System Performance and Challenges**
   Factors like poor vein visibility, low image quality, or finger misplacement can affect accuracy. Zhou & Kumar (2012) emphasized the importance of robust preprocessing and multi-instance fusion (e.g., using more than one finger) to improve identification reliability. [9,10]

2.4 Applications and advantages of vein recognition

The research will analyze how vein-based biometrics are being deployed in high-security and consumer environments—such as access control systems, ATM and mobile banking authentication, e-passport issuance, healthcare record protection, and forensic identification—and will highlight their core advantages:

- **Internal, Inviolable Patterns:**
  Unlike fingerprints or faces, vein patterns lie beneath the skin and cannot be easily forged or lifted from surfaces, providing a level of security that is inherently tamper-resistant (Ding et al., 2005).

- **Contactless and Hygienic Capture:**
  Infrared imaging enables non-contact acquisition of vein patterns, reducing hygiene concerns and improving user comfort in public or medical settings (Wang et al., 2008).

- **High Stability and Uniqueness:**
  Vein networks are stable over a person's lifetime and sufficiently unique—even in small feature sets (≈13 minutiae points per hand)—to achieve extremely low error rates (0% EER in Wang et al.'s study) when matched via robust techniques like the modified Hausdorff distance (Wang et al., 2008).

- **Robustness to Environmental Variations:**
  Deep-analysis and preprocessing methods (e.g., threshold segmentation, skeletonization) make vein recognition resilient to noise, lighting changes, and minor misalignments, ensuring consistent performance across diverse conditions (Ding et al., 2005; Wang et al., 2008).

2.5 Comparison between vein recognition and other biometrics

Biometric recognition technologies have become pivotal in enhancing security and authentication systems worldwide. Common biometric modalities include fingerprint recognition, facial recognition, iris scanning, and vein recognition. Among these, vein recognition has emerged as a promising alternative due to its unique advantages in terms of security, usability, and robustness.

1. **Security and Spoof Resistance**
   Vein recognition utilizes the unique patterns of blood vessels beneath the skin surface, typically captured using near-infrared (NIR) imaging. Unlike fingerprints or facial features

that are visible externally and more susceptible to forgery, vein patterns are internal, making them significantly more difficult to spoof or replicate (Ding et al., 2005). Fingerprint scanners, while widespread, have faced vulnerabilities through lifted prints and artificial replicas (Jain et al., 2004). Similarly, facial recognition systems can be deceived by high-resolution photographs or 3D masks (Galbally et al., 2014). The internal nature of vein patterns provides vein recognition with a heightened security level.

2. **Hygiene and User Convenience**

   Vein recognition systems are contactless, capturing images of the hand or finger vein patterns without physical touch (Wang et al., 2008). This non-intrusive property is particularly advantageous in environments demanding high hygiene standards, such as hospitals and public facilities. Conversely, fingerprint scanners require direct contact, raising concerns about contamination and wear on the sensor surface (Jain et al., 2004).

3. **Stability and Permanence**

   The vascular structure of individuals is stable over time, and the patterns do not significantly change with age or external conditions (Ding et al., 2005). This permanence contrasts with facial recognition, which can be affected by aging, facial hair, or makeup (Galbally et al., 2014), and with fingerprint recognition, which can be compromised by skin injuries or wear (Jain et al., 2004). Iris recognition also offers high stability but requires precise positioning and cooperation from users.

4. **Environmental Robustness**

   Vein recognition systems operate effectively under varying lighting conditions due to their reliance on NIR imaging, which penetrates the skin and highlights vascular patterns (Wang et al., 2008). In contrast, facial recognition can suffer from poor performance in low light or with occlusions (Galbally et al., 2014). Fingerprint scanners may also experience reduced accuracy due to dirt, moisture, or sensor degradation.

5. **Limitation**

   Despite these advantages, vein recognition systems can be more expensive and require specialized hardware, limiting their widespread adoption compared to fingerprint and facial recognition (Ding et al., 2005). Additionally, physiological conditions such as poor blood circulation or injuries can affect vein pattern visibility. Conclusion Vein recognition presents several significant advantages over traditional biometric modalities, including enhanced security due to internal pattern uniqueness, hygiene benefits from contactless acquisition, and robustness against environmental and temporal variations. However, cost and hardware requirements currently restrict its broader deployment. As technology advances and prices decrease, vein recognition is poised to become a more common biometric authentication method in security-sensitive applications. [11,12,13,14]

2.6 Challenges and future improvements for vein recognition.

Finger vein recognition technology has shown promising potential as a secure and reliable biometric modality. However, several challenges remain that hinder its widespread deployment and optimal performance. This section summarizes the key challenges identified in recent literature and outlines possible future improvements.

2.6.1 Challenges

1. Limited Datasets

One major challenge is the scarcity of large-scale, diverse datasets needed to effectively train and evaluate deep learning models. Current publicly available datasets often lack sufficient variations in finger positioning, rotation, displacement, and sensor types, limiting the robustness and generalization capability of recognition systems.

2. Image Quality Issues

Image acquisition is frequently affected by varying illumination conditions, user behavior, physiological factors, and environmental temperature. These factors contribute to poor-quality vein images exhibiting irregular shading, optical blurring, and noise, which can cause the extraction of false features or missing critical vein patterns, ultimately reducing recognition accuracy.

3. Deep Learning Model Limitations

Although deep learning has significantly advanced finger vein recognition, challenges remain, including overfitting due to relatively small datasets, high computational and memory demands, and a lack of model interpretability. Additionally, preprocessing steps struggle to fully compensate for rotation and displacement variations in input images. Designing unsupervised or weakly supervised restoration models also remains an open problem.

4. Generalization

Existing models often fail to generalize well to unseen data captured under different conditions or by alternative sensors, which impairs system reliability in real-world scenarios.

5. Presentation Attack Detection (PAD) Challenges

Presentation attacks pose a serious security threat. However, PAD methods for finger vein systems face several limitations:

- The availability of spoofing datasets is limited, restricting the development and evaluation of effective PAD algorithms.
- Traditional PAD approaches based on handcrafted features tend to lack generalization, while deep learning-based PAD methods require further development to improve adaptability and scalability.
- Integrating PAD with recognition modules must be carefully managed to avoid increasing false rejection rates.
- Many PAD methods, despite their robustness in controlled environments, lack practical usability in real-world applications.

6. Multimodal Biometric System Challenges

Combining finger vein recognition with other biometric modalities introduces additional complexities:

- Robust feature extraction is complicated by variations in rotation, scale, and sensor differences.
- There is limited research on template protection and cancelable biometrics in multimodal fusion systems.
- Hybrid fusion approaches often demand high computational resources, highlighting the need for lightweight, efficient fusion techniques.

2.6.2 Future Improvements

1. Better Datasets

Developing large-scale, comprehensive datasets with diverse acquisition conditions, including varied finger positions, sensor types, and environmental settings, is essential to advance model training and validation.

2. Advanced Deep Learning Models

Future research should focus on memory-efficient architectures, improved loss functions, and enhancing the interpretability of deep models to better handle the complexities of finger vein patterns.

3. Enhanced PAD Methods

The development of generalized deep learning-based PAD techniques is necessary, along with seamless integration of PAD and recognition systems to optimize overall security without compromising user convenience.

4. Multimodal Fusion Optimization

Research should explore more efficient feature-level and hybrid fusion strategies, and investigate cancelable biometric methods to secure biometric templates within multimodal systems.

5. Real-World Applicability

Greater emphasis must be placed on balancing robustness and usability in both PAD and recognition frameworks to facilitate real-world deployment and user acceptance. Conclusion Finger vein recognition holds significant promise as a secure biometric modality. Nonetheless, challenges such as limited datasets, image quality issues, deep learning constraints, PAD vulnerabilities, and multimodal fusion difficulties need to be addressed. Future research focused on advanced datasets, improved model architectures, enhanced anti-spoofing mechanisms, and practical system design will be critical for the advancement and real-world applicability of vein-based biometric systems.

2.6.3 Conclusion

Finger vein recognition holds significant promise as a secure biometric modality. Nonetheless, challenges such as limited datasets, image quality issues, deep learning constraints, PAD vulnerabilities, and multimodal fusion difficulties need to be addressed. Future research focused on advanced datasets, improved model architectures, enhanced anti-spoofing mechanisms, and practical system design will be critical for the advancement and real-world applicability of vein-based biometric systems. [84,85,86,87,88,89]

Chapter 3: Literature review

3.1 Review of academic papers

Vein recognition has emerged as a promising biometric identification technique due to its high accuracy, resistance to forgery, and internal physiological basis. Unlike external biometrics such as fingerprints or facial features, vein patterns lie beneath the skin, making them difficult to replicate or alter. A significant body of research has explored various aspects of this technology, including image acquisition methods, pattern extraction techniques, and classification algorithms.

Miura et al. (2004) were among the first to propose a method for finger vein authentication using repeated line tracking, which laid the foundation for subsequent studies in this area. Their results demonstrated a low false acceptance rate (FAR) and false rejection rate (FRR), proving the feasibility of vein-based identification systems. Building on this, Wang et al. (2008) introduced a robust finger vein recognition system using modified Hausdorff distance and binary pattern matching. This approach enhanced recognition accuracy and processing speed.

Later studies expanded the scope of vein recognition to other body parts, such as the palm and dorsal hand veins. Zhang et al. (2010) developed a palm vein recognition system that utilized a near-infrared (NIR) imaging technique and applied 2D Gabor filters for feature extraction. Their system achieved a recognition rate of over 98%, confirming the effectiveness of NIR-based imaging for capturing subcutaneous vein patterns. Additionally, Kumar and Prathyusha (2009) explored dorsal hand vein authentication using texture-based features, showing promising results in terms of both security and user convenience.

More recent work has incorporated deep learning techniques into vein recognition systems. Yang et al. (2019) proposed a convolutional neural network (CNN)-based approach for finger vein recognition, demonstrating improved performance in terms of feature representation and generalization to different datasets. Their study emphasized the potential of combining classical image processing with modern machine learning to improve biometric authentication systems.

Overall, the existing literature confirms that vein recognition is a reliable and secure biometric modality with a growing body of evidence supporting its application in real world systems. These findings continue to inspire further research into improving imaging techniques, feature extraction algorithms, and classification methods for enhanced performance. [15,16,17,18,19]

3.2 Types of vein recognition

Vein pattern recognition is an emerging subfield of biometric identification that leverages the unique patterns of blood vessels beneath the skin. Multiple anatomical sites have been investigated for vein-based authentication, each offering distinct advantages in terms of accuracy, usability, and resistance to spoofing. The four primary types include finger vein, palm vein, wrist vein, and dorsal hand vein recognition.

1. Finger Vein Recognition

Finger vein recognition is the most commercially developed and widely adopted vein biometric modality. It involves capturing subcutaneous vascular patterns within the fingers using near-infrared (NIR) imaging. This approach is valued for its compact sensor size, user convenience, and high accuracy. The paper by Miura et al. (2004) is foundational in this area, introducing repeated line tracking for feature extraction in finger veins.[15]

2. Palm Vein recognition

Palm vein recognition captures the vein patterns in the palm of the hand. Introduced and commercialized by Fujitsu, this modality offers a larger vein area, enabling higher feature richness and improved recognition accuracy. However, it typically requires a larger sensor and more controlled hand placement. Studies such as Kang et al. (2014) have demonstrated the robustness of palm vein recognition under varying illumination and environmental conditions.[20]

3. Wrist Vein Recognition

Wrist vein recognition is a less explored but promising modality due to the accessibility of veins in the wrist area and the potential for unobtrusive acquisition (e.g., through wearable devices). Research by Yuan and Kim (2014) demonstrated wrist vein recognition using multispectral imaging, achieving competitive performance compared to other modalities.[21]

4. Dorsal Hand Vein Recognition

This modality focuses on the vein patterns on the back of the hand (dorsal side). It offers a larger surface area compared to finger veins and is less sensitive to hand movement than palm vein systems. Wang et al. (2008) conducted comparative studies between finger and dorsal hand veins, concluding that dorsal hand vein images provide complementary features that can enhance recognition performance in multimodal systems.[22]

3.2.1 Comparison and Integration

While finger vein recognition remains the most widely deployed due to its small form factor and strong commercial backing (e.g., Hitachi), palm and dorsal hand vein systems are considered more robust in terms of vein coverage and data richness. Moreover, the integration of multiple vein modalities—referred to as multimodal vein biometrics—has shown promise in enhancing system accuracy and spoof resistance. The paper by Kumar and Zhou (2012) [23], although primarily focused on finger-based identification, provides insights into multimodal systems and can be indirectly related to the broader vein biometric discussion. [15,20,21,22,23]

3.3 Common databases used in research

Open vein image databases are a precious resource for advancing biometric recognition research. The databases offer normalized and varied samples of vein patterns, as required in training recognition systems and objective performance testing. Through the databases, researchers can compare their algorithms against existing benchmarks, enabling reproducibility and comparability of results between studies.

Some of the databases that have been extensively utilized include the CASIA Multi-Spectral Palmprint Database, the PUT Vein Database, and the HKPU Finger Vein Database. Each of these databases possesses some distinctive characteristics and merits for utilization in training and testing systems:

CASIA Palmprint Image Database and CASIA Multi-Spectral Palmprint Image Database are two large-scale biometric databases constructed by the Institute of Automation, Chinese Academy of Sciences, for palmprint recognition research.

The CASIA Palmprint Image Database contains 5,504 gray-scale palmprint images from 312 subjects, their left and right palms. There were 16 images for each subject captured by a special palmprint recognition device that turned into 8-bit gray-level JPEG images. This database supports online palmprint recognition systems for PDAs and ordinary PCs. [30,83]

Figure 3 - 1 Real time palmprint recognition system working on PDA

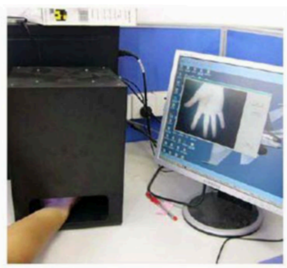


Figure 3 - 2 self- developed palmprint recognition device

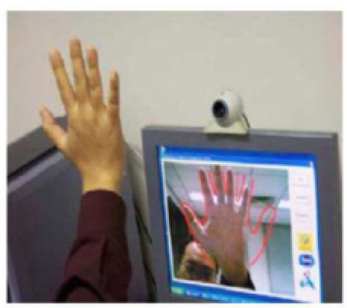


Figure 3 - 3 Palmprint recognition system working on PC with USB web camera

The CASIA Multi-Spectral Palmprint Image Database is made up of 7,200 palm images from 100 subjects captured using a home-designed multi-spectral imaging sensor. Two sessions were conducted with a month gap for each subject, with three samples per session. Each sample includes six images captured simultaneously under six various electromagnetic spectrums (460nm, 630nm, 700nm, 850nm, 940nm, and white light). The device is based on a solid color and homogeneous background with a CCD camera at the bottom and a spectrum adjustment automatic control circuit. In addition, no physical constraint was placed on the posture of the hand in the hopes of enhancing sample diversity and simulating real-world conditions.[31]

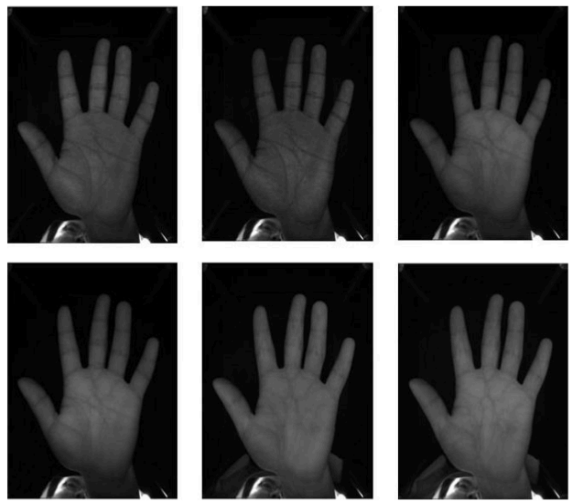


Figure 3 - 4 Six typical palmprint images in the database

These databases provide abundant and various palmprint images for the development of palmprint recognition methods.

The PUT Vein Pattern Database was developed by researchers from the Institute of Computer Science, University of Wrocław, Poland, to combat the lack of standardized databases applied in vein pattern recognition. It can be freely used for research purposes.

PUT vein pattern database contains 2,400 images, comprising 1,200 images with palm vein patterns and 1,200 images with wrist vein patterns. Images are of both the hands of 50 students with 100 various patterns for both palm and wrist areas. Images were captured in three sessions of four images each, with a gap of at least one week between consecutive sessions. Volunteers were asked to In case of palm region volunteers were asked to put his/her hand on the device to cover the acquisition window, in a way that line below their fingers coincident with its edge. No additional positioning systems were used. In the case of the wrist region only construction allowing to place the palm and wrist in a comfortable way was used to help position a hand.[32]

The Hong Kong Polytechnic University Finger Image Database contains finger vein and fingertip tissue images acquired simultaneously from volunteers. The majority of the data was acquired from April 2009 to March 2010. The database currently contains 6,264 images obtained from 156 subjects, all in bitmap format. It is worth observing that approximately 93% of the subjects were younger than 30 years old. The images were acquired by two different sessions, with a minimum interval of one month and maximum interval of six months between the two, forming an average interval of 66.8 days. Six samples of index and middle finger images were given by the volunteer for each session. One image of the fingertip veins and one image of the fingertip tissue on the left hand formed each sample. In total, the subject contributed 24 images in a single session; i.e., 12 images were contributed for each of the fingertip vein and fingertip tissue classes.[33]

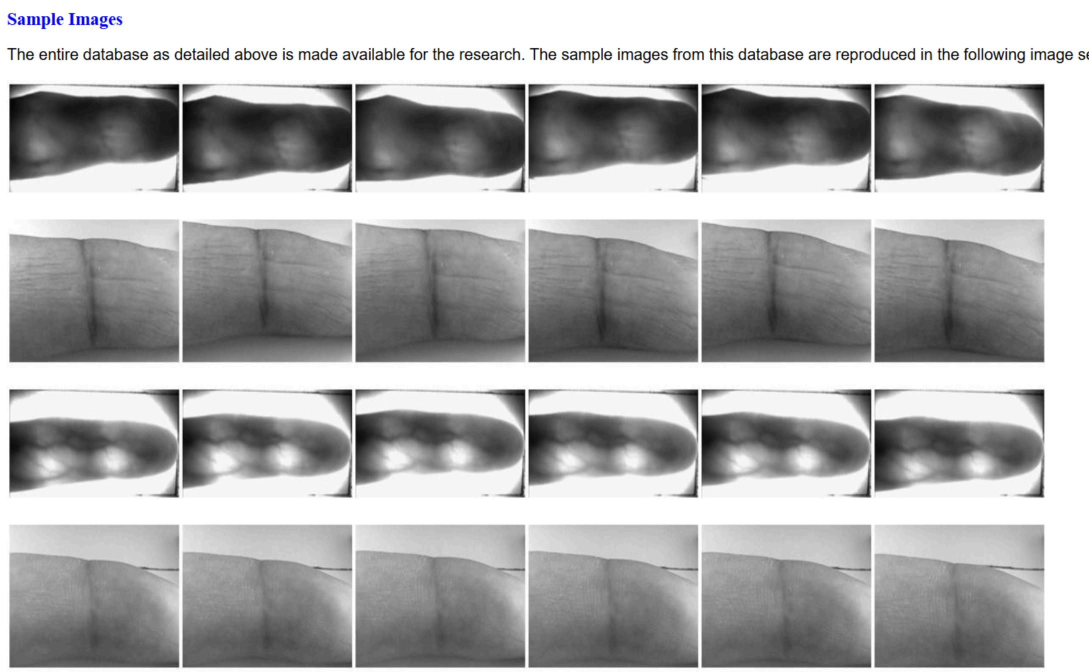


Figure 3 - 5 Sample image of (HKPU) database

Publicly available vein image databases are essential for advancing biometric recognition research. They provide standardized and diverse data for training and evaluating systems, enabling reproducibility and fair comparisons. Databases like CASIA, PUT Vein, and HKPU each offer unique features that support various aspects of vein recognition studies. While collected under controlled conditions, these datasets significantly contribute to the development of accurate and reliable recognition systems.

3.4 Hardware used in vein recognition

The hardware used in vein recognition systems is critical to the accuracy, usability, and performance of the technology. Vein recognition technology operates by detecting subcutaneous vascular patterns as a biometric measure, and is therefore a reliable biometric alternative to fingerprint or facial recognition systems.

Commercial vein recognition systems use a variety of imaging technologies to find the veins under the skin. These include visible light imaging, near-infrared (NIR) imaging, mid-infrared imaging, X-ray imaging, ultrasound imaging, and thermal imaging. Different technologies have a unique set of strengths and weaknesses with respect to practicality, safety, cost, and quality of vein detection.

In this section we consider the six primary imaging methods that have been employed in vein recognition hardware. All of the methods suggest interesting capabilities; however, we focus more of our attention on Near-Infrared (NIR) Imaging technology which is currently the most popular and successful technology used when developing biometric vein recognition systems. NIR imaging is accepted as the norm for vein recognition systems because it penetrates a few millimeters into our skin and provides excellent contrast between veins and other surrounding tissue. As a result, NIR imaging technology is the preferred choice in practical applications such as healthcare, banking, or secure authentication.

Figure 3 - 6 Different Types of Vein Recognition Devices Based on Imaging Technology

1. Visible Light Imaging

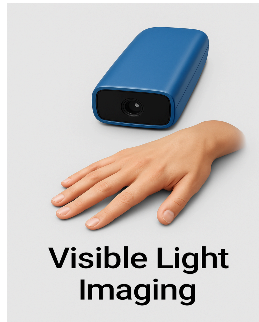


Figure 3 - 7 A compact camera device capturing hand vein patterns using visible spectrum light

Visible light imaging uses commodity cameras (i.e. webcams, and smartphones) and visible lighting, to form images of veins. The vein images are formed from ambient or directed white light, creating a contrast in vein detection from how veins appear naturally under normal lighting conditions. Visible light imaging is a cost-effective method that does not require specialized infrared lighting, but does have inherent limitations associated with the optical properties of skin and blood vessels.

The visible light imaging method captures vein images by detecting small differences in light absorbed and/or reflected from subcutaneous blood vessels, and surrounding tissue. Since the visible light penetrates to a limited depth of the skin (with veins more than two-three millimeters below the skin), most veins will only appear very faintly, and need digital enhancement techniques (for example, Gabor filter, or difference image processing). The ambient light, skin color, tones of shadows, and other reflections that distract from the image capture can affect the quality of the processed image captured.

Advantages:

- Utilizes existing hardware like webcams or smartphone cameras.
- Cost-effective and easy to deploy.

Disadvantages:

- Poor contrast and low depth penetration.
- Sensitive to skin tone, ambient lighting, and image noise.
- Limited use in practical biometric systems.

Visible light imaging has mostly been used in experimental or low-security applications due to its reliability issues. It is not favored for high-stakes authentication environments [91]

2. **Mid-Infrared Imaging**

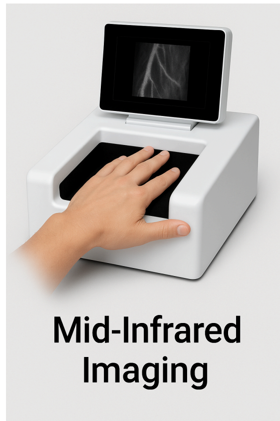


Figure 3 - 8 An advanced imaging device utilizing mid-infrared wavelengths to visualize deeper vascular structures in the hand.

Mid-Infrared (MIR) imaging operates in a longer wavelength range than NIR (typically 3–5 µm). This means it can extend to deeper tissue levels and may have the potential to exhibit richer biometric features, however it has limited use due to technical complexity and higher cost.

MIR systems employ specialized sensors such as Mercury Cadmium Telluride (MCT) sensors. These sensors are elite detectors due to their sensitive nature however they are expensive (often costing hundreds of dollars each) and they require complex and expensive cooling systems. Therefore, one of the only areas where MIR imaging has been explored in detail is in the area of medical diagnostics due to its potential, and it is not commonly found in vein recognition.

Advantages:

- The potential of deeper imaging and clearer tissue.
- Less affected by the superficial skin layer conditions.

Disadvantages:

- Sensors are expensive and cooling systems are required.
- Systems can be bulky and complex.

Despite the merits for future applications, currently MIR imaging is not practical for portable or commercial vein recognition technologies. [92,93]

3. X-Ray Imaging

Figure 3 - 9 A specialized X-ray device capable of visualizing internal vascular structures for high-resolution biometric analysis.

X-rays (X-ray imaging) produce high-energy radiation to obtain high-resolution imaging of internal structures including bones and blood vessels. Although this represents deep imaging with highly detailed images, the health risks and logistical issues associated with implementing X-ray for biometric vein recognition mean that it is not widely utilized for this application.

Due to the nature of X-ray systems, there are health risks where radiation shielding is necessary, regulatory compliance exists and trained operators must be used. While X-ray imaging does effectively depict vein placement, the detriments associated with health risks and system complexity outweigh any associated positive outcomes in the application of identification verification.

Advantages:

- High-resolution internal imaging.
- Effectively depicts vein pathways.

Disadvantages:

- Ionizing radiation.
- Expensive and not portable.

- Health concerns with repeat exposures.

Therefore, X-ray imaging is restricted to clinical use cases and does not have a foothold in consumer instances, potential authenticated scenarios securely. [94,95]

4. Ultrasound Imaging

Figure 3 - 10 An ultrasound machine used to capture real-time vascular images beneath the skin surface using sound waves.

Ultrasound imaging uses high-frequency sound waves to create real-time images of internal body structures - bone, organs, and blood vessels. It's a well-established technique in medicine but has generally not been applied to biometrics.

An imaging system uses a transducer to send sound pulses into the body. The sound waves are reflected by internal structures (like a vein), sending echoes back to the transducer and allowing an image to be constructed. Although ultrasound will generate accurate pictures showing where veins are and will even measure blood flow, ultrasound generally requires contact with skin, conductive gel on the transducer, and trained operators.

Advantages:

- High precision - generating medical quality images.
- Can measure vein size, shape, vein morphology and blood flow.

Disadvantages:

- Needs to be in contact with your skin, and requires skin preparation.
- Not easily portable and bulky. Hard to use for rapid authentication.

Research continues to develop portable and touchless ultrasound to eventually be useful for biometric recognition. [96,97]

5. Thermal Imaging

Figure 3 - 11 A handheld thermal camera showing vein patterns based on skin surface temperature differences

Thermal Imaging tracks the infrared radiation (heat) that all objects give off. Because veins will be cooler than surrounding tissue due to the dynamics of blood flow, infrared cameras see veins as dark lines on thermal maps.

Thermal cameras are passive and do not require any sort of light or radiation to operate. They simply see temperature variability that exists on the skin surface, and utilize that to determine vascular patterns. Recent strides in computer vision and artificial intelligence have improved thermal vein recognition.

Advantages:

- Non-contact, passive capture.
- No need for lights.

Disadvantages:

- Low spatial resolution.
- Can be influenced by ambient temperatures and movement.

Thermal imaging is used for surveillance and access control purposes. With thermal imaging capabilities, thermal technology utilizes some usability and non-invasiveness benefits of imaging, but is not the same as NIR-based methods. [98,99]

6. Near-Infrared Imaging

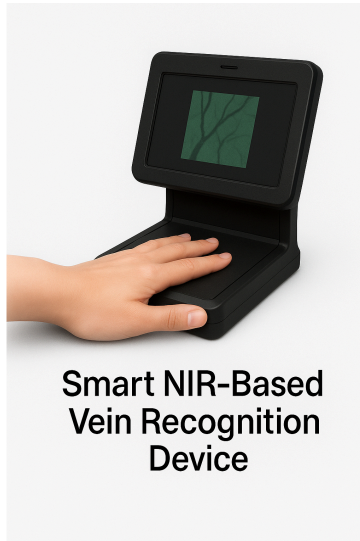


Figure 3 - 12 A contactless scanner that uses near-infrared light to capture detailed vein patterns for biometric authentication

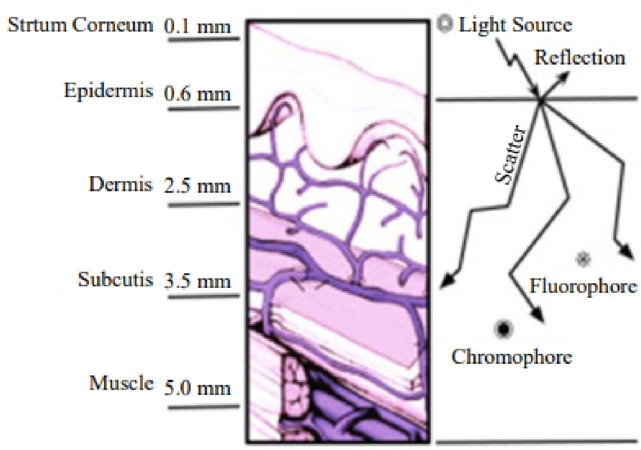


Figure 3 - 13 Interaction of blood vessels with infrared light

The near-infrared (NIR) imaging arrangement is an essential part of vein recognition hardware, as it is dependent upon the optical characteristics of hemoglobin as it is imaged by near-infrared light. When veins possess deoxygenated hemoglobin, they absorb greater NIR wavelengths (typically 700–1000 nm) than the tissue surrounding them which is why veins appear darker while the surrounding tissue reflects lighter when an image is taken. This phenomenon allows for vein patterns beneath the skin to be visualized.

It is important to note that NIR images with high incident illumination are difficult to achieve because fingers and hands have complicated anatomy. To capture a high-contrast image, it is necessary to recognize that blood can both absorb light and scatter light through the soft tissues and bones. Furthermore, according to a 2022 IET article, scattering of light from bone can act as a secondary source of light just above a joint, and can create variations in brightness and contrast saturation in NIR images.

To mitigate the shortcomings above, modern hardware designs implement one of or a combination of three illumination systems: transmission, reflection and side-illumination. Devices like the Hitachi TS-E3F1-602UE and FV1000 use side illumination with the intent to make veins visually clearer. More advanced systems also integrate NIR lasers instead of standard LEDs as they produce less light leakage and provide more even illumination overall. The Kauba hardware model uses multiple lasers and introduces an open-source hardware model, all the while showing how lighting systems can be calibrated to produce better images that produce minimal artifacts. Systems like those by Kim and Kauba integrate NIR laser configurations encompassing arrays of lasers to minimize the leakage of illumination light sources and ensure illumination is uniform.

Furthermore, the vein recognition system proposed by Chat et al. (2025) serves as a small form factor, hygienic, and low-cost example of a pragmatic device application. The system utilizes a near-infrared (NIR) camera that detects wavelengths most suitable for vein visualization provided by near-infrared (NIR) LEDs chosen for their emission in the hemoglobin-most; 'hemoglobin' is to be used as a reference 'hemoglobin' is to be eliminated; absorbing wavelength range. Light scattering sheets are supplied to homogenously spread illumination and to the greatest extent possible, remove excess shadows or overexposure that might obscure more subtle representations of veins. Using this structured illumination design provided better vascular performance capture.

Chate's design incorporates a hand presence sensor to start contactless biometric acquisitiowhen it detects a hand. This touch-free acquisition enhances user hygiene and ease of use, especially in a public setting, like in a medical environment. All the computational processes for the system, such as image acquisition, contrast enhancement (using CLAHE and Gaussian filtering), and biometric matching (using Hellinger distance) are done using a Raspberry Pi 3. While a Raspberry Pi is relatively inexpensive compared to industrial computing hardware, the small form-factor computer produced sufficient power to complete all of the processing, which highlights that high-quality vein recognition can be achieved without industrial computing hardware.

Together, these hardware components—NIR camera, LEDs or lasers, diffusers, presence sensors, and embedded processors—show that high-performance vein recognition systems can be low-cost and portable. Chate et al.'s work demonstrates a deployment that arrived at 99.59% accuracy, and an Equal Error Rate (EER) of 1.45%, while being low power and compact. Overall, combined with other relevant studies, it is likely that a well-designed combination of optics, sensing, and embedded computation can facilitate vein recognition in diverse environments—from hospitals and ATMs to smart homes—where space, cost, and user comfort are paramount. [35,35]

3.5 Vein image preprocessing techniques:

One of the main challenges in Vein-recognition systems is the low quality of captured images. This is often due to indistinct vein patterns and unwanted noise in hand images, which can lead to false detection. To address this, image enhancement techniques are essential for improving image quality, making vein patterns more visible, and reducing errors during the detection process.[41]

Vein enhancement, also known as preprocessing, is a critical step applied before the recognition process. Its main goal is to improve the visibility of captured vein patterns by applying image processing techniques such as noise removal and illumination correction. This step ensures higher image quality, which directly improves the accuracy and efficiency of subsequent processes like feature extraction and matching. Once noise is reduced, segmentation techniques are used to separate the vein pattern from the background.[42]

Various methods have been proposed for effective image enhancement, these include some classical techniques such as histogram equalization, and contrast stretching, as well as more advanced and adaptive approaches like Fase Median-Based Filtering (FMBF) and Hybrid Cumulative Histogram Equalization (HCHE). Classical methods, implemented using tools like OpenCV, are easy to use and effective for general enhancement. However, specialized methods like FMBF focus specifically on detecting and removing noisy pixels, while HCHE focuses on enhancing contrast in Vein-dense areas. A combination of both approaches can help determine the most suitable preprocessing pipeline for vein recognition systems.

3.5.1 Histogram Equalization:

Histogram equalization is a technique that increases the dynamic range of pixel intensities in an image. It works by redistributing the pixel intensities so that the output image has a more uniform histogram. The goal is to enhance image contrast, making darker regions brighter and enhancing overall visibility. Instead of "flattening" the histogram completely, its "spreads" the intensity distribution more evenly across the available range. This process assigns new intensity values to pixels based on their original levels and can be applied to the entire image or just specific regions.[41]

3.5.1.1 Results from applying Histogram equalization

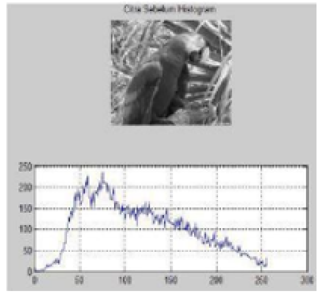


Figure 3 - 14 Histogram input

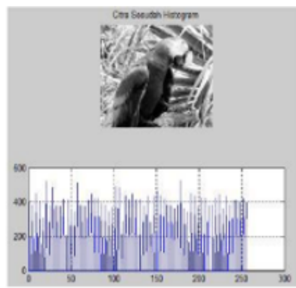


Figure 3 - 15 Histogram output

The Figure explain about that the output image of histogram distribution is much more evenly than the input image, with a more evenly distributed histogram will increase the spread of grayscale value so that the output image will seem brighter and more visible.[41] This technique is a widely used scheme for contrast enhancement in a variety of applications due to its simple function and effectiveness.[43]

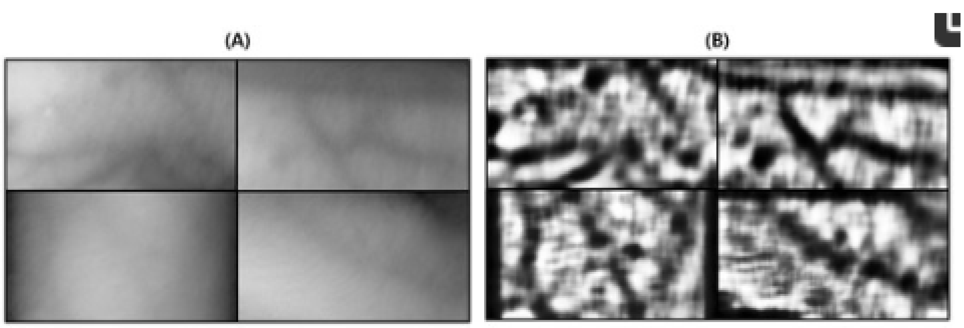


Figure 3 - 16 Vein images with histogram normalization and equalization applied: (A) is the original image, and (B) is the result of applying histogram equalization. The contrast of venous vessels became clear through histogram smoothing.

The contrast in an image captured by an NIR camera is poor because low-frequency components make up most of the screen; this makes it difficult to distinguish vein components with the naked eye. The histogram equalization algorithm can sharpen the image by equalizing the maximum brightness in the image. [90]

3.5.2 Contrast Stretching:

Contrast stretching (often called normalization) is a simple image enhancement technique that attempts to improve the contrast in an image by expanding the range of intensity values to cover a desired range.[44] The implementation of this method is by specifying the desired minimum and maximum value limits over which the pixel values in the image are rescaled.[41] There are four types of contrast stretching methods global, linear, modified global, and modified linear contrast stretching techniques.[44]

3.5.2.1 Results from applying contrast stretching

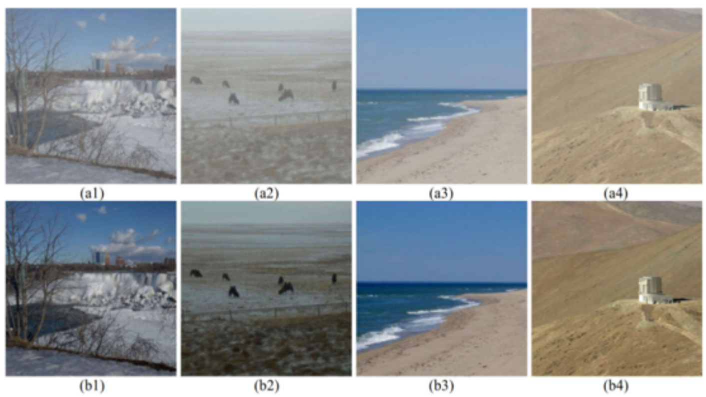


Figure 3 - 17 Applying contrast stretching on some low-contrast images

Figure 3-10 illustrate the effectiveness of applying the contrast stretching technique to a variety of real world low-contrast color images, the top row shows the original degraded images, which suffer from dull colors, low detailed visibility and poor contrast. while the second row shows the images after applying the technique, the images display noticeable improved contrast, and enhanced color clarity making the details much more visible. The enhanced images are not only visually clearer but also more suitable for further image analysis or recognition tasks.

3.5.3 Fast Median-Based Filtering and Hybrid Cumulative Equalization techniques:

In infrared (IR) vein-pattern imaging, the captured images often suffer from impulse noise, which can significantly reduce recognition accuracy. To address this issue a Fast median based filter (FMBR) is introduced as a detected noise reduction technique. It's designed to detect and eliminate noisy pixels based on the infrared imaging mechanism, without requiring prior image knowledge of the image or any manually present parameters. It maintains edge and texture quality while offering a low computational load. In parallel, Hybrid Cumulative Histogram Equalization (HCHE) is applied for contrast enhancement. it enhances the visibility of vein patterns. which adaptively boosts the visibility of vein patterns—particularly in “hot” object regions—while minimizing background interference.[47]

3.5.3.1 Noise in IR images:

One of the major limitations in IR images is the low signal-to-noise (S/N) ratio, which means the signal captured by the sensor is weak while the noisy level is high. This is common in uncooled IR cameras, which are which are widely used due to their lower cost but tend to produce noisier images. The high noise is caused by the sensors and read-out circuits of IR cameras, and the low IR signal detected by IR sensors is caused by the degradation of the IR signal radiating from objects in bad atmospheric weather. To enhance image quality and improve the adoption of IR-based applications, some form of image preprocessing is necessary. Improvements in impulse noise removal and contrast enhancement are the crucial tasks of IR image preprocessing.[47]

3.5.3.2 Noise detection using FMBF technique:

The FMBF technique includes a dedicated noise detection algorithm tailored for IR images. Based on the physical characteristics of IR imaging, if the gray-level of a central pixel $g_{(x,y)}$ is either the maximum g_{max} or minimum g_{min} within a local window of neighboring pixels S_{xy} it is classified as noisy and should be replaced. Otherwise, the pixel is considered a signal pixel and remains unchanged. The noise algorithm detection method checks the gray-level $g_{(x,y)}$ with g_{min} and g_{max} to consider whether the pixel $p_{(x,y)}$ is noise or signal.

The proposed noise detection is based on the IR imaging mechanism. Therefore, FMBF can exactly identify the noisy pixels and replace them in IR images. The IR image’s edges, text information and details of objects are not damaged while being processed by the proposed FMBF.[47]

3.5.3.3 Noise removal using FMBF technique

After detecting the noisy pixels, the pixel with median gray-level inside the window is adopted replacing the noisy pixels.

In the proposed approach, the procedure to find out median gray-level is performed by the sort algorithm with a low computation complexity. In addition, it only processes the noisy pixels, but not the signal pixels. Sorting is the main computation load of the noise removal, so in order to speed up the noise removal, reducing the computational load is critical. A suitable sort algorithm to use is the Radix sort algorithm, which is faster than typical sorting methods like Quick Sort or Heap Sort.

Unlike traditional median filters that process every pixel, FMBF only filters the noisy pixels, which significantly reducing the processing time. Although extra computation is required to determine the maximum and minimum gray-level in the noise detection procedure. The computation complexity of doing this is O(n), which is still less than the computational complexity of Radix sort $O(n \log_d q)$. Thus, the proposed FMBF can theoretically save time in noise removal.[47]

3.5.3.4 Results from applying FMBF technique

In order to verify the validity of the proposed approach, four life-time IR images of palm-dorsa are collected and used as the test samples for our study. Each IR image has 640 H × 480 V pixels and each pixel is represented by 256 gray-levels. As shown in Figure 3-13 (a1-a4), the IR images all display low contrast and brightness. The vein-patterns are hard to observe in these images. They have to be preprocessed to improve the image quality for the future postprocessing.

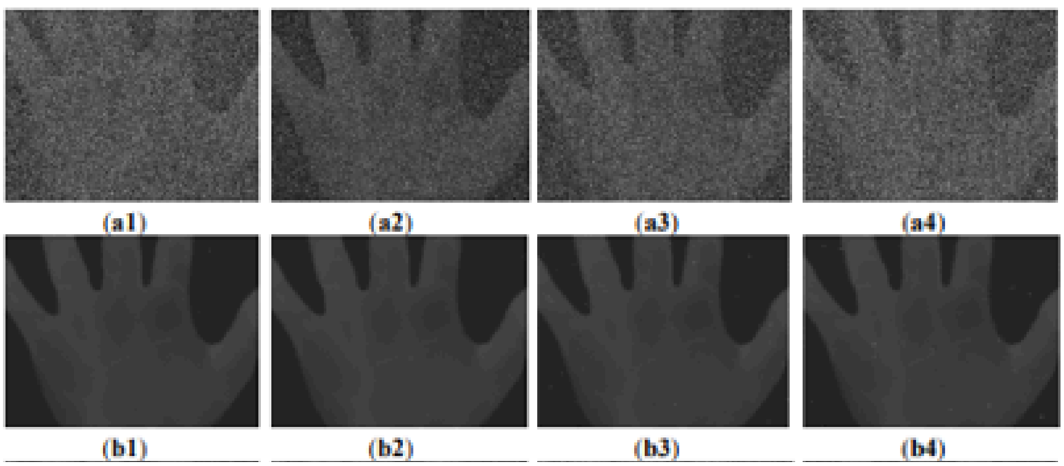


Figure 3 - 18 Comparison of IR vein images before (a1–a4) and after (b1–b4) noise reduction using Fast Median-Based Filtering (FMBF). The filtered images demonstrate enhanced clarity and preserved texture.

These results demonstrate that FMBF not only reduces impulse noise effectively but also preserves critical texture details, making it well-suited for IR vein image enhancement.

3.5.4 Contrast Enhancement Using Hybrid Cumulative Histogram Equalization (HCHE)

Histogram equalization (HE) is a widely used method for enhancing image contrast, but it has some limitations. It enhances primarily the large area scene features wit approximate gray-level, rather than the small area objects. To address this issue, Hybrid Cumulative Histogram Equalization (HCHE) is introduced to adaptively and effectively enhance IR images, The most important property of HCHE is that the enhancement effect on hot objects is more than that on large area backgrounds.

HCHE consists of two main stages: the adaptive threshold selection and the HCH generation. The first stage adaptively selects a suitable threshold that divides the histogram into hot objects and backgrounds. The second stage is based on two different kinds of information about the histogram to generate two different cumulative histograms. One enhances hot objects and the other enhances backgrounds. These are then merged into a single hybrid histogram. This dual-enhancement mechanism allows HCHE to overcome the inherent limitations of standard HE.[47]

3.5.4.1 Results from applying HCHE

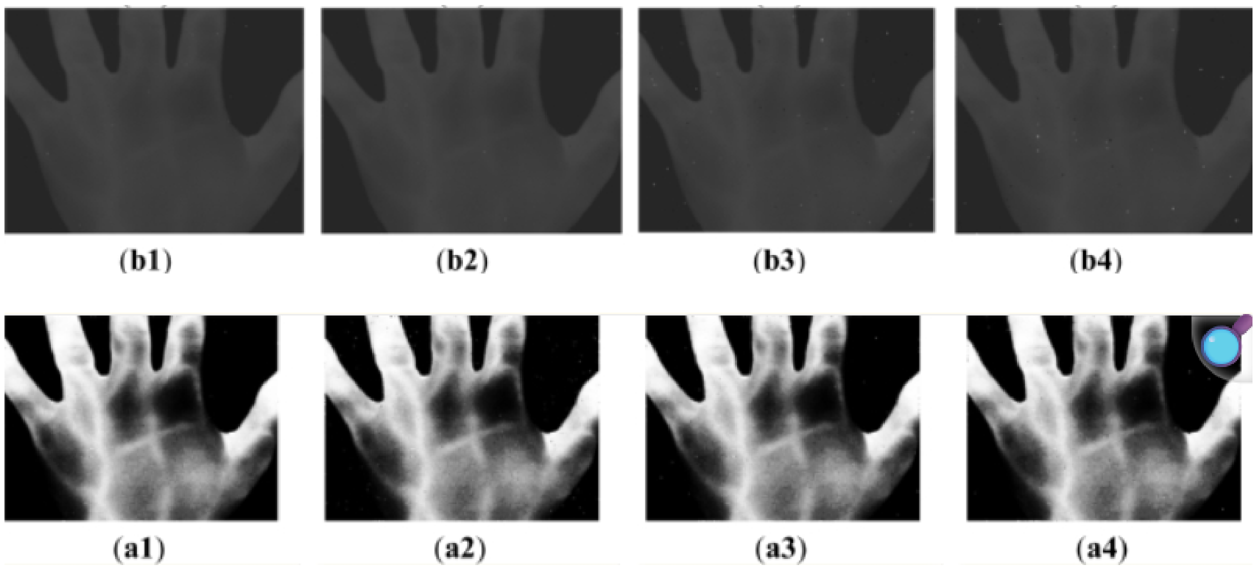


Figure 3 - 19 (a1-a4) The results of (b1-b4) enhanced by HCHE respectively.

These results highlight the effectiveness of HCHE in adaptively enhancing hot object regions—such as veins—while avoiding over-enhancement of large background areas. The improved contrast and clarity in the processed images (a1–a4) make them more suitable for further recognition tasks.

3.6 Algorithms used for pattern recognition

3.6.1 Introduction

The images captured of vein patterns through near-infrared (NIR) imagining hardware, contains not only vein patterns but also irregular shading and noise. Therefore, regions in which the veins are and are not sharply visible exist in a single image. Vein-patterns should be extracted precisely from the captured images, and the process must be executed speedily in order to satisfy requirements for user convenience.[48] Early system relied on traditional image processing techniques such as line tracking and template matching to identify characteristic features of vein patterns, these methods have been widely used due to their simplicity. However, these techniques are sensitive to poor image quality or light variations in hand placement. Recently, machine learning and deep learning techniques have been integrated, such as Convolutional Neural Networks (CNNs), which automatically learn and detect complex features in vein patterns with higher accuracy. This section explores both traditional and modern algorithmic techniques used in vein pattern recognition.[49]

3.6.2 Line Tracking

3.6.2.1 Introduction

One widely used traditional method for extraction vein-patterns from near-infrared (NIR) images is Line tracking particularly repeated line tracking approach, this method extracts patterns by tracking the dark lines in the images. extraction of the pattern is based on the number of times the tracking lines pass through the points. [48]

3.6.2.2 How it works

The process starts with a randomly selected pixel, which is called the "current tracking point", The algorithm moves pixel by pixel along the dark pixels, following the direction where the pixel intensity dips, indicating a potential vein. At each step, The algorithm checks the neighboring pixels to detect a valley-like shape, if a valley-shaped dip is detected, the algorithm calculates the direction in which the valley is deepest. then the current tracking point moves to the pixel closest to this direction, if no valley is detected in any direction, the current tracking point is not on a dark line and a fresh tracking operation starts at another position. To ensure full coverage and robustness, the process is repeated from multiple start points. Tracking frequency is recorded in a matrix called the locus space, where frequently tracked pixels are more likely to represent veins. [48]

3.6.2.3 Extraction of the finger-vein patterns

The positions in the locus space where high values are stored are those tracked frequently in the line-tracking procedure. That is, the positions with high values in the locus space have high probabilities of being the positions of veins. Therefore, the paths of finger veins are obtained as chains of high-value positions in the locus space.[48]

3.6.2.4 Matching

In this step, a comparison made between the input image and the stored image to ensure they are belonging to the same person or not.[12] in this process, the extracted pattern is converted into matching data in order to make the comparison with the stored one. [48]

The matching process is as follows:

Step1: Labeling of the locus space:

A threshold value is determined, and based on this value, the pixels with values smaller than the threshold are labeled as part of the background, and those that have a greater value or equal to the threshold are labeled as part of the vein region. [48]

Step2: Spatial reduction and relabeling of the locus space

To prepare the vein data for matching, the locus space is reduced one third of its original size to improve efficiency. This reduction is achieved by averaging values within non-overlapping 3×3-pixel blocks. The resulting image is then labeled into three levels: pixels value in range 0 to 85 are converted to 0 which represents the background, pixels values with range 86 to 170 are converted to 128 (Threshold value) are represents ambiguous regions, and pixels values with range 171 to 255 are converted to 255 which represents the veins.[48]

Step3: Matching of data:

In this step, the system evaluates how will the extracted vein pattern from a new image (input data) aligns with a stored reference pattern (registered data). This is done by calculating a ratio. The ratio is defined as the difference between two sets of data. Each pixel is examined to see if a vein region in one image overlaps with a background region in the other, which counts as a mismatch. The mismatch ratio is then computed by dividing the total number of mismatched pixels by the total number of vein pixels in both images. A lower mismatch ratio indicates a higher similarity, meaning a better match between the input and stored vein patterns.[48]

3.6.2.5 Advantages

Repeated line tracking enhances the reliability of vein detection by emphasizing actual vein patterns and reducing the impact of noise. To improve efficiency, the algorithm avoids unnecessary repetition by skipping starting points that are too close to each other, as they often result in similar tracking paths. Instead, it uses the Monte Carlo method to randomly select diverse starting points across the image. Additionally, by reducing the size of the locus space—the matrix that stores tracking frequencies—the system lowers computation time without losing important vein details, since finger vein patterns are typically sparse and spread out.[48]

3.6.2.6 Limitations

While the line tracking method is effective in extracting vein patterns, it has several limitations. The method is sensitive to image quality; low-contrast or noisy near-infrared (NIR) images can lead to inaccurate tracking paths. This sensitivity arises because the algorithm relies on detecting dark lines corresponding to veins, which may not be prominent in poor-quality images.

Additionally, the method heavily depends on the selection of starting points for tracking. If these points are not optimally chosen, the algorithm may fail to capture the complete vein pattern. Although the Monte Carlo method introduces randomness to select diverse starting points, it can also lead to variability in results, affecting the repeatability and consistency of the recognition process.

3.6.2.7 Experimental Results

In "Feature Extraction of Finger-Vein Patterns Based on Repeated Line Tracking and Its Application to Personal Identification" by Miura et al. (2004). An experiment was held in order to evaluate the effectiveness of the Line tracking algorithm for finger vein-recognition system. A total of 678 finger-vein images were used, captured from 678 fingers of 101 volunteers. The captured images were obtained using a near-infrared (NIR) imaging system.

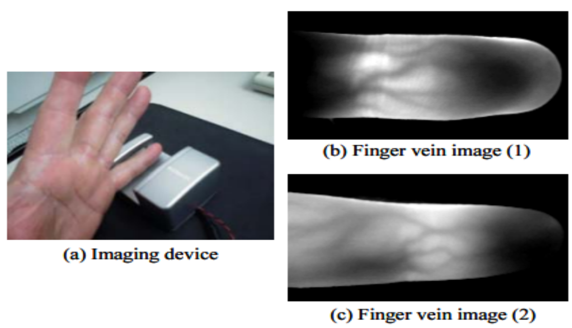
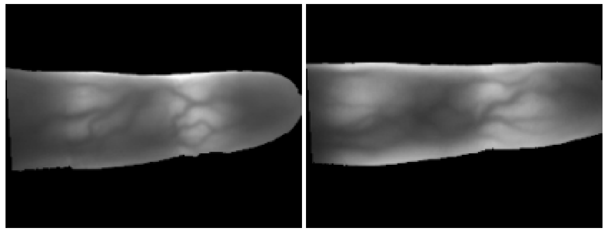
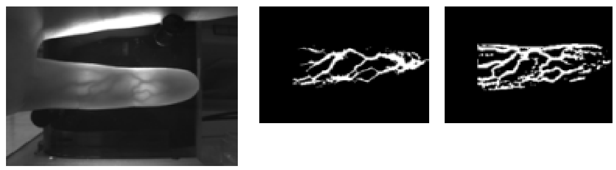


Figure 3 - 20 Prototype of finger-vein imaging device (a) and examples of infrared images of finger (b, c)



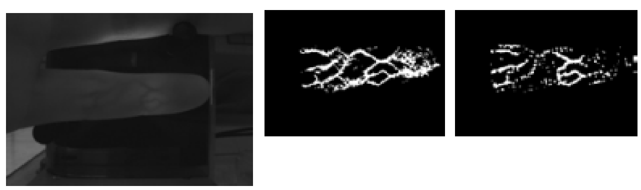
a b

Figure 3 - 21 Finger-vein images used in the experiment. a Original image (1). b original image (2)



a b c

Figure 3 - 22 Results for extracted finger veins in the brightness infrared finger image a. Brightness image. B. Proposed method. C. Matched filter



a b c

Figure 3 - 23 Results for extracted finger veins in the darkest infrared finger image. a. Darkest image. B. Proposed method. C. Matched filter

For the recognition task, a 1:1 verification scenario was used, where a newly captured image was compared to a stored template using a similarity measure. The performance of the system was evaluated using False Acceptance Rate (FAR) and False Rejection Rate (FRR). The results demonstrated strong recognition accuracy, even with image noise and contrast variation, showing that the repeated line tracking method is a robust approach for extracting finger vein patterns from NIR images. The mismatch ratios between same-finger and different-finger pairs were compared, showing that the proposed method achieved better separation between genuine and imposter matches.

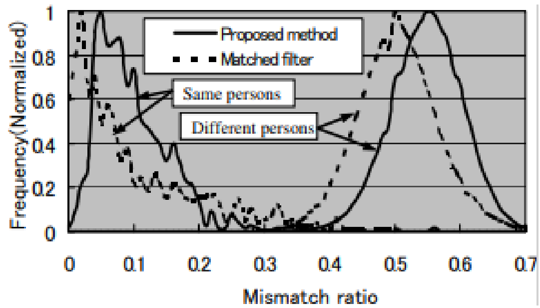


Figure 3 - 24 Mismatch ratio for the same person and among different persons

Using these results, the Equal Error Rate (EER)—the point at which FAR and FRR are equal—was calculated. The proposed method achieved an impressively low EER of 0.145% at a mismatch ratio of 37.6%, compared to 2.36% for the conventional method at 38.4%. This demonstrates that the proposed method is significantly more accurate. Moreover, since fingerprint-based systems typically show EERs ranging from 0.2% to 4%, the results confirm that finger-vein recognition using repeated line tracking offers highly competitive accuracy.

3.6.3 Convolutional Neural Network (CNN)

3.6.3.1 Introduction

Traditional methods often have difficulties in providing excellent recognition performance for various kinds of vein images. To address this challenge, Convolutional Neural Networks (CNNs) have been proposed for vein pattern extraction. which is a class of training-based deep learning methods.[53]

Moreover, traditional methods usually include image capture, image data pre-processing, feature extraction, and classification or any analysis tasks, However, deep learning especially Convolutional Neural Networks (CNNs), changes that, it can extract abstract but efficient features by supervised or semi-supervised learning. The recognition process has been extremely simplified by DL-based methods.[54]

CNNs networks have become popular research in the field of vein-patterns due to their powerful capabilities in image feature extraction.[52]

3.6.3.2 Convolutional Neural Network (CNN) Architecture

CNNs consists of multiple layers that works together in order to extract vein-patterns. CNNs typically consist of input layer, where the input image is fed into the model.[58] it holds the data raw input pixel data and passes it to the next layer for feature extraction [59]. The next layer is convolutional layer, its the main building block of CNNs, the prime purpose is to extract features such as edges, textures, or patterns from the input dataset [59]. it contains multiple layers The first convolutional layer extracts low-level features such as edges, corners, and lines. Next layer extracts higher-level features. And the highest-level features are extracted in the last convolutional layer. [59]. The next layer is the pooling layer which reduces the resolution of the previous feature maps through compressing features and lowering the computational complexity of the network, It also helps make the extracted features more robust to noise and slight distortions. Another purpose of the pooling layer is to provide tolerance to small variations for previously learned features. As a result, pooling ensures that the network focuses on the most important patterns. The last layer is the fully connected layer It takes the input from the previous layer and computes the final classification or regression task.[58]

3.6.3.3 Application of CNN Layers in Vein Pattern Recognition

In the context of vein recognition, the input layer typically receives near-infrared (NIR) images of the veins. Which are preprocessed into a consistent format. during training, Convolutional layers then extracts low-level features such as lines and edges that corresponds to vein patterns, then as the layers goes deeper, the network captures more complex features such as bifurcations and branching structures. Pooling layers help reduce the effect of minor changes like hand position or illumination, ensuring robust performance. Finally, fully connected layers use the learned features to classify or verify the identity based on vein patterns.

In recognition system, there are two phases: the first one is registration phase, where the image of the vein is captured by NIR imaging, and then extract the feature vector through the CNN. The other phase is the authentication phase; a new vein image is processed in the same way to extract its feature vector. Then the Euclidean distance is calculated between the two vectors obtained, if the distance is less than the threshold then it can be considered that the two images are belong to the same person and the authentication is successful, otherwise authentication failed, The value of threshold is obtained by plenty of experiments in which we compare the Euclidean distance between intra-class and inter-class and choose a proper threshold as a judgment standard. And its value can be adjusted flexibly according to the practical applications, which makes it stricter for acceptation or rejection. [55]

The most important part of a CNN-based vein recognition system is extracting the most representative and robust feature vectors. The general vein structure among individuals appears similar. A CNN can be trained by inputting a large number of images to get the ability to extract the most representative vector. Also, feature vectors of new images can be extracted by this already trained model. Therefore, properly training the CNN to get the most suitable model to extract finger vein features vectors is extremely important. [55]

3.6.3.4 Advantages

CNNs offer significant advantages in image recognition tasks due to their ability to efficiently extract features with much lower computational cost. Furthermore, pooling enhances the robustness of the network by minimizing the impact of spatial variations such as position or lighting changes. [60]

In CNNs the entire vein recognition process is simplified, as traditional image processing, feature extraction and matching methods are no longer as complicated. The main advantage of CNNs is their ability to achieve high accuracy and strong performance across various metrics. [62] Other benefit is the reduced number of parameters to be learned; this leads to less noise during the training process. The reason is that the number of parameters depends on the kernel width. The wider the kernel width, the lager the number of parameters in the model. [59]

3.6.3.5 Limitations

Despite their success, CNNs have several limitations, one major challenge is their dependency on large number of labelled data. often requiring thousands or even millions of samples to train effectively. The number of parameters becomes larger if regularization techniques, such as weight decay are not properly applied, the dropout rate should be carefully tuned, as a low rate can increase the number of iterations needed for convergence. [59]

Another critical factor is the learning rate, which must be optimally set. A Very high or very low rate will lead to optimization problems and reduce the effective capacity of the network. [20] Moreover, CNNs are often considered "black box" models because the features they extract are abstract and difficult to interpret. Additionally, the training process can be computationally intensive, requiring powerful hardware and optimized software to ensure stability and efficiency.[60]

3.6.3.6 Experimental Results

3.6.3.6.1 Experimental data

In "Palm Vein Recognition Based on Convolutional Neural Network" article by Yong-Yi FANJIANG1, Cheng-Chi LEE2,3, ∗, Yan-Ta DU1, Shi-Jinn HORNG. AlexNet and VGG-16 and VGG-19 were used for palm vein recognition experiment, which they are types of CNN. two datasets were established of palm veins. The first dataset contains 20 images from each 50 individual, for a total of 1000 experimental images. The second dataset contains twenty images from each of 63 individuals, for a total of 1 260 experimental images. The size of a captured image is 640 × 480 pixels. For AlexNet and VGGNet, the size must be changed to 227 × 227 and 224 × 224, respectively. The image acquisition uses a near-infrared camera to acquire palm vein images, the training set and validation set, were established in the experimental process. Of these images, 80% were used for training, and 20% were used for validation.

3.6.3.6.2 Results

3.6.3.6.2.1 Experimental Results of the First Dataset

In this paper, the experimental process includes the following: randomly selecting the training image and validation sets, adjusting the batch value according to the performance of the hardware, and adjusting the learning rate., the final numbers of iterations were 800, 800, and 1 000 in AlexNet, VGG-16 and VGG-19, and the accuracy rates were 96%, 97.5%, and 98.5%, respectively.

Finally, to evaluate the model, False acceptance rate and false rejection rate were used the statistics of our performance metrics for the three models are as follows:

No. Models	FAR (%)	FRR (%)
1 AlexNet	0	0.77
2 VGG-16	0	0.65
3 VGG-19	0	0.6

3.6.3.6.2.2 Experimental Results of the Second Dataset

In this study, we divided the image dataset into two sets, namely a training set and a validation set. For the training and validation of the three models AlexNet, VGG-16, and VGG-19, we set the number of iterations to be 1000 times. The palm vein images in the database were collected by using a near-infrared light camera. Since these were contactless shots, each image had a different resolution and needed to be preprocessed. To obtain the best result of image contrast enhancement while avoiding noise amplification, The Contrast limited adaptive histogram equalization (CLAHE) was used. Figure 17(a) shows a raw image, and Fig. 17(b) shows the enhanced image.

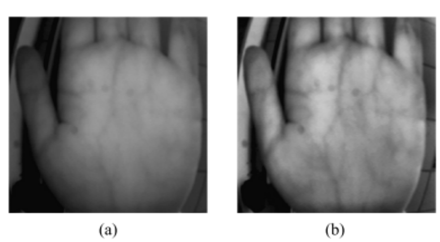


Figure 3 - 25 (a) Original image; (b) Enhanced image

The training processes of the three models were as follows:

No. Models	Iterations	Results
1 AlexNet	1000	99.35%
2 VGG-16	1000	99.45%
3 VGG-19	1000	99.5%

Finally, False acceptance rate and false rejection rate were used, the statistics of our performance metrics for the three models are as follows:

No. Models	FAR (%)	FRR (%)	Accuracy (%)
1 AlexNet	0	0.5	99.35
2 VGG-16	0	0.35	99.45
3 VGG-19	0	0.3	99.5

3.6.3.6.2.3 Conclusion

The paper presents a palm vein recognition method using CNN architectures like AlexNet and VGG, which simplify traditional processes such as feature extraction and matching. The models demonstrated high performance, with the first dataset (1,000 images from 50 individuals) achieving a False Rejection Rate (FRR) of 0.6%, and the second dataset (1,260 images from 63 individuals) reaching an FRR of 0.3%. Applying CLAHE preprocessing improved contrast and boosted CNN accuracy to 99%. However, results were sensitive to image quality and GPU hardware. Future work aims to enhance image preprocessing to handle noise and shadows, and to expand the method to finger vein recognition for mobile security applications.

3.7 Biometric traits

3.7.1 Introduction

Biometric system uses a part of body as personal characteristics for authentication. There are many characteristics but not all characteristics are useful. To design an effective system, it is very important to decide which characteristics the system uses. [78]

General criteria for selection of biometric features as follows:

- Universality: everyone should have this distinguishable trait
- Uniqueness: no two persons should be the same in terms of this trait
- Permanence: it should be invariant with time
- Collectability: it can be measured quantitatively in addition; the following criteria can be considered.
- Performance: achievable identification accuracy, resource requirements, and robustness

- Acceptability: to what extent people are willing to accept it
- Circumvention: how easy it is to cheat the system. [78]

3.7.2 Comparison between vein recognition and other biometrics

In **vein recognition**, the **universality** is high because everyone has veins, also the **distinctiveness** is high, since vein patterns are different among individuals. The veins are usually invariant; it remains stable throughout a person's life. The **performance** is also considered high, because vein recognition system offers a real-time result with low error rates. Finally, Veins are located beneath the skin, making them extremely difficult to forge, so **circumvention** resistance is also rated high. However, **collectability** and **acceptability** are rated medium, although modern systems are contactless, the acquisition process can be influenced by environmental factors such as lighting, temperature, or humidity, and biological factors, e.g., the thickness of the layers of human tissues and diseases, such as anemia, hyperthermia, or hypotension, which can affect image quality.[40]

In **fingerprint** and **face recognition**, several biometric traits are rated high such as **universality**, **distinctiveness**, **performance**, and **acceptability**. However, **Permanence** is considered medium, because fingerprints can be worn down or altered due to injury or heavy use. Also, **collectability** is considered medium, as fingerprints system typically requires physical contact with sensors, which can be impacted by dirt, moisture, or dry skin. **Collectability** for faces are also medium. In this case, non-specific cameras can be employed, but significant changes in the appearance due to the growth of a full beard or wearing masks affect facial recognition. **Circumvention** risk is medium in both cases, since it's possible to spoof fingerprints and faces by using silicon fingers (for fingerprints) and photos, videos, or 3D dace masks (for faces). [40]

In **hand geometry**, the **universality** is medium, as while most people have two hands, certain individuals may lack the ability to provide usable samples due to limb loss or deformity. **Distinctiveness** is rated medium to high; hand geometry is considered to be unique characteristics in human beings. Since hand geometry entirely depends on the shape of hand and do not collect data points like fingerprint recognition, distinctiveness of fingerprints is considered higher than of hand geometry. **Permanence** is medium since the hand has a higher possibility to change with time, for example, with weight loss or gain, the shape of the hand may change. Since hand geometry recognition entirely depends on the shape of hand, it will affect the performance of the recognition system. so, the **performance** is also medium. However, **collectability** is high, as hand geometry is easy to capture and doesn't suffer from the smudging or surface issues seen in fingerprints. The **acceptability** trait in hand geometry is well accepted as the method is non-invasive and quick, leading to user comfort and compliance, so its high, the last trait is **circumvention** that rated as medium, since hand geometry recognition is based on the overall shape of the hand and a good imposter attack will require a precise replica of an authorized user's hand. It is hard to create such replica but not impossible. [79]

Iris recognition performs well across most traits, the **universality** is high, as nearly everyone has at least one scannable eye. Even in the unfortunate chance should an individual be blind in both eyes, the iris can be still be scanned, even though it will be much more difficult for the modality to capture a clean image of the iris. **Distinctiveness** is also high, because the complex texture of the iris is unique, even among identical twins. ensuring precise individual identification. Also, the iris is very stable and the structure of it hardly changes over the lifetime of an individual. In addition, the iris is considered to be an internal organ. Thus, it is not prone to the harsh conditions of the external environment, so the **permanence** is also high. **Collectability** ranges from medium to high, as iris images can be captured even at a distance or through eyeglasses, but still require proper lighting and alignment. **Performance** is high, iris recognition demonstrates high accuracy and speed, with low false acceptance and rejection rates. [80] However, **acceptability** is low in some contexts, as cultural sensitivities or discomfort with eye scanning may lead to user resistance. [81] **Circumvention** resistance is rated low to medium; while the iris is hard to fake, certain attacks using patterned contact lenses or poor-quality images may succeed if liveness detection is not implemented. [81]

Retinal recognition is one of the most secure modalities, nearly all biometric traits are considered high. Since most individuals have a retina that can be scanned, unless they suffer from severe eye diseases. Also, the blood vessel pattern in the retina is extremely unique, even between identical twins, making it one of the most distinctive biometric traits. The retina structure remains stable over time unless it's affected by serious conditions such as diabetes or glaucoma. Retina recognition system possesses extremely high levels of accuracy. In fact, under optimal conditions, the error rate can be as low as 1 in 1 million. So, **universality**, **distinctiveness**, **permanence**, and **performance** are all rated high. **Circumvention** is extremely high, Because of its stability and richness, it is almost impossible to spoof a Retinal Recognition system. However, **collectability** is rated medium, the collectability is medium, even if the individual is fully cooperative, it can still be difficult to a collect a high quality, raw image of the Retina. This is because the scan area is so small, when compared to the other Biometric modalities. Also, the **acceptance** of Retinal Recognition by the general public is extremely low. [82]

3.7.3 Table Comparison

Table 1 Comparison between biometrics and Vein recognition

Biometric system	Fingerprint	Face recognition	Hand geometry	Iris recognition	Retinal Scanner	Vein recognition
Universality	High	High	High	High	High	High
Distinctiveness	High	High	Med-High	High	High	High
Permanence	Medium	Medium	Medium	High	High	High
Acceptability	High	High	High	Low	Low	Medium
Collectability	Medium	Medium	High	Med-High	Medium	Medium
Performance	High	High	Medium	High	High	High
Circumvention	Medium	Medium	Medium	Low to Med	Low	Low

3.8 Performance metrics

To evaluate the reliability and effectiveness of vein recognition system. The Equal Error Rate (EER) is measured through some experiments:

1. In "Extraction of Finger-Vein Patterns Using Maximum Curvature Points in Image Profiles" by Naoto Miura experiment:

Database used: Proprietary finger vein dataset
Method used: Maximum curvature method (a traditional image-based technique)

EER results: 0.145%.[100]

2. In "Convolutional Neural Network-Based Finger-Vein Recognition Using NIR Image Sensors" experiment:

Database used: Finger vein images with varying quality: good, medium, and low.
Method used: Fine-tuned pre-trained CNNs, specifically VGG-16 and AlexNet.
EER results:
Good quality: 0.396%

Medium quality: 1.275%

Low quality: 3.906%

The best results came from VGG-16 fine-tuned on vein difference images.[101]

3. In “Multimodal biometric identification: leveraging convolutional neural network (CNN) architectures and fusion techniques with fingerprint and finger vein data” experiment:

Database used: SDU-DB and PolyU (containing both vein and fingerprint images).
Method used: Deep learning-based multimodal recognition using VGGNet, ResNet-50, and DenseNet with three fusion strategies:

- Early fusion (raw image-level),
- Late fusion (feature-level),
- Score fusion (output-level).
  All images were enhanced using CLAHE preprocessing.

EER results:

PolyU dataset (ResNet + score fusion): ~0.79%

SDU-DB (ResNet late fusion): ~2.47%

SDU-DB (ResNet-50 overall): ~1.11%.[102]

Equal Error Rate (EER) is a key metric for evaluating the accuracy of vein recognition systems. Traditional methods typically achieve EERs between 0.1% and 3%, while feature-based and early deep learning methods often reduce this range to 0.1%–1.7%. Recent CNN-based approaches, especially those using techniques like CLAHE preprocessing or multimodal fusion, have further improved performance, achieving EERs below 1% in many cases. However, image quality remains a critical factor, with low-quality inputs still causing EERs to rise above 3%.

Biometrics Method	Accuracy	Cost	Size of Template	Long term stability	Security level
Facial Recognition	Low	High	Large	Low	Low
Iris Scan	High	High	Small	Medium	Medium
Finger Print	Medium	Low	Small	Low	Low
Finger Vein	High	Medium	Medium	High	High
Voice Recognition	Low	Medium	Small	Low	Low
Lip Recognition	Medium	Medium	Small	Medium	High

Figure 3 - 26 Comparison of Different biometric methods

Chapter 4: Milestones

4.1 Historical Background and Evolution

The evolution of finger vein recognition technology can be traced back to the early 2000s, with significant advancements emerging in 2005 when Hitachi Ltd. introduced the first commercial finger vein biometric authentication system. This development represented a pivotal transition from theoretical exploration to real-world implementation, laying the foundation for further research and commercial deployment.

The first device capable of scanning finger veins employed near-infrared light to capture the subcutaneous vascular patterns within the finger. These patterns, being both unique to each individual and internal to the body, provided a highly secure and spoof-resistant biometric modality. The initial applications of this technology were predominantly in high-security domains such as banking systems (notably ATMs), access control, and employee time attendance systems, where both accuracy and security were critical.

Subsequent milestones include:

- 2010–2015: Rapid improvements in imaging sensors and pre-processing algorithms significantly enhanced image quality and matching performance.
- Circa 2015: Integration of deep learning and convolutional neural networks (CNNs) began to transform the landscape of finger vein recognition, enabling more robust feature extraction and improving recognition accuracy under varying environmental conditions.
- 2016 onwards: Introduction of Presentation Attack Detection (PAD) mechanisms aimed at identifying and mitigating spoofing attempts, further solidifying the system's resilience.
- The emergence of multimodal biometric systems that combine finger vein data with other biometric modalities (e.g., fingerprint, iris, or facial recognition) to increase reliability and reduce false acceptance/rejection rates.
- Development of open-access benchmark datasets and standardized evaluation protocols that fostered consistent comparison of algorithms across academic studies and industrial implementations.

These milestones reflect a trajectory of continuous innovation, driven by the need for higher security, improved usability, and broader applicability. Today, finger vein recognition stands as a critical component in the broader ecosystem of biometric authentication technologies, valued for its accuracy, liveness detection capability, and resistance to forgery.

4.2 When AI and deep learning were added to improve accuracy and speed

The concept of using finger vein patterns for biometric identification was first proposed by Kono et al. in 2002. Since then, many researchers have shown interest in this modality. One of the early foundational works was by Miura et al. (2004), who introduced the Repeated Line Tracking (RLT) method for extracting vein patterns. This approach laid the groundwork for later techniques, such as the Maximum Curvature (MC) method (Miura et al., 2007) and its various enhancements (Tagkalakis & Fotopoulos, 2015; Syarif et al., 2017; Vasquez et al., 2017). Gabor filters have also been widely used in preprocessing and feature extraction due to their strength in texture discrimination (Fang et al., 2018; Hong et al., 2017). One major challenge in traditional methods has been handling finger movement and rotation, which prompted researchers like Mohd Asaari et al. (2014) to combine finger vein data with finger geometry to enhance robustness. Feature extraction techniques such as Local Binary Patterns (LBP), along with its variants like Personalized Best BitMap (PBBM) and Local Line Binary Pattern (LLBP), have also shown promising results.

In more recent years, the application of deep learning—particularly Convolutional Neural Networks (CNNs)—has started to gain traction in the field of vein recognition. Deep learning allows not only for automatic feature extraction but also for the classification and processing of images in an end-to-end manner. While its use is still less widespread in finger vein recognition compared to domains like face recognition and general computer vision, it has shown promising results. Early efforts like those by Ahmad Radzi et al. (2016) and Das et al. (2019) demonstrated the potential of CNNs for high-accuracy recognition, marking a significant shift from handcrafted methods to learning-based approaches. [49]

Artificial intelligence is bridging the gap between human and machine capabilities. One of prominent fields of AI is Computer vision, The primary goal of computer vision is to make tasks include image detection, image tagging, image recognition, and so on.

deep learning advancements have significantly boosted the performance of computer vision systems. Among these, Convolutional Neural Networks (CNNs) play a foundational role in most modern computer vision algorithms. CNNs is a method of deep learning that takes an input image and assigns importance (learnable biases and weights) to various objects in the image, distinguishing one from the other.

One of the earliest CNN architectures was LeNet, LeNet was named after its creator, Yann LeCun. Yann LeCun created a network for handwritten digit identification in 1989, building on the work of Kunihiko Fukushima, a Japanese scientist who designed the neocognitron (essential image recognition neural network).

The LeNet-5, which describes the primitive components of CNN, might be regarded as the beginning of CNN. LeNet-5 was not well-known because of hardware equipment paucity, particularly GPUs (graphics processing units).

As a result, there was little research on CNN between 1990 and 2000. The success of AlexNet in 2012 opened the door for computer vision applications, and many various forms of CNNs, such as the R-CNN series, have been raised. CNN models now are quite different from LeNet, although they are all based on it. [70]

Deep learning began to play a role in finger vein recognition in the early 2010s, with initial work by Hoshyar et al. in 2011 using a Multilayer Perceptron (MLP) model. However, the real shift toward modern deep learning occurred in 2016 when Ahmad Radzi et al. became among the first to apply Convolutional Neural Networks (CNNs) to finger vein images. Their reduced-complexity four-layer CNN demonstrated high recognition accuracy, though it was tested on a private dataset. This marked a significant turning point, as CNNs allowed for automatic feature extraction and improved robustness. In 2019, Das et al. further advanced the use of CNNs by introducing a five-layer architecture that achieved over 95% accuracy on multiple public datasets, solidifying deep learning as a powerful tool for finger vein recognition. [71,72]

4.3 Big improvements in recognition accuracy and processing speed:

Deep learning significantly enhanced the accuracy and efficiency of vein-based biometric system. particularly through the use of Convolutional Neural Networks (CNNs). DL significantly enhances hand vein recognition by automating feature extraction and improving accuracy. Traditional vein recognition methods are sensitive to variations in lightning and hand positioning. Making them less reliable in real-world application. In contrast CNNs automatically extracts complex patterns and variations in vein structure with minimal human intervention. Additionally, CNNs ability to learn from large datasets enables continuous improvement and adaptation, offering superior security and reliability for biometric authentication.[34] For instance, Fanjiang et al. demonstrated that applying CNNs in vein recognition achieved accuracy rates up to 99%. which proves the efficiency of using CNNs in biometrics. [62]

There are two key advantages in CNNs: weight sharing in CNNs layers, that helps reduces the number of parameters in the network, making computationally efficient, and dimensionality reduction through pooling layers, which helps minimize computation while preserving important spatial features. [38] These design features make CNNs both computationally efficient and highly scalable. Moreover, CNNs support end-to-end learning, eliminating the need for manual feature engineering and enabling better generalization from large datasets. [74]

Deep learning methods do not require too much human intervention and can obtain deep features with better stability by using a large number of training samples. (high) CNNs is more effective than other approaches in feature extraction and classification. In "Fingerprint recognition using convolution neural network with inversion and augmented techniques" by Reena Garg, two models of CNN were trained on finger-print images, are applied to extract images from finger-print images. The accuracy achieved with this approach is 91% and 93% for VGG16 and VGG19 respectively. [76]

In terms of processing speed, the adoption of distributed training has become essential due to CNN's high computational demands. significant advancements can be made to address this issue, enabling their use in real-time and large-scale biometric systems. Improvements in hardware acceleration, optimized network architectures, and advanced training strategies have made CNNs faster and more practical for deployment. Techniques such as distributed training, parallel computing, and model compression are commonly employed to accelerate performance and reduce latency. These developments have made it feasible to implement CNN-based systems even in resource-constrained environments, such as mobile devices and IoT platforms, without compromising accuracy. [77]

Despite their success, CNNs also have challenges, CNNs required large data sets and huge computational power for training. The collection of large-scale biometric datasets can be labor-intensive. CNNs require a lot of experience to tune models, in turn, rely on the ability of researchers. [75]

The ongoing development of new CNN architectures is a promising direction in artificial intelligence. These models continue to improve in both speed and accuracy, making them increasingly suitable for real-time biometric systems. In particular, CNNs are expected to play a vital role in vein-based recognition and may also expand into areas like medical imaging and bioinformatics, where precise visual analysis is essential. [75]

4.4 Real world application

Though vein recognition technology goes from the laboratory to the application environment because of its level of accuracy, difficulty in spoofing, and contactless appeal. Because of these aspects, vein recognition technology has attracted attention in secure environments due to its consideration for hygiene and integrity of identity. Many different sectors including banking, healthcare, government services, and enterprise security have decided to use vein-based biometric systems to authenticate users and protect sensitive information. This section outlines a number of different examples of where vein recognition technology has been implemented in different industries around the world.

Banking and Finance sector

Hand vein biometric sensors, primarily finger vein recognition, have been popularized in the financial industry due to the high security and resistance to spoofing. Countries such as Japan, Poland, Turkey, and Hong Kong have incorporated finger vein scanners into ATMs that allow customers to authorize secure transactions without cards or PINs. Not only in the physical banking sector, but financial institutions in Poland and the UK also utilize vein biometric authentication as an extra layer of protection for online banking that is more secure than traditional passwords or thumbprint scans. Since vein patterns are internal and nearly impossible to replicate there is a selection bias towards this type of technology by banks to prevent identity theft and dubious access. While they are not as widely implemented as facial recognition or fingerprint recognition, vein biometrics adoption in finance is incremental, especially in areas that develop security innovations.[37]

Healthcare Sector

MFA (Medical Faculty Associates) in the USA has been treating about 1 million patients annually. They determine its traditional clipboard-based patient registration process to be both slow and prone to error and insecure. Often, an accurate verification of a patient's identity wouldn't be verified, leading to improper billing, and an increased need of validation about medical identity theft. In an effort to address this challenge, MFA installed Fujitsu's PalmSecure™ biometric system to hasten check-ins, prevent duplicate medical files for patients, have an additional layer of security, and enhance the patient experience with a fast, touchless verification process.

In mid-2009, MFA chose Fujitsu's Med-Serv 50 Kiosk, which includes Fujitsu's PalmSecure™ biometric solution, for their OB/GYN clinic. They conducted a pilot using the kiosk and palm vein scanning technology.

So, how does this work?

PalmSecure™ utilizes near-infrared (NIR)light to scan the veins on a patient's palm.

The vein patterns are unique to each individual and catching these without contact can leverage security benefits for MFA.

During registration, the PalmSecure™ scan creates a biometric template of the patient's palm vein pattern.

The biometric template is then associated with the patient's electronic health record (EHR) in the MFA system.

When the patient comes in for their next visit to MFA, they simply scan their palm again and the system will match the palm scan to the pre-existing template and connect to the patient's EHR profile. profile.[38]

Figure 4 - 1 GWU Care Center

Government and Public Services Sector

Hand vein biometrics, especially palm vein authentication has been implemented in government agencies extensively in Japan, where security and efficiency of processes were paramount. The Japan Agency for Local Authority Information Systems (J-LIS) adopted the technology for the Resident Registry Network (JUKI-net), which enables all local hosts to securely verify identity while protecting identifiable or sensitive information about residents. The JUKI-net system included approximately 10,700 terminals implemented across Japan which had the ability to significantly decrease the administrative costs of IDs and managing physical ID cards, passwords, and other types of devoted services. The "visible" palm and hand vein authentication technology limited the breaches of identifiable data with circumstances that showed only particular authorized individuals to interact with identifiable data, in strict compliance. As an additional example, Japan’s Naka City Public Library implemented palm vein scans in 2006, and patrons were able to sign out books with a simple scan of their hand which was a service and experience that 90% of the people who borrowed items from the library over the course of 20,000 items preferred due to expediency and convenience. Many of these examples in Japan, as researched by my research team, demonstrate that vein biometrics create secure options for public services while creating a shredding positive user experience and convenience for when using government services; thereby creating standards for other governments or others to further explore advanced authentication systems.[37]

Figure 4 - 2 Book lending system

Conclusion

In an era marked by unprecedented advancements in digital security, the growing demand for robust, accurate, and tamper-resistant biometric authentication systems has ushered in a new generation of technologies—of which vein recognition stands at the forefront. This report has undertaken an exhaustive exploration into the realm of vein recognition, illuminating the scientific, technical, and practical aspects of this unique biometric modality. From its underlying principles rooted in near-infrared imaging to its sophisticated implementation through traditional algorithms and deep learning architectures, vein recognition emerges as a highly promising method for secure personal identification.

Unlike external biometrics such as fingerprints or facial features—which are vulnerable to forgery, theft, and degradation over time—vein recognition operates on an internal physiological trait that is both stable and obscured from plain sight. The uniqueness of each individual's vascular patterns, their lifetime permanence, and the significant difficulty involved in replicating them, combine to provide a security framework that is both resilient and reliable. These attributes, coupled with the hygienic and contactless nature of acquisition, make vein recognition an especially valuable tool in post-pandemic scenarios where user comfort and health safety are paramount.

This project has delved into the different types of vein-based biometrics—finger, palm, wrist, and dorsal hand vein recognition—each with its own unique trade-offs in terms of usability, feature richness, and device complexity. The comparative analysis clearly showed that while finger vein recognition currently leads in commercial deployment, other modalities such as palm and dorsal hand vein recognition offer superior data depth and can serve as powerful components in multimodal biometric systems. Such diversity underlines the flexibility of vein recognition and its potential to be customized to fit specific use cases and environments.

Moreover, the comprehensive literature review revealed that researchers have made notable progress in enhancing the precision and resilience of vein recognition systems. Innovations in preprocessing techniques—such as histogram equalization, contrast stretching, and advanced filtering mechanisms like FMBF and HCHE—play a pivotal role in compensating for image noise, low contrast, and anatomical variability. These efforts ensure that vein features can be extracted and matched with high fidelity even under non-ideal conditions.

In addition, the project has critically evaluated two major classes of feature extraction and matching algorithms: traditional line tracking methods and modern deep learning approaches. While line tracking methods, such as repeated line tracking, offer simplicity and high interpretability, they can be constrained by image quality and lack the generalization power required for diverse real-world scenarios. On the other hand, CNN-based models offer superior feature representation and have demonstrated exceptional recognition accuracy in controlled experiments. Nevertheless, the success of deep learning models is heavily dependent on the availability of large, labeled datasets—a challenge that remains a significant barrier to practical deployment.

The report also gave considerable attention to real-world applications, demonstrating that vein recognition is already in use across sectors such as banking, healthcare, public service, and forensics. By offering stronger resistance to spoofing and forgery than conventional biometrics, it provides a higher level of trust in systems that demand the highest standards of identity assurance. However, despite these strengths, practical deployment still faces hurdles—particularly related to hardware costs, system complexity, and the societal acceptance of newer biometric technologies. Public trust, ethical concerns, and privacy implications must also be taken into account as this technology becomes more widespread.

Importantly, the challenges that vein recognition currently faces—ranging from limited datasets and presentation attack vulnerabilities to system generalization issues—should not be seen as roadblocks but as areas of opportunity. The future of vein-based authentication lies in interdisciplinary research that combines biology, optics, computer vision, and artificial intelligence. It will require innovations not only in algorithm development but also in sensor hardware, data acquisition methodologies, user experience design, and cybersecurity practices.

In conclusion, vein recognition represents a significant evolution in the field of biometric authentication, offering a compelling blend of privacy, security, and technological sophistication. While not without its limitations, its continued advancement signals a transformative shift in how individuals will verify their identities in the digital age. As this report has shown, with ongoing research and strategic implementation, vein recognition has the potential to become one of the most trusted and widely adopted biometric modalities in high-security applications worldwide. Its adaptability across sectors, resilience against spoofing, and the capacity for seamless integration into multimodal systems position it as a critical technology for the future of secure identity verification.

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