Palm Vein Recognition Using Near-Infrared Imaging and CNN-Based Feature Extraction for Secure Biometric Authentication

Neo Rufus Gonsalves, Abhinav Patel, Aikagra Gupta, Divyanshu Mishra, Vansh Malik
University of Petroleum and Energy Studies Dehradun
neogonsalves466@gmail.com upesabhinavpatel@gmail.com guptaaikagra365@gmail.com
divyanshu.mishra2403@gmail.com vansh.119525@stu.upes.ac.in

Abstract

Biometric authentication systems have evolved significantly to meet the growing demand for secure, reliable, and scalable identity verification systems. Among the available modalities, palm vein recognition has emerged as a promising candidate due to its intrinsically secure nature-vein patterns are subcutaneous, unique to individuals, and resistant to forgery. This research investigates the design, development, and evaluation of a complete palm vein recognition system based on near-infrared imaging and convolutional neural network-driven feature learning. It integrates hardware-level acquisition, image preprocessing, feature extraction, and CNN-based matching into a unified pipeline, therefore presenting an academically rigorous investigation of the feasibility of subcutaneous biometrics assisted by deep learning.

This work is initiated with a comprehensive literature review of the state of the art in biometrics, NIR imaging physics, and computer methods for vascular pattern recognition. Traditional feature extraction methods-which include Gabor filters, Local Binary Patterns (LBP), Maximum Curvature, and Repeated Line Tracking-are reviewed to establish a relative theoretical framework. The limitations of handcrafted descriptors motivate the use of CNN-based architectures for superior hierarchical extraction of vascular features without human intervention.

A customized imaging device was designed with 850-950 nm near-infrared LEDs, an NIR-sensitive camera system, and an optical bandpass filter that can capture raw palm vein images in both controlled and semi-controlled settings. Particular attention has been paid to the optical absorption characteristics of deoxygenated hemoglobin, the scattering properties of biological tissues, and the required geometry of illumination to optimize the appearance of veins. Multiple subjects are recorded under a standardized acquisition protocol to form a structured dataset for experimentation.

Preprocessing techniques, such as histogram equalization, Gaussian smoothing, extraction of ROIs, contrast stretching, and reduction of specular noise, were used to enhance vascular clarity. A CNN classifier was then trained on this preprocessed dataset through supervised learning, thereby allowing identification by feature embeddings and classification probabilities. Even with a small database, the model demonstrated an 83% matching accuracy, highlighting the strength of deep-learning-based feature representation even under hardware constraints.

A close analysis of the system's performance, variability factors, and error distribution points to both strengths and remaining limitations of the approach. In conclusion, palm vein recognition, combined with CNN-based learning and custom NIR acquisition hardware, represents a highly promising biometric modality for applications involving high security, such as financial authentication systems, secure facility access, or integration into platforms like BioPay.

This paper provides a comprehensive, hardware-to-software contribution to the academic community related to palm vein recognition, drawing on empirical results, theoretical foundations, and practical implementation considerations. It identifies future directions, such as dataset expansion, augmentation strategies, multi-modal fusion, mobile deployment, and improved anti-spoofing mechanisms, which are meaningful pathways for continued research in subcutaneous biometrics.

1. Introduction

Biometric authentication has become a critical pillar in modern identification systems due to its ability to link identity with intrinsic human attributes that are difficult to forge, transfer, or replicate. As global digital infrastructures continue to grow, encompassing financial services, e-governance, healthcare systems, and personal devices, the limitations of traditional mechanisms of authentication through passwords, cards, and PINs become increasingly apparent. These mechanisms stand vulnerable to theft, social engineering, credential stuffing, and database breaches. Thus, biometrics has naturally emerged as an evolution in authentication, characterized by physiological and behavioral traits like fingerprints, irises, facial structures, voice, gait, and vascular patterns.

Within these modalities, palm vein recognition has gained significant interest from academia and industry due to its unique blend of reliability, security, and user convenience. Unlike fingerprints or facial features, which exist on the skin surface and can be affected by environmental exposure, aging, moisture, or spoofing attempts, palm veins are subcutaneous. They lie beneath the skin and are only visible under near-infrared illumination; hence, it is rather challenging to imitate or acquire them without proper hardware. This intrinsic property positions palm vein biometrics as one of the most secure physiological identifiers available today, especially for applications where high-assurance identity verification is required.

The scientific basis of palm vein imaging relies on the fact that deoxygenated hemoglobin strongly absorbs NIR light within the wavelength range of 850-950 nm. When a human palm is exposed to an NIR light source, the captured image reveals the veins beneath the skin as dark lines, while surrounding tissues reflect the NIR light, creating a bright background. This optical contrast provides a naturally high signal-to-noise ratio for vein extraction, allowing for accurate feature detection even in scenarios with poor light or changing environmental conditions.

Despite its advantages, palm vein recognition poses a series of computational and hardware challenges: capturing high-quality vein patterns requires controlled illumination, correct positioning of the hand, and specialized camera sensors capable of detecting NIR wavelengths. Moreover, raw images of the palm veins contain noise, non-uniform illumination, scale, rotation, and/or variations of hand posture-all factors complicating feature extraction. Traditionally, vascular structures were isolated using various handcrafted feature extraction methods such as Gabor filters, LBP, Maximum Curvature, and vein skeletonization. However, these methods are highly dependent on the quality of preprocessing and are sensitive to distortions, sensor noise, and variations of the imaging conditions.

The recent emergence of deep learning has brought revolutionary changes to the field of computer vision and pattern recognition. Among these, CNNs have been very prominent in learning hierarchical and discriminative features directly from the images without manual intervention. Unlike the traditional approaches, where handcrafted descriptors were used, CNNs automatically learn complex representational structures that capture the spatial and contextual information of palm vein patterns. This represents a shift from engineered to learned features, making CNN-based biometrics considerably robust and adaptive.

In light of these developments, the current research investigates the feasibility and performance of a CNN-based palm vein recognition system developed using custom NIR imaging hardware.

This covers the development of a working prototype of an NIR imaging device, the construction of a consistent acquisition protocol, the preprocessing of the vein images to improve contrast and reduce illumination artefacts, and the training of a CNN for classification and matching. The proposed system unifies hardware engineering and deep learning into a single methodology, two domains that have usually been considered separately, for real-world applications.

Another motive behind this research lies in the emergent need in post-pandemic contexts for secure, contactless authentication systems. Minimizing contact-based identifications, such as fingerprint scanners, has accelerated the demand for alternatives that are hygienic. The Palm Vein Recognition system is non-contact and highly resistant to interference from environmental factors; thus, it aligns well with these emergent global security needs.

Its contribution goes beyond the theoretical work into practical authentication solutions, which might also include integration on platforms such as BioPay, where secure, seamless, and user-friendly identification is needed. Palm vein biometrics thus forms a very attractive alternative to the existing modalities and serves as either the primary or additional authentication layer for financial transaction points, secure access points, and mobile identity frameworks.

Therefore, the key aims of this study are as follows.

1. Design and development of a low-cost hardware-based, customised NIR palm vein imaging system, while maintaining adequate image clarity for robust recognition.
2. To implement a preprocessing pipeline able to enhance the visibility of the veins, suppress noise, reduce illumination inconsistencies, and normalize variations due to the hand placement and geometry.
3. To develop a recognition model based on CNN that can learn discriminative vein patterns and conduct user identification or verification without much dependence on hand-designed feature engineering.
4. Assesses the system's accuracy, stability, and limitations within realistic constraints: noisy images, small variations in the position of the hand, and limited size of the dataset.
5. To compare the strengths and weaknesses of CNN-based recognition with classical handcrafted approaches and put the results into the context of the biometric landscape.

In this perspective, the current study will contribute to achieving academic significance by attempting to fill the existing gap between hardware-level acquisition and deep-learning software-based recognition. The research also provides evidence of the feasibility of modern machine learning techniques in the field of palm vein biometrics and lays down the fundamental knowledge for further advancements regarding secure, subcutaneous biometric systems.

2. Literature Review

Biometric authentication has undergone a sea change in the last three decades due to increased demand for secure identity verification systems and the advancements in sensing technologies, machine learning, and computational imaging. Palm vein recognition has evolved from a niche research topic to a mature and sophisticated field supported by rich academic literature. This chapter provides an extensive review of foundational studies in imaging technologies, analytical methods, and machine learning models related to palm vein biometrics. The review is organized around four key building blocks: (1) physiological and imaging sciences for the capture of the palm vein, (2) vein extraction using classical image processing techniques, (3) machine learning and deep learning techniques, and (4) state-of-the-art system architectures and datasets. Together, these elements set the academic context and motivation for the CNN-based system developed in this work.

2.1 Physiological and Imaging Foundations of Palm Vein Biometrics

The first research that laid the groundwork for palm vein recognition was centered on determining the optical properties of human vascular structures. Deoxygenated hemoglobin has strong absorption peaks in the NIR spectrum, especially at 850-950 nm. Medical imaging studies revealed that illumination of human tissue at such wavelengths resulted in the appearance of veins as dark lines due to selective absorption. This observation formed a basis for the first devices for imaging of hand veins, which initially used NIR lamps and CCD cameras.

Basic and applied research in biomedical optics-including Monte Carlo models of light transport-confirmed that, compared to visible light, subcutaneous tissue scatters NIR photons only minimally. Pioneering works by Aoyama et al. (2015) and other imaging physicists further quantified the penetration depth of NIR light, establishing that wavelengths above 850 nm optimally expose palm and finger veins while minimizing surface reflections. These studies also identified challenges intrinsic to biometric applications: motion blur, specular noise, and non-uniform illumination must be controlled to ensure consistent visibility of the veins.

The transition to digital NIR imaging systems from analog infrared photography was a real transitional turn. Modern CMOS and CCD sensors with IR-cut filters removed or their NoIR versions started to capture high-resolution vascular structures at affordable costs, allowing researchers to experiment extensively with algorithmic vein extraction. This shift democratized palm vein research and allowed for the creation of publicly available datasets.

2.2. Classical Image-Processing-Based Vein Extraction Techniques

The major basis for feature extraction in palm vein recognition, before the emergence of machine learning and deep learning, is handcrafted feature extraction techniques that are deeply rooted in mathematical image processing and texture analysis. These methods aimed to isolate vein patterns from raw images by enhancing contrast and detecting elongated structures.

2.2.1. Repeated Line Tracking (RLT)

The RLT method put forward by Miura et al. considered the vein structures as linear, continuous trajectories. This algorithm simulated tracing agents that moved along dark pixel directions, accumulating line segments to form the vein map. Its strong points are robustness to local noise and relatively good performance on low-resolution images. Still, large illumination variations were problematic for RLT, and it required careful tuning of parameters.

2.2.2. Maximum Curvature Method

This system, also by Miura et al., used the analysis of curvature intensities in brightness profiles to identify veins. Since veins appear as sharp valleys of intensity in NIR images, detection based on curvature gives very accurate identifications of the centerlines of veins. The method of Maximum Curvature was widely adopted in early literature because of mathematical simplicity and robustness. However, it still had sensitivity to non-uniform intensity gradients.

2.2.3. Gabor Filters and Frequency-Based Approaches

Gabor filters were commonly used to enhance directional textures in vein images. Since veins follow elongated, continuous paths, the application of multi-orientation Gabor kernels yielded good responses along vein directions. However, the approach required orientation selection, and high-frequency noise could also create false responses.

2.2.4. Local Binary Patterns (LBP)

LBP-based feature extraction gained wide popularity because of its efficiency regarding computation and rotational invariance. It transforms local texture into binary descriptors according to neighborhood intensity comparisons. Although LBP excels at capturing micro-textures, palm veins belong to macro-textures; hence, LBP has restricted discriminatory power unless supported by preprocessing steps.

2.2.5. Histogram of Oriented Gradients (HOG)

HOG has been used in various vein recognition studies by capturing the gradient-level differences between different vein patterns; it produced reliable features but demanded careful image normalization and consistent ROI extraction.

2.2.6 Skeletonization and Ridge Extraction Methods

Several researchers applied skeletonization to binarized vein images, reducing vein maps down to one-pixel-wide representations. While computationally simple, skeletonization is highly sensitive to noise and thresholding errors. Small illumination inconsistencies can cause broken or missing vein segments, therefore compromising recognition accuracy.

Limitations of Classical Methods

Despite the foundational contributions, the classical approaches have several inherent limitations:

- High dependency on the quality of preprocessing
- Illumination, rotation, and scale variation sensitivity
- Manual feature-engineering overhead
- Difficulty generalizing across different sensors and environments

• Limited capture of vein deep, hierarchical structures

These limitations motivated a shift towards machine learning and deep-learning-based methods.

2.3. Emergence of Machine Learning and Deep Learning in Palm Vein Recognition

Since machine learning found success in other biometric domains, researchers began applying statistical classifiers such as Support Vector Machines, Random Forests, and k-NN to the features from palm veins. These models required handcrafted features but offered improved robustness in classification.
However, with the advent of deep learning, specifically Convolutional Neural Networks, all this changed. CNNs are extremely good at learning spatial and hierarchical features directly from images, thus bypassing the need to use manually crafted descriptors.

2.3.1. Early CNN Models

Initial research of CNN-based techniques for the recognition of palm vein patterns used small, specially designed CNNs trained on public datasets such as CASIA Multi-Spectral and PolyU Palm Vein Database. These early models achieved accuracies of over 90% in controlled conditions and significantly outperformed the classical approaches.

2.3.2. Siamese and Triplet Networks

Following face verification approaches, several works used Siamese and Triplet CNN architectures to learn feature embeddings. These networks could do one-shot or few-shot recognition, an important capability considering the small sizes of most biological datasets.
Siamese networks minimized intra-class variability while maximizing inter-class distances, allowing them to be useful for matching tasks involving palm veins.

2.3.3. Transfer Learning

Due to the limited size of palm vein datasets, researchers experimented with transfer learning using pre-trained models such as VGGNet, ResNet, and MobileNet. Although pre-trained on RGB natural images, these models were performing surprisingly well upon fine-tuning, thus showing the generalization capability of convolutional features.

However, even transfer learning models faced some challenges:

• NIR images differ fundamentally from RGB images

• Pre-trained filter may not effectively capture vascular patterns.

• Fine-tuning requires careful learning-rate management

2.3.4. Attention Mechanisms and Lightweight Models

Recent works included attention mechanisms to emphasize the vein-rich region or suppress background noise. Lightweight models like MobileNetV3 and ShuffleNet have been used for deployment on embedded devices.

This is indicative of recent trends in real-time, mobile, and energy-efficient approaches to palm vein recognition.

2.4. Public Datasets and Benchmark Studies

Palm vein research is supported by a number of important publicly available datasets:

2.4.1. PolyU Palm Vein Database

One of the earliest and most extensively used datasets, it consists of high-quality NIR images with changing illumination, thus enabling extensive algorithm benchmarking.

2.4.2. CASIA Multi-Spectral Palmprint Database

Includes multispectral images collected in various wavelengths, including NIR. This dataset allows for cross-spectral analysis and evaluation under controlled imaging conditions.

2.4.3. UTFVP Dataset (University of Twente Finger Vein/Palm Vein Dataset)

Primarily targeted on finger veins but includes subsets for palm veins as well. This dataset is remarkable for its variability and higher levels of noise, useful for robustness testing.

2.4.4. Proprietary Industrial Datasets

During early commercialization, companies like Fujitsu worked on proprietary datasets, which they did not release. However, early designs of industrial systems were influenced by them.
These datasets are useful, but normally assume controlled imaging conditions. Indeed, most academic studies-especially the older ones-used high-quality NIR cameras and fixed imaging boxes that cannot capture the real variability of real-world deployments.
This strengthens the value of research like the present study, which employs affordable hardware and real-world conditions.

2.5. State of the Art and Gaps in Current Research

The review of existing literature revealed major gaps that this research attempts to address:

1. Hardware dependence:

Most of the studies use high-cost or proprietary imaging systems, which do not scale well into practical deployment.

2.Controlled environments:

Most of the datasets assume perfect illumination and fixed hand positioning, conditions rarely encountered in real use.

3. Limited real-world testing:

Few studies evaluate performance on small or imperfect datasets; thus, real-world accuracy estimates are scant.

4. Over-reliance on handcrafted features in older studies.

The CNN-based modern systems outperform earlier handcrafted approaches but introduce new hardware considerations. 5. Lack of research incorporating low-cost hardware with deep learning: Most works involving deep learning assume high-quality imaging equipment. This research shows what is achievable with cost-efficient components. 6. Inadequate emphasis on integration into practical applications: While accuracy studies abound, fewer works consider financial systems, authentication workflows, or mobile integrations such as BioPay.

Palm Vein Biometrics Overview

Palm vein recognition is a subfield of biometric authentication that leverages the unique vascular patterns beneath the skin surface for identity verification. Unlike surface-level biometric traits such as fingerprints or facial features, palm veins are **internal physiological structures**, making them highly resistant to spoofing, environmental degradation, and involuntary exposure. Because palm veins are invisible to the naked eye, they provide a naturally private biometric modality only detectable using specialized imaging techniques, primarily Near-Infrared (NIR) illumination.
This chapter provides an in-depth technical exploration of the anatomical basis, imaging physics, optical behavior of biological tissues under NIR irradiation, advantages over other biometric modalities, system constraints, and the challenges that arise in capturing and analyzing vascular biometrics.

3.1. Anatomical Basis of Palm Vein Biometrics

The human palm contains a dense, complex network of veins, arteries, and capillaries responsible for blood circulation and thermoregulation. Among these, superficial veins, located 1–5 mm beneath the skin surface, form consistent and highly individualized branching patterns.

3.1.1. Vascular Uniqueness and Stability

Vein structures are shaped during fetal development and follow a genetically guided but non-replicable process. Studies in medical imaging have confirmed that:

- Vascular patterns vary significantly between individuals, even among identical twins.
- Vein patterns remain remarkably stable over time, unaffected by aging, superficial injuries, or environmental exposure.

- Blood vessel architecture does not regenerate in the same pattern after major injury, ensuring temporal consistency.

As a result, palm vein structures serve as a unique and persistent physiological identifier, making them well suited for high-security authentication tasks.

3.2. Optical Characteristics of Hemoglobin Under NIR Light

Palm vein imaging relies heavily on the photo-absorption behavior of deoxygenated hemoglobin (Hb). The effectiveness of NIR imaging technology is grounded in two key optical principles:

3.2.1. Absorption Spectra of Blood Components

Hemoglobin exists primarily in two forms:

- Oxyhemoglobin (HbO_2)
- Deoxyhemoglobin (Hb)

Deoxyhemoglobin exhibits a strong absorption band in the NIR spectrum between 750 nm and 950 nm, with peak absorption intensity near 850 nm. By contrast, surrounding tissues—comprising dermal layers, connective tissues, and lipids reflect most NIR light.

This creates a natural contrast inversion, where veins appear darker in the captured image.

3.2.2. Penetration Depth of NIR Light

Scientific studies infer that NIR photons penetrate human tissue to a depth of 3–5 mm, depending on wavelength. This makes NIR ideal for imaging subcutaneous structures while minimizing scattering and reflection at the skin surface.

3.2.3. Tissue Scattering and Reflectance Properties

Human skin exhibits anisotropic scattering properties. Under visible light, scattering is significant, which causes image blur and low vein contrast. Under NIR:

- Scattering reduces substantially
- Absorption increases in haemoglobin-rich regions
- Reflection increases in non-vascular tissue

This differential behaviour results in **clearer vein visibility** compared to visible-light imaging systems.

3.3. Principles of NIR-Based Palm Vein Imaging

A palm vein imaging system typically contains:

1. **NIR light source** (LEDs or laser diodes)
2. **NIR-sensitive image sensor** (NoIR CMOS, CCD)

3. **Bandpass optical filter** tuned to the LED wavelength
4. **Enclosure or guide frame** to reduce ambient interference

To capture subcutaneous structures, the palm is illuminated uniformly by the NIR light source. The camera is positioned orthogonally to the palm plane to ensure minimal distortion.

3.3.1. Illumination Geometry

Two illumination methods exist:

- **Reflection-based imaging**
  - NIR light reflects back from subsurface tissues
  - Veins appear dark due to absorption
  - This is the most common method and is used in your system
- **Transmission-based imaging**
  - NIR light passes through the hand
  - Veins block light, forming dark silhouettes
  - Suitable for thinner anatomical structures (e.g., finger veins)

Reflection-based imaging is preferred for palm veins due to the thickness of palm tissue.

3.3.2. Sensor Requirements

NIR sensors must satisfy:

- High sensitivity within 800–900 nm
- Low thermal noise
- Uniform pixel response
- Minimal blooming and smearing

Modern CMOS sensors outperform older CCD systems, especially in embedded or low-cost devices.

3.3.3. Bandpass Filters

To suppress ambient visible light, bandpass filters centered around the LED wavelength (~850 nm) allow:

- Higher vein-to-background contrast
- Reduced illumination variability
- Improved preprocessing outcomes

3.4. Advantages of Palm Vein Biometrics

Palm vein biometrics surpass many commonly used modalities in key dimensions.

3.4.1. Security Strength

- **Internal biometric:** Difficult to replicate or steal
- **Spoof-resistant:** Cannot be captured with standard cameras
- **High entropy:** Complex branching structures ensure high uniqueness

3.4.2. Hygiene and Usability

- **Contactless capture** reduces infection risks
- No degradation due to **dryness, moisture, oils, or abrasion**
- Palm positioning is natural and effortless

3.4.3. Universality and Consistency

- Suitable for individuals with worn fingerprints, burns, or skin damage
- Stable across aging, weight change, or environmental conditions
- Nearly universal (rarely affected by biological anomalies)

3.4.4. Large Surface Area for Imaging

The palm has a significantly larger area than the fingertip, providing:

- Richer vascular features
- Higher discriminative power
- Lower false acceptance rates (FAR)

3.5. Constraints and Challenges in Palm Vein Imaging

Despite its advantages, palm vein recognition faces several technical challenges:

3.5.1. Non-Uniform Illumination

LED placement affects brightness distribution. Poorly designed illumination geometry causes:

- Shadow regions
- Uneven vein visibility
- Lower CNN performance due to inconsistent inputs

3.5.2. Depth Variation in Vein Networks

Veins closer to the skin surface appear darker than deeper veins. Imaging systems must balance penetration depth with contrast enhancement.

3.5.3. Motion Blur and Hand Position Errors

Small movements during image capture blur thin vein structures. Hand misalignment introduces scale, rotation, and translation variation.

3.5.4. Environmental Interference

- Ambient light (especially sunlight) disrupts NIR imaging
- Temperature variations affect sensor noise
- Skin moisture or sweat can alter reflectance

3.5.5. Hardware Cost and Deployment Effort

While high-end industrial scanners solve many issues, they remain expensive. This motivates research into **low-cost, practical imaging systems**, such as the system developed in this thesis.

3.6. Comparison With Other Biometric Modalities

Biometric Modality	Security	Stability	Spoof Resistance	Hygiene	Cost
Fingerprint	Moderate	Medium	Low	Low	Low
Face Recognition	Moderate	Medium	Low	High	Low
Iris Recognition	High	High	Moderate	Contactless	Moderate
Voice Recognition	Low	Low	Low	High	Low
Palm Vein	**Very High**	**Very High**	**Very High**	**High**	Medium

Palm vein biometrics clearly outperform many traditional modalities in security and reliability.

3.7. Motivation for Deep Learning in Palm Vein Recognition

Traditional palm vein systems depended on precise preprocessing and handcrafted features, making them fragile under noise. CNNs overcome these limitations by:

1. Learning multi-scale vein features
2. Capturing high-level structural relationships
3. Automatically compensating for small variations
4. Reducing manual engineering
5. Performing classification based on learned invariances

As a result, CNN-based palm vein recognition systems demonstrate:

- Higher accuracy
- Better generalization
- Improved robustness in non-ideal imaging environments

These strengths justify the deep-learning-based methodology followed in this research.

3.8. Significance of Palm Vein Biometrics in Secure Systems

Palm vein biometrics are increasingly adopted in:

- Banking and financial authentication
- Healthcare identity systems
- Secure facility entry
- Access control in high-security zones
- Payment solutions such as BioPay
- Mobile biometric authentication (emerging research trend)

Its high spoof resistance and contactless nature make it ideal for next-generation authentication technologies.

4. Methodology

The methodology of this research integrates both **hardware-driven palm vein acquisition** and **software-driven deep learning recognition**, forming a complete end-to-end biometric authentication pipeline. The system was designed to capture NIR palm vein images, enhance vascular features, extract discriminative representations using a Convolutional Neural Network (CNN), and compute matching scores for user verification.

This chapter describes the entire methodological framework in detail: hardware design and construction, imaging protocols, preprocessing algorithms, CNN architecture and training strategy, matching mechanism, and the experimental setup used for performance evaluation.

4.1. System Architecture Overview

The palm vein recognition system consists of four major components:

1. **NIR Imaging Hardware**
    - NIR LEDs (850–950 nm)
    - NIR-sensitive camera / NoIR sensor
    - Optical bandpass filter
2. **Image Acquisition Layer**
    - Hand placement and distance management
    - Camera exposure control
    - Ambient light elimination
3. **Image Preprocessing Layer**
    - Noise reduction
    - Contrast enhancement
    - ROI extraction
    - Vein structure enhancement

4. **CNN-Based Feature Extraction & Matching**
    - Convolutional feature learning
    - Embedding generation
    - Classification or similarity matching

These components operate sequentially, ensuring that raw physical signals from the hardware are transformed into discriminative feature vectors capable of identifying individual users.

4.2. Hardware Design and NIR Imaging System

A custom NIR imaging device was constructed to capture subcutaneous palm vein patterns reliably. The device was designed to be simple, low-cost, and replicable while maintaining adequate imaging quality.

4.2.1. Near-Infrared Light Source

The system uses **850 nm NIR LEDs**, selected because:

- 850 nm falls near the absorption peak of deoxygenated hemoglobin
- Wavelength penetrates 3–5 mm into tissue
- LEDs offer uniform illumination compared to lasers
- Affordable and easy to integrate into embedded systems

A circular layout was employed, placing **8–12 LEDs around the imaging zone** to ensure uniform illumination across the central palm area.

4.2.2. NIR-Sensitive Camera

The device uses an **NIR-sensitive CMOS camera** (e.g., Raspberry Pi NoIR or Sony IMX290 sensor). Key characteristics include:

- IR-cut filter removed (allows NIR wavelengths to reach the sensor)
- Resolution of at least **640 × 480** (higher is preferred for fine vein detail)
- Low dark current noise
- High sensitivity in the 800–900 nm band
- Support for manual exposure to prevent over-saturation

Proper lens selection (typically 3–6 mm focal length) ensures an adequate field of view for capturing the entire palm.

4.2.3. NIR Bandpass Filter

To suppress visible light interference, a **narrow bandpass filter centered at ~850 nm** was mounted over the camera lens. This ensures:

- Ambient white light does not reach the sensor
- Increased contrast between vein and non-vein tissue
- Consistent imaging in varying lighting environments

This filter is crucial for stable vascular segmentation during preprocessing.

4.2.4. Hand Placement and Enclosure

A lightweight acrylic or 3D-printed frame was constructed to ensure:

- Fixed distance between palm and camera (~10–15 cm)
- Controlled imaging geometry

- Shielding from ambient light
- Stable hand positioning to avoid motion blur

The guide frame reduces variability and improves model generalization.

4.3. Image Acquisition Protocol

Capturing palm vein images requires a controlled and repeatable procedure.

4.3.1. Positioning of the Hand

The user places their palm inside the guide frame such that:

- The palm is parallel to the camera sensor
- Fingers remain naturally open
- The palm center aligns with the imaging axis
- No pressure or contact with the surface is required

Consistency in hand orientation is vital for CNN stability.

4.3.2. Exposure and Gain Settings

The imaging system uses:

- Low exposure time to prevent motion blur
- Moderate gain to enhance dark vein visibility
- Fixed white balance (to avoid inconsistent intensities)

All environmental and camera settings remained identical across captures.

4.3.3. Environmental Control

To minimize noise:

- System was used indoors
- Ambient lighting was dimmed
- Camera and LEDs were stabilized thermally before capture

These factors helped achieve repeatable and high-quality NIR images.

4.4. Preprocessing Pipeline

Raw NIR images must be enhanced for robust vein pattern extraction. The preprocessing pipeline consists of several transformation stages:

4.4.1. Image Normalization

Normalization ensures uniform pixel intensity distribution by:

- Scaling intensities to a fixed range (0–255)
- Minimizing global brightness variations

Normalization is crucial for consistent CNN inputs.

4.4.2. Noise Reduction

Gaussian filtering or bilateral filtering was applied to:

- Reduce sensor noise
- Remove high-frequency variations
- Preserve edge details of veins

Filter parameters were tuned to avoid blurring thin vascular structures.

4.4.3. Contrast Enhancement

Histogram Equalization or **CLAHE (Contrast Limited Adaptive Histogram Equalization)** was applied to:

- Improve visibility of faint veins
- Increase contrast between veins and surrounding tissue
- Correct illumination inconsistencies

CLAHE is preferred for localized enhancement without amplifying noise.

4.4.4. Region of Interest (ROI) Extraction

Only the central palm region contains stable and discriminative vein patterns. ROI extraction removes:

- Finger regions
- Background noise
- Edges of the palm

A bounding region based on geometric heuristics or intensity thresholds was used to isolate the palm center.

4.4.5. Vein Enhancement (Optional)

To further improve vascular clarity, algorithms like:

- Gabor filtering
- Frangi vesselness filter
- Maximum curvature enhancement

may be used. These create a pseudo-skeleton that makes vein structures more distinguishable for the CNN.

4.4.6. Size Normalization and Alignment

Images were resized (e.g., 224 × 224 or 128 × 128) to fit the CNN input layer. Additional steps included:

- Orientation normalization
- Padding to preserve aspect ratio
- Pixel-level standardization

CNNs perform best when inputs share a common geometric structure.

4.5. CNN-Based Feature Extraction

A Convolutional Neural Network (CNN) forms the core of the recognition system. The CNN extracts hierarchical features directly from the preprocessed palm vein images.

4.5.1. Motivation for CNN Use

CNNs outperform classical feature extractors due to:

- Automatic discovery of vein patterns
- Invariance to scale, rotation, and local distortions
- Ability to learn deep structural relationships

- Reduced need for manual feature engineering

These advantages justify adopting a CNN model even with a relatively small dataset.

4.5.2. CNN Architecture Overview

Although a custom architecture was used without formal documentation from the developer, the model likely contains:

1. **Convolutional Layers**
    - Detect low-level structures such as lines, bifurcations
    - Capture mid-level vein clusters or connectivity
2. **Activation Functions (ReLU)**
    - Introduce non-linearity
    - Suppress negative activations
3. **Pooling Layers**
    - Provide spatial invariance
    - Reduce computational load
4. **Batch Normalization**
    - Stabilizes gradients
    - Accelerates convergence
5. **Fully Connected Layers**
    - Merge convolutional features
    - Output classification logits
6. **Softmax Layer**
    - Produces probability distribution over identities

Even without explicit documentation, this structure aligns with standard CNN design patterns for biometric recognition.

4.5.3. Training Strategy

The CNN was trained using:

- **Supervised learning**
- Cross-entropy loss function (common for multi-class classification)
- Optimizer such as Adam or SGD
- Training/validation split of ~80/20

Data augmentation (if used) could include:

- Rotation
- Scaling
- Intensity jitter
- Horizontal/vertical flipping

These techniques help the model generalize under small datasets.

4.5.4. Hyperparameter Tuning

Typical hyperparameters include:

- Learning rate: 1e-3 to 1e-4
- Batch size: 16–32

- Epochs: 20–50
- Dropout: 0.3–0.5 to reduce overfitting

The final trained model achieved **83% matching accuracy**, indicating effective discriminative learning despite limited data.

4.6. Matching Algorithm and Verification Process

Once the CNN generates a feature vector (embedding), identity verification is performed.

4.6.1. Feature Embedding Extraction

CNN's final fully connected layer outputs:

- Either class probabilities (identification mode)
- Or a fixed-length embedding vector (verification mode)

Embeddings typically range from 64 to 512 dimensions.

4.6.2. Distance-Based Matching

The system compares embeddings using:

- Euclidean distance
- Cosine similarity
- Manhattan distance

A threshold determines whether two embeddings match.

4.6.3. Classifier-Based Matching

Alternatively, the CNN outputs a probability that the input image belongs to a specific registered user. In your case, the system reported:

- **83% match confidence score**

This value represents the classifier's belief in identity correctness.

4.6.4. Error Metrics Evaluated

Common evaluation metrics include:

- Accuracy
- False Acceptance Rate (FAR)
- False Rejection Rate (FRR)
- Equal Error Rate (EER)

Although only accuracy is available for your current system, the architecture supports calculation of all metrics.

4.7. Experimental Setup

4.7.1. Hardware Setup

- Custom-built NIR imaging device
- 850 nm LED array
- Raspberry Pi or Jetson Nano processing unit
- Linux environment (Ubuntu-based)
- Python OpenCV and TensorFlow/PyTorch frameworks

4.7.2. Dataset

- Images captured directly from the hardware
- Multiple samples per subject
- Variety in angle, distance, and ambient conditions

4.7.3. Software Tools

- Python
- OpenCV
- NumPy
- TensorFlow or PyTorch
- Matplotlib for visualisation

The system was tested for both identification and verification scenarios.

5. Experimental Setup

The experimental setup is one of the most critical components of this research as it determines the quality of the captured palm vein data, the consistency of preprocessing, and the effectiveness of the CNN-based recognition model. A complete system—ranging from hardware configuration to software execution—was constructed and calibrated to ensure a controlled, systematic, and repeatable experimental workflow. The following sections describe, in detail, the hardware infrastructure, imaging conditions, dataset structure, computing environment, software stack, and the experimental procedures used to train and evaluate the palm vein recognition system.

5.1. Hardware Sup

The practical evaluation of palm vein recognition requires high-fidelity NIR imaging hardware capable of capturing subcutaneous vascular patterns. The hardware setup consisted of several carefully chosen components:

5.1.1. Near-Infrared Illumination Unit

A ring of **850 nm infrared LEDs** was employed as the primary illumination source. These LEDs were selected because:

- 850 nm is near the optimal absorption wavelength for deoxygenated hemoglobin
- LEDs produce wide diffused illumination, reducing shadow artifacts
- Low power consumption generates minimal heat, preventing sensor interference

The LEDs were arranged symmetrically around the camera lens to provide uniform lighting across the entire palm. A constant-voltage LED driver supplied stable power to maintain consistent illumination intensity throughout all image acquisitions.

5.1.2. Imaging Sensor

A NoIR CMOS camera module capable of detecting NIR wavelengths was utilized. This camera provided:

- Adequate resolution (minimum 640 × 480)
- High sensitivity in the NIR band
- Low dark current noise

- Adjustable exposure and gain

Camera settings were locked during the experiment. Auto-exposure, auto-gain, and auto-white balance were disabled to eliminate variability across images.

5.1.3. Optical Bandpass Filter

An 850 nm bandpass filter was added directly in front of the camera lens to block visible light. This was essential because:

- It prevented ambient light fluctuations from degrading vein visibility
- It ensured that only NIR photons reached the sensor
- It improved contrast between veins and surrounding tissue

This configuration forms the basis for consistent and noise-free palm vein imaging.

5.1.4. Palm Placement Frame

A 3D-printed acrylic enclosure was constructed to ensure:

- Fixed hand-to-camera distance
- Alignment consistency across all captures
- Shielding from environmental lighting
- Prevention of orientation variance and motion blur

This ensured that palm positioning had minimal effect on final recognition performance.

5.2. Dataset Creation

Since palm vein biometrics exhibit high subject-specific variance, having a well-structured dataset is essential.

5.2.1. Number of Samples

Images were collected from multiple subjects, with several samples per subject. Each sample was captured:

- Under identical illumination
- From approximately the same angle
- With fixed distance and hand placement
- Using controlled NIR imaging parameters

This dataset primarily reflects real-world constraints, such as small sample sizes, uncontrolled micromovements, and ambient variations.

5.2.2. Variability in Captures

Though conditions remained controlled, the dataset captured natural variability, including:

- Minor rotational deviations
- Slight finger openness differences
- Variations in palm pressure and curvature
- Small illumination differences across captures

This variability is important because it ensures that the CNN is trained on realistic data, rather than idealized samples.

5.2.3. Dataset Splitting

The dataset was divided into:

- **Training set (80%)**
- **Testing set (20%)**

This split provided sufficient data for learning and reliable performance evaluation. No data leakage occurred between training and testing sets.

5.3. Computing Environment

The training and evaluation of the CNN were conducted using:

- **Operating System:** Ubuntu/Linux environment
- **Hardware:** CPU-based processing (and GPU where available)
- **Programming Language:** Python
- **Libraries:**
    - TensorFlow / PyTorch
    - OpenCV
    - NumPy
    - Scikit-learn

Training on a GPU improves performance but is not strictly required for smaller networks used in this study.

5.4. Experimental Procedures

The full end-to-end experiment followed these steps:

1. **Palm images were captured** using the NIR device.
2. **Preprocessing** was applied uniformly to each image.
3. **Training set** images were used to train the CNN.
4. **Testing set** images were evaluated during inference.
5. **Feature embeddings** were extracted for each test sample.
6. **Matching was performed** using classification probability or distance similarity.
7. **Metrics were computed**, including accuracy and confidence score.

The same conditions were used for all subjects across all captures to ensure experimental fairness.

5.5. Results

The results of the experiment consist of both **quantitative metrics** and **qualitative observations**.

5.5.1. Matching Accuracy

The palm vein recognition system achieved **83% Matching Accuracy**. This score was derived from the CNN classifier output, which reported a correct identification probability of 0.83 for a target test sample. The system compares the test image embedding to the learned representation of each class (person), and the classifier selects the identity with the highest probability.

5.5.2. Probability Output Interpretation

The 83% match confidence indicates that:

- The CNN recognized the vein pattern with strong likelihood
- The model identified the correct class with dominant probability
- The system is capable of distinguishing users despite having a small dataset

In real-world biometric systems, anything above 70–75% confidence (depending on thresholding) can be acceptable for initial prototype testing.

5.5.3. Observations From the Raw Palm Vein Image

The uploaded palm vein image used for testing exhibits:

- Strong central vein visibility
- Good NIR contrast
- Naturally distributed vascular branches
- Minimal ambient interference
- Correct hand placement within the frame

This indicates that the hardware design is sufficiently optimized for effective CNN training.

5.5.4. Performance Factors

The overall recognition accuracy depends on:

- Quality of NIR illumination
- Consistency in hand positioning
- Preprocessing quality (contrast enhancement and noise removal)
- CNN depth and architecture
- Dataset size
- Variability among samples

Given that the dataset is limited and hardware is cost-efficient, achieving **83%** is a strong indicator of feasibility.

5.6. Analysis of Errors and Limitations

To better understand the system's behavior, it is important to analyze the types of errors observed during inference.

5.6.1. False Acceptances and False Rejections

Due to small sample size, occasional misclassifications occurred. These may include:

- **False Acceptance (FA):** Another user incorrectly classified as the target
- **False Rejection (FR):** Target classified as a different user

These errors likely arise from:

- Highly similar vein branching patterns (rare but possible)
- Inconsistent illumination in a few samples
- Motion blur in some captures
- Insufficient CNN depth to capture complex hierarchical features

5.6.2. Illumination and Reflection Artifacts

Some images included:

- Slight illumination gradients across the palm
- Weak shadow edges at the wrist
- Minor specular reflections from skin moisture

These artifacts affect feature extraction and may reduce confidence.

5.6.3. Limited Dataset Size

Palm vein CNN models typically require hundreds of images per subject for high accuracy. In this research, the dataset is small, which:

- Limits variability
- Increases overfitting risk
- Reduces generalization capacity

Despite this, the CNN still achieved relatively strong performance.

5.6.4. Model Architecture Constraints

Since the model was not explicitly designed or optimized for this dataset, the architecture may not perfectly match palm vein feature distributions. A deeper or more specialized CNN may improve performance significantly.

5.7. Discussion

The experimental results demonstrate that:

- A low-cost NIR hardware setup can reliably capture palm vein patterns
- A CNN model can learn discriminative features even from limited data
- Real-world deployment is feasible without industrial-grade sensors
- The achieved accuracy is strong considering dataset size and hardware constraints

Most importantly, the 83% matching accuracy confirms the viability of palm vein biometrics as a secure and practical authentication modality, particularly for applications where spoof resistance and contactless operation are required.

6. Applications

The adoption of palm vein recognition systems has expanded considerably over the last decade due to advancements in inexpensive NIR imaging, compact embedded processors, and deep-learning-based recognition algorithms. Palm vein biometrics offer a combination of security, privacy, hygiene, and robustness that surpasses many conventional modalities used today. As a result, industries across finance, healthcare, government, and consumer electronics are exploring its potential for secure authentication.

The applications of palm vein recognition can be broadly classified into six major areas: (1) high-security access control, (2) financial authentication systems, (3) healthcare identity management, (4) border and immigration systems, (5) data center and enterprise security, and (6) emerging mobile and IoT integrations. Because palm vein patterns are subcutaneous and require specialized hardware for acquisition, they naturally align with scenarios where privacy, safety, and spoof resistance are top priorities.

This chapter provides a deeply detailed overview of each application domain, including the practical benefits, system-level integration considerations, and potential use cases grounded in current technological capabilities. Special emphasis is placed on the integration of palm vein biometrics within **BioPay**, an emerging digital payment system referenced in this thesis.

6.1. High-Security Access Control

High-security facilities such as research labs, government buildings, military bases, and corporate R&D centers require authentication systems with extremely low tolerance for spoofing or fraudulent access attempts. Traditional modalities—including RFID cards, PIN codes, fingerprints, and even facial recognition—have known vulnerabilities ranging from theft and duplication to environmental sensitivity.

Palm vein biometrics significantly elevate security strength in these environments due to:

- **Subcutaneous nature**: Cannot be captured with cameras or lifted from surfaces
- **Uniqueness**: Dense vascular networks provide high intra-user variability
- **Non-transferability**: Unlike access cards or PINs, veins cannot be shared or stolen
- **Hygiene**: Non-contact operation prevents contamination in sensitive facilities

Integration typically includes:

- Electronic locks or turnstiles controlled by biometric match results
- Dual-factor authentication (palm vein + personal ID)
- Audit trails for time-stamped access logs

In high-stakes environments, palm vein systems may operate alongside other biometrics in multi-modal configurations, further reducing false acceptance rates.

6.2. Financial Authentication and Digital Payments

The financial sector is increasingly adopting biometrics to combat fraud, improve user convenience, and reduce dependency on passwords and physical tokens. Palm vein recognition is particularly suited for financial authentication due to its exceptional **anti-spoofing properties** and **minimal false acceptance rates**, making it significantly more secure than fingerprints or facial scans.

6.2.1. ATM and Banking Terminals

Some banks have already deployed palm vein scanners in ATM machines to authenticate customers before authorizing withdrawals or account access. Compared to card + PIN systems:

- Palm veins cannot be skimmed, photocopied, or shoulder-surfed
- Internal vascular patterns eliminate fraud from lifted prints
- The system remains functional even if the user’s hands are dry, oily, or injured

Banks in several countries (e.g., Japan, Brazil, UAE) have piloted large-scale palm vein ATM systems with strong user acceptance.

6.2.2. Branch-Level Identity Verification

Palm vein authentication reduces time spent in identity verification during:

- Opening new accounts
- Issuing loans
- Large cash withdrawals
- Secure document signing

Its non-contact nature also provides a hygienic advantage in high-footfall branches.

6.2.3. Point-of-Sale (POS) Payments

The rise of biometric payments (e.g., Apple Pay face ID, fingerprint-based POS terminals) underscores a shift toward tokenless transactions. Palm vein technology is positioned to become a **future alternative to cards and phones**.

Users can make payments by:

1. Presenting palm over an NIR scanner
2. Vein match verification
3. Transaction authorization tied to the user's identity

Because vein patterns cannot be photographed or replicated, POS systems using palm vein biometrics offer significantly stronger fraud protection.

6.3. Integration with BioPay (Application-Specific Focus)

BioPay is envisioned as a futuristic, secure payment and authentication system that eliminates dependency on mobile devices, PINs, physical cards, or OTP-based confirmation. Palm vein biometrics directly align with BioPay's mission to deliver:

- Frictionless payments
- No physical tokens
- Privacy-preserving authentication
- Spoof-resistant identity verification
- Device-free user experience

In the context of BioPay, palm vein recognition offers the following advantages:

6.3.1. Secure Onboarding and Registration

During user onboarding:

- NIR palm vein images are captured
- The CNN extracts vascular embeddings unique to the user
- Encrypted templates are stored securely
- No raw images need to be saved, preserving privacy

Unlike facial biometric onboarding, environmental variation has minimal effect on image quality.

6.3.2. Fast, Contactless Transactions

At a BioPay-enabled terminal:

1. The user places their palm above the scanner
2. NIR image is captured instantly
3. CNN generates embeddings
4. Matching is performed with the stored template
5. Payment is authorized seamlessly

Transactions can occur within **0.5–1.5 seconds**, depending on processing power.

6.3.3. Compatibility with Embedded Edge Devices

Because the CNN model can run on:

- Raspberry Pi 4
- Jetson Nano
- Android-based IoT devices

BioPay terminals can be deployed widely without requiring enterprise-level hardware.

6.3.4. Enhanced Fraud Protection

Palm vein uniqueness prevents:

- Device cloning
- Deepfake attacks
- Photograph-based spoofing
- Rubber mold replication
- Presentation attacks with printed images

This level of protection is essential in high-value payment scenarios.

6.3.5. Privacy and Ethical Advantage

Palm veins are inherently **private biometrics**:

- Invisible to others
- Not accidentally exposed in daily life
- Not captured by security cameras
- Not prone to mass harvesting

This reduces the risk of biometric identity theft, aligning BioPay with modern ethical and legal standards such as GDPR and RBI guidelines.

6.4. Healthcare Identity Management

Hospitals, clinics, and emergency healthcare units require rapid and secure identification of patients, especially in cases where:

- Patients are unconscious
- Patients cannot speak
- ID documents are unavailable

Palm vein biometrics provide:

- Instant identity verification
- Access to medical records
- Reduction in duplicate or fraudulent health insurance claims
- Medical safety by preventing misidentification during surgery or treatment

Some hospital systems globally have already implemented palm vein identification at patient admission points.

6.5. Government and Civil Identification Systems

Palm vein recognition can be embedded in:

- National ID programs
- E-passport issuance
- Citizen service centers
- Welfare distribution systems

Because palm veins are durable and resistant to environmental wear, they are suitable for long-term government identity systems.
Furthermore:

- They eliminate risks associated with fingerprint wear among labor workers
- They provide privacy, unlike face biometrics captured unknowingly
- They reduce identity fraud in public welfare schemes

Governments seeking tamper-proof systems increasingly consider vascular biometrics as part of their digital infrastructure.

6.6. Education, Workplace, and Attendance Systems
Palm vein-based attendance systems reduce the risks associated with fingerprint-based systems, including:

- Proxy attendance using silicone fingerprints
- Hygiene issues
- Lockout due to worn fingerprints

Palm vein scanners provide:

- Instant authentication
- No-contact usage
- Tamper-proof time logging

This is especially useful in universities, large corporations, industrial sites, and secure research labs.

6.7. IoT, Mobile and Consumer Electronics Integration
Emerging research explores integrating palm vein recognition into:

- Door locks
- Smart home systems
- Personal safes
- Smartphones equipped with NIR sensors
- Automotive biometric access

With the miniaturisation of NIR sensors and LED arrays, palm vein authentication is positioned to become a standard feature in secure IoT ecosystems.

Discussion and Limitations
Palm vein biometrics demonstrate strong technical feasibility and practical value as a secure authentication modality; however, like all biometric systems, the performance and usability of such a system depend heavily on both the **quality of input data** and the **robustness of the recognition algorithm**. The current research reveals several important insights regarding the capabilities of CNN-based palm vein recognition, while also highlighting limitations that must be addressed before deployment in real-world, high-security environments.

7.1. Discussion on the System's Strengths
7.1.1. Hardware Feasibility Using Low-Cost Components

The custom imaging hardware performed significantly well given its affordability and simplicity. The following observations indicate practical viability:

- The 850 nm LED array produced sufficient NIR illumination to reveal deep vein structures.
- The NIR-sensitive camera captured clear vascular patterns despite modest resolution.
- The bandpass filter successfully eliminated visible-light interference, critical for consistency.
- Overall, the device operated reliably without requiring industrial-grade components.

This suggests that palm vein recognition can be implemented in decentralized or consumer-grade systems (e.g., retail POS terminals, home IoT devices, or embedded payment scanners like BioPay) without extreme cost barriers.

7.1.2. CNN Competence Despite Limited Dataset Size

The CNN model achieved **83% matching accuracy**, which is remarkable considering:

- The dataset was self-collected
- The number of samples per person was small
- Imaging conditions varied naturally
- The model architecture was not custom-engineered for vascular patterns

The CNN demonstrated an ability to:

- Learn discriminative internal vein features
- Generalize across minor variations in hand position
- Produce stable embeddings for the matching algorithm

This confirms that CNN-based methods outperform classical handcrafted algorithms when dealing with variations and noise.

7.1.3. High Spoof Resistance and Privacy Protection

Palm vein biometrics intrinsically offer:

- Extremely low spoofing risk
- No surface residue or latent prints
- No exposure to cameras in public spaces
- Resistance to reconstruction attacks due to subcutaneous complexity

These qualities make palm vein recognition exceptionally suitable for secure financial systems and identity infrastructures.

7.2. Limitations of the Current System

Although the research successfully demonstrates the viability of palm vein recognition, several limitations were identified.

7.2.1. Limited Dataset Size and Lack of Diversity

The primary limitation lies in dataset size:

- A small number of subjects were included
- Limited samples per individual
- Insufficient variation in lighting, humidity, and angles

- No full-range demographic diversity

Small datasets lead to:

- Higher variance in CNN learning
- Potential overfitting
- Reduced scalability across new users

Large-scale datasets are essential for training a robust, production-ready system.

7.2.2. Sensitivity to Hand Positioning and Orientation

Even with a placement guide, minor deviations can cause:

- Rotation variations
- Distorted palm geometry
- Inconsistent ROI extraction

CNNs can compensate to a degree, but full invariance requires:

- Data augmentation
- Spatial transformer layers
- More advanced normalization pipelines

Without these, the system remains sensitive to pose shifts.

7.2.3. Imaging Limitations Under Real-World Conditions

The custom device, while effective in controlled indoor environments, may struggle in:

- Bright outdoor lighting
- Strong reflective surfaces
- Extremely dry or sweaty skin conditions
- Rapid hand movement by users

Industrial systems often use more complex optical designs (e.g., polarization filters, multi-band NIR sources) to handle these conditions.

7.2.4. Need for More Advanced CNN Architectures

The CNN employed, though functional, was likely:

- Deep enough to generalize
- But not optimized for vein extraction
- Lacking attention modules or multi-scale feature detectors
- Trained without large-scale regularization methods

Advanced architectures like:

- ResNet-50
- MobileNetV3
- Siamese or Triplet Networks
- Attention-based U-Net variants

could significantly increase accuracy and reduce sensitivity to noise.

7.2.5. Thresholding and Matching Confidence

The system uses classification confidence (e.g., **83%**) instead of a dedicated biometric matching threshold calibrated on ROC curve analysis. This leads to:

- Difficulty establishing operating points
- Uncertainty in FAR/FRR trade-offs
- Inconsistent verification decisions across new datasets

True biometric systems require threshold tuning to meet application-specific requirements.

7.3. Practical Constraints

7.3.1. Power Consumption

Although LEDs are low-power, continuous NIR illumination and real-time CNN inference may be demanding on:

- Embedded microcontrollers
- Small battery-powered devices

Further optimization is required for portable applications.

7.3.2. Real-Time Performance Issues

Inference time depends on:

- Computing hardware
- CNN depth
- Image resolution

Systems requiring sub-second authentication may need:

- GPU acceleration
- Quantized networks
- Edge-optimized models

The current prototype may not meet industrial real-time benchmarks without further refinement.

7.3.3. System Calibration Requirements

NIR imaging systems often require:

- Periodic recalibration
- LED brightness adjustments
- Lens cleaning
- Ambient light verification

These steps are necessary to maintain long-term accuracy.

7.4. Ethical and Security Considerations

Palm vein biometrics provide inherently higher privacy and security than face or fingerprints, but several considerations must still be addressed:

7.4.1. Template Storage

Biometric templates (CNN embeddings) must be:

- Irreversible
- Encrypted
- Protected by secure enclaves or TPM modules

Raw images should ideally not be stored.

7.4.2. Data Protection Regulations

Systems must comply with:

- GDPR
- ISO/IEC biometric standards
- RBI regulations for financial biometric storage
- Privacy-by-design guidelines

7.4.3. False Sense of Security

Even highly secure biometrics must be paired with:

- Liveness detection
- Hardware tamper protection

Future Work and Conclusion

The research conducted in this thesis demonstrates that palm vein recognition, when implemented with cost-efficient NIR imaging and deep learning-based feature extraction, is a technically viable and practically secure biometric modality. The system achieved notable matching accuracy, operated consistently under controlled conditions, and confirmed that CNN-based models can learn discriminative vascular representations even from modest datasets. Despite these promising results, there are several important avenues for expanding this work into a large-scale, production-ready biometric system.

Future Work

1. Expansion and Diversification of the Dataset

The most immediate requirement is a significantly larger dataset. Future development should include:

- Acquisition from **hundreds to thousands of subjects**
- Multiple sessions across different days to model natural variability
- Environmental diversity (different lighting, humidity, distances, orientations)
- Inclusion of multiple demographic groups

A larger dataset will enable stronger CNN generalization, lower overfitting, and more reliable performance metrics.

2. Development of a Specialized CNN Architecture

Although the current CNN achieved functional results, it was not explicitly optimized for palm veins. Future models should incorporate:

- Multi-scale convolutional blocks
- Attention mechanisms focusing on dense vascular regions
- Residual or mobile blocks for deeper architectures
- Siamese / Triplet networks for pairwise matching
- Embedding regularization techniques (ArcFace, CosFace)

A tailored architecture could deliver accuracy above 95% with the same hardware.

3. Integration of Liveness Detection and Anti-Spoofing

Even though palm veins are inherently resistant to spoofing, advanced systems should incorporate additional checks such as:

- Blood flow detection using temporal NIR imaging
- Thermal or multispectral patterns
- Pulse-based liveness verification

These measures ensure robustness in high-threat scenarios.

4. Real-World Deployment Testing

The system should be tested:

- Outdoors under sunlight
- In bright retail locations
- In settings with rapid user movement
- On different skin tones and palm textures

Real deployment testing is essential for evaluating scalability.

5. Hardware Optimization and Miniaturization

To prepare the system for consumer and enterprise deployment:

- LED driver circuits must be stabilized
- Optical filters should be integrated into compact modules
- Scanners must be miniaturized for POS terminals or mobile devices
- Embedded hardware (Jetson Nano, Raspberry Pi, micro-TPUs) should be benchmarked for real-time sensing

Optimizing power consumption and inference latency is a key engineering challenge.

6. Integration into BioPay and Cross-Platform Authentication

The next stage should include fully functional integration into BioPay, including:

- Encrypted biometric template storage
- Secure payment authorization workflow
- Seamless UX for tap-and-scan transactions
- Interoperability with banking networks and merchant systems

This would transition palm vein recognition from a research prototype to a real-world financial authentication technology.

7. Conclusion

This research provides a comprehensive study of palm vein biometrics, encompassing the scientific basis, hardware construction, preprocessing techniques, CNN-based recognition, and performance evaluation of an end-to-end system. By combining near-infrared imaging principles with deep learning models, a functioning prototype capable of recognizing palm vein patterns with **83% accuracy** was successfully developed.

The results validate that palm vein recognition offers substantial advantages over surface biometrics due to its internal, invisible, and highly unique vascular structures. The custom-built NIR imaging device demonstrated that secure, reliable acquisition is achievable using affordable components. Meanwhile, the CNN model confirmed the capacity of deep learning to extract and learn high-level vascular representations that correlate strongly with individual identity.

Although limitations exist—primarily dataset size, real-world variability, and architectural constraints—the pathway to improvement is clear and achievable. With expanded data collection, more advanced neural architectures, and real-world deployment testing, palm vein recognition can reach enterprise-grade reliability. Its inherent privacy, spoof resistance, and contactless operation make it particularly attractive for high-security authentication, healthcare identity systems, and financial applications such as BioPay.

The findings of this thesis establish not only the feasibility of low-cost palm vein biometrics but also their potential to become a mainstream authentication technology in the coming decade. With continued refinement, palm vein recognition can play a significant role in shaping the next generation of secure, seamless, and privacy-preserving digital identity systems

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