IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 3, March 2026

DOI: 10.17148/IJARCCE.2026.15372

CNN-Based Dorsal Hand Vein Authentication Using Triplet Loss Metric Learning

J Adithye[1], Abhimanyu R[2], Abhijith S Kurup[3], Adithiya S[4], Girija V R[5]

Undergraduate, Department of Computer Science, College of Engineering Kottarakkara, Kerala, India[1-4]

Professor, Department of Computer Science, College of Engineering Kottarakkara, Kerala, India[5]

Abstract: Hand vein biometrics has emerged as a reliable authentication modality due to the uniqueness and internal nature of vascular patterns. Unlike surface-based biometrics such as fingerprints or facial recognition, vein patterns are less susceptible to environmental variations and spoofing attacks. This work presents a CNN-based dorsal hand vein biometric authentication framework that combines a ten-stage preprocessing pipeline with deep metric learning-based feature extraction. The preprocessing pipeline includes Gaussian smoothing, automatic hand region detection, wrist removal using distance-transform thickness profiling, finger removal using convex hull-based techniques, Otsu segmentation, CLAHE contrast enhancement, Sato vesselness filtering, feathered mask application, and tight crop resize to 224×224 pixels to isolate the stable metacarpal vein region.

A four-block CNN backbone is trained using online semi-hard triplet loss mining with an identity-based batch sampler to generate discriminative 128-dimensional L2-normalized embeddings for biometric matching. A manually collected dataset of 5220 dorsal hand vein images from 261 individuals (522 hand identities, with left and right hands treated as separate biometric identities) captured under controlled near-infrared illumination was used for training and evaluation. Experimental results demonstrate a recognition accuracy of 99.12% and an Equal Error Rate of 1.32%, confirming the effectiveness of the proposed framework for secure hand vein biometric authentication.

Keywords: Authentication, Biometric Recognition, Convolutional Neural Network (CNN), Dorsal Hand Vein Recognition, Embedding, Metric Learning, Near-Infrared Imaging, Online Semi-Hard Mining, Triplet Loss, Vessel Enhancement.

I. INTRODUCTION

Biometric authentication systems are widely used for identity verification in modern security and access control applications. Traditional biometric modalities such as fingerprint recognition, facial recognition, and iris scanning have been extensively deployed due to their convenience and accuracy. However, these methods are often affected by environmental conditions, surface damage, and potential spoofing attacks using artificial replicas or printed images. As a result, there is increasing interest in developing more secure and reliable biometric technologies that are resistant to forgery and environmental variations.

Hand vein recognition has emerged as a promising biometric approach because vascular patterns are located beneath the skin and are unique to each individual. These internal vein structures are difficult to replicate or forge, making vein-based biometrics inherently more secure than many surface-based modalities. Near-infrared (NIR) imaging technology enables the visualization of subcutaneous vein patterns by exploiting the absorption characteristics of deoxygenated hemoglobin. When illuminated with near-infrared light, vein regions appear darker compared to surrounding tissue, allowing the vascular network to be captured using an infrared-sensitive camera.

Recent advances in computer vision and deep learning have significantly improved the performance of biometric recognition systems. Convolutional Neural Networks (CNNs) have demonstrated strong capability in extracting discriminative features from complex image patterns. In vein recognition systems, deep learning models can automatically learn distinctive vascular features and generate compact feature representations that improve recognition accuracy. However, practical hand vein recognition systems still face challenges such as variations in hand positioning, illumination changes, background noise, and the presence of non-informative regions like fingers and wrists. Additionally, raw infrared images often contain low contrast and noise that obscure the vascular structures required for reliable recognition.

To address these challenges, this work presents a CNN-based dorsal hand vein biometric authentication framework integrating a ten-stage preprocessing pipeline with deep metric learning-based feature extraction. The preprocessing

DOI: 10.17148/IJARCCE.2026.15372

pipeline includes Gaussian smoothing, automatic hand region detection, wrist removal, finger removal, Otsu segmentation, CLAHE, Sato vesselness filtering, feathered masking, and tight crop resize to isolate the stable metacarpal vein region. A CNN backbone is trained using online semi-hard triplet loss mining to generate discriminative L2-normalized embeddings for biometric matching.

The main contributions of this work are as follows:

- A ten-stage preprocessing pipeline to isolate the stable metacarpal vein region.
- A four-block CNN trained with online semi-hard triplet loss mining generating 128-dimensional L2-normalized embeddings.
- A manually collected dataset of 5220 dorsal hand vein images from 261 individuals (522 hand identities).
- Experimental evaluation demonstrating 99.12% recognition accuracy and 1.32% EER.

II. RELATED WORK

Vein-based biometric recognition has gained significant attention due to the uniqueness and internal nature of vascular patterns. Several studies have explored palm vein and hand vein recognition systems using near-infrared imaging and various feature extraction techniques.

In 2015, Tome and Marcel proposed a palm vein database and experimental framework for reproducible research using a contactless sensor system [1]. Their approach enhanced vein patterns using Gabor filters and extracted features using Local Binary Patterns (LBP) before matching them through histogram-based methods. Although the system demonstrated reliable recognition performance, it showed strong dependency on the specific contactless sensor used.

Sater et al. (2019) proposed a promising palm vein classification database and evaluated different classification methods for palm vein recognition [2]. Their work highlighted the importance of dataset quality and proper feature extraction for improving biometric system performance.

Khan et al. (2014) introduced a multispectral palmprint encoding and recognition method that extracted regions of interest using finger-valley landmarks and encoded features using contour codes [3]. The method achieved low error rates on the PolyU and CASIA datasets. However, the performance of the system was affected by variations in hand rotation and deformation during image acquisition.

Several studies have also explored palmprint recognition using handcrafted feature extraction techniques. Minaee and Abdolrashidi (2014) investigated palmprint recognition using textural features [4]. In another study, Minaee and Abdolrashidi (2014) proposed a multispectral palmprint recognition method using statistical and wavelet features to improve recognition accuracy [5]. Later, Minaee and Abdolrashidi (2015) explored the use of joint wavelet–DCT features for multispectral palmprint recognition, demonstrating improved feature representation capability [6].

Other research has focused on improving preprocessing and classification techniques. Thamri et al. (2020) proposed a multispectral palmprint recognition system using log-Gabor filters and feature reduction techniques such as Kernel Principal Component Analysis (KPCA) [7]. Although the system achieved high classification accuracy, it required multiple spectral sensors, which increased hardware complexity and system cost.

In another study, Tome and Marcel (2015) investigated the vulnerability of palm vein recognition systems to spoofing attacks [8]. Their research demonstrated that paper-printed spoof samples could successfully bypass certain recognition systems, highlighting the need for effective liveness detection mechanisms in biometric systems.

Deep learning approaches have also been explored to improve vein recognition performance. Gumaei et al. (2018) proposed a multispectral palmprint recognition system using an autoencoder combined with a regularized extreme learning machine classifier [9].

Obayya et al. (2020) proposed a contactless palm vein authentication system using a convolutional neural network optimized with Bayesian optimization [10]. Their model achieved high recognition accuracy of approximately 99.4%, but the system remained sensitive to variations in hand rotation and positioning.

More recently, Marattukalam et al. (2023) presented a wrist vascular biometric recognition system using deep learning techniques [11]. Their approach utilized a U-Net architecture for vein segmentation and a Siamese neural network for

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 3, March 2026
DOI: 10.17148/IJARCCE.2026.15372

feature matching. Although the system achieved promising results, it relied on a relatively small dataset, which may limit its generalization capability in large-scale applications.

Early foundational work in vein biometrics includes Marattukalam et al. (2021), who proposed N-shot palm vein verification using Siamese networks, achieving reliable recognition with limited enrollment samples [12], Miura et al. (2004), who introduced repeated line tracking for finger-vein feature extraction [13], Kumar and Prathyusha (2009), who proposed hand vein triangulation combined with knuckle shape for personal authentication [14], and Wang et al. (2007), who demonstrated that infrared imaging of dorsal hand vein patterns provides stable and discriminative biometric signatures [15].

Thapar et al. (2018) introduced PVSNet, a Siamese network architecture trained using triplet loss and adaptive hard mining strategies, establishing an important baseline for deep metric learning in palm vein authentication [16].

Recent research has increasingly focused on deep learning–based architectures for palm vein and palmprint recognition. Zhong et al. (2021) proposed a binarized dual ResNet architecture combined with Siamese learning for palmprint recognition, enabling efficient feature extraction and improved matching performance in biometric systems [17]. Jaswal et al. (2022) developed a deep Siamese network for contactless palm vein identification using semi-hard triplet mining, demonstrating improved robustness under varying imaging conditions [18].

Zhao et al. (2021) introduced a fusion framework that integrates palmprint and palm vein features using a Siamese network combined with online hard example mining, which improves recognition accuracy by learning discriminative multimodal biometric representations [19]. Subsequently, Marattukalam et al. (2024) proposed a dense-head probabilistic Siamese network for multi-finger vein recognition, achieving efficient and accurate biometric identification using deep representation learning [20].

The analysis of previous studies indicates that many existing vein recognition systems rely either on handcrafted feature extraction methods or deep learning models trained on limited datasets. In addition, several approaches do not incorporate robust preprocessing pipelines to isolate the stable vascular region. To address these limitations, this work presents a CNN-based dorsal hand vein authentication framework that integrates an advanced preprocessing pipeline and deep metric learning-based feature extraction to improve the recognition accuracy and reliability of vein biometric systems.

III. DATASET

A dataset of dorsal hand vein images was manually collected to support the development and evaluation of the proposed biometric authentication system. Publicly available hand vein datasets are limited and often captured under different imaging conditions. Therefore, a custom dataset was created to ensure consistent acquisition conditions and sufficient variability for training and evaluating the proposed recognition framework.

A total of 261 individuals participated in the dataset collection process. Both the left and right hands of each participant were enrolled as separate biometric identities, resulting in 522 unique hand identities. For each hand identity, 10 images were captured, resulting in a dataset containing 5220 images in total. The data collection procedure was conducted in accordance with institutional ethical guidelines and approved by the relevant ethics committee at the institution.

The image acquisition process was carried out under controlled indoor lighting conditions to maintain consistent illumination during data capture. Near-infrared imaging was used to visualize the vascular structures beneath the skin, exploiting the differential absorption of deoxygenated hemoglobin to render vein regions darker than surrounding tissue. This property enables the clear capture of dorsal hand vein patterns using an infrared-sensitive camera.

During data collection, participants were instructed to place the dorsal side of their hand within the camera’s field of view while images were captured. Multiple images were recorded for each subject to include slight variations in hand orientation and positioning. The captured images contained the full hand region, including fingers and wrist areas, which were later processed through the preprocessing pipeline to isolate the stable metacarpal vein region used for biometric recognition.

The dataset provides sufficient diversity in vascular patterns across individuals while maintaining consistent acquisition conditions. The collected images were organized based on subject identity and used for both training and evaluation of the deep learning model used in the proposed biometric authentication system.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 3, March 2026

DOI: 10.17148/IJARCCE.2026.15372

IV. SYSTEM METHODOLOGY

The proposed system is designed to perform reliable hand vein biometric authentication by combining image preprocessing, deep learning-based feature extraction, and embedded system deployment. The overall framework consists of multiple stages including image acquisition, image preprocessing, deep learning-based feature extraction, and authentication. The system is trained and evaluated using the hand vein dataset described in Section III. The system is designed to operate on an embedded platform to enable practical real-world deployment.

A. Image Acquisition

The first stage of the system involves acquiring dorsal hand images using near-infrared imaging. As described in Section III, NIR illumination causes vein regions to appear darker than surrounding tissues due to the absorption characteristics of deoxygenated hemoglobin, allowing the vascular pattern beneath the skin to be captured using an infrared-sensitive camera. The captured images contain the dorsal hand region along with background information and other non-relevant regions that must be processed before feature extraction.

B. Image Preprocessing

Image preprocessing is an important step in vein recognition systems as raw images often contain noise, background regions, and non-informative parts of the hand such as fingers and wrist areas. The preprocessing pipeline consists of ten stages designed to enhance vascular structures and isolate the region of interest suitable for biometric analysis.

The process begins with Gaussian smoothing to reduce sensor noise present in the captured images. After noise reduction, Otsu-based automatic hand region detection crops and centers the hand, removing unnecessary background. Geometric analysis then removes the wrist region by analyzing the distance-transform thickness profile to detect the wrist-palm transition boundary. Convex hull-based finger removal then isolates the stable metacarpal vein region by identifying inter-finger valleys. Following region isolation, Otsu segmentation produces a binary hand mask. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance local contrast and highlight subtle vascular patterns. A Sato vesselness filter then amplifies the tubular vein structures within the image. A feathered mask with soft boundary fading is applied to suppress edge artifacts introduced by the Sato filter. Finally, a tight crop and resize to 224×224 pixels is performed, followed by Z-score normalization to standardize intensity distribution for CNN input.

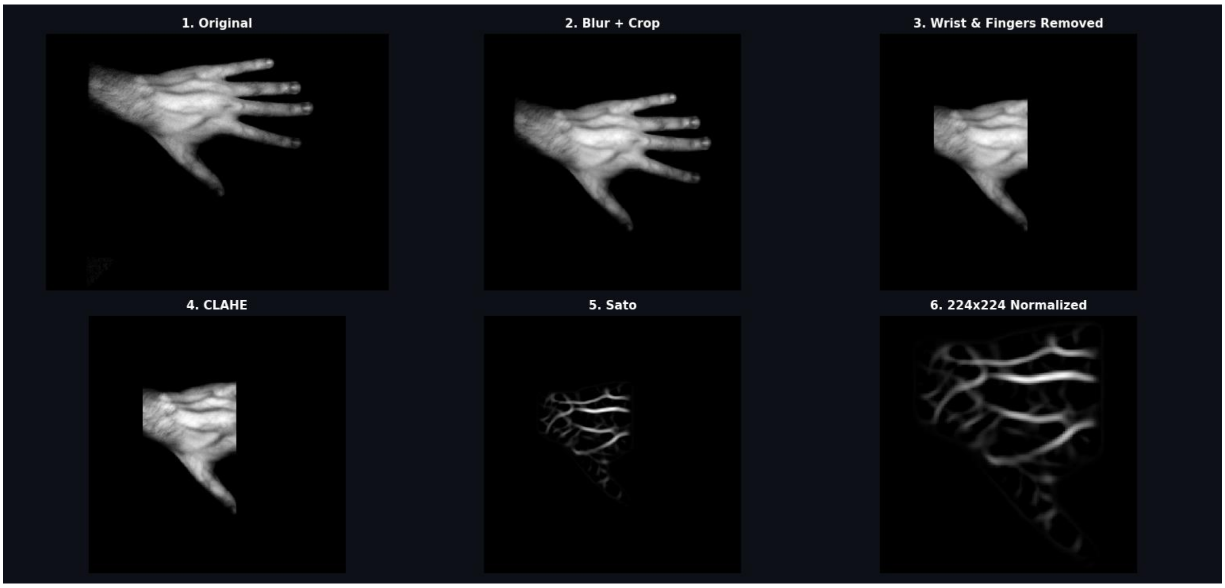

Fig. 1 Preprocessing pipeline for dorsal hand vein enhancement illustrating six representative stages from the complete ten-stage pipeline: (1) Original NIR image, (2) Gaussian blur and smart crop, (3) Wrist and finger removal, (4) CLAHE contrast enhancement, (5) Sato vesselness filtering, and (6) Final 224×224 normalized output.

C. Feature Extraction Using Deep Learning

The enhanced vein images are used as input to a convolutional neural network designed to extract discriminative vascular features. The neural network learns feature representations that capture the unique vein patterns present in each individual. Instead of directly classifying images into identity classes, the model is trained using a metric learning

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 3, March 2026

DOI: 10.17148/IJARCCE.2026.15372

approach with online semi-hard triplet mining to generate discriminative L2-normalized embedding vectors for biometric matching.

D. Authentication Process

During authentication, a captured vein image is processed through the preprocessing and feature extraction stages to generate an embedding representation. This embedding is compared with stored template embeddings in the database using Euclidean distance. If the computed distance falls below a manually determined threshold of 0.25, selected empirically for optimal authentication performance, the identity is considered verified. Otherwise, authentication is rejected.

E. Embedded System Deployment

The proposed system is implemented on a Raspberry Pi 4 Model B to enable edge-based biometric authentication. Deploying the system on an embedded platform allows the authentication process to run locally without requiring continuous connection to a cloud server. This approach reduces latency, improves privacy, and enables low-cost deployment in real-world applications.

In addition to image-based recognition, a thermal sensing mechanism is integrated into the system to verify that the presented hand belongs to a live subject. The thermal sensor measures the surface temperature of the hand and ensures that the biometric sample originates from a living individual. This additional verification layer helps prevent spoofing attacks using printed images or artificial replicas.

V. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The proposed biometric authentication framework integrates image acquisition, preprocessing, deep learning-based feature extraction, and embedded system deployment into a unified architecture. The system is designed to process dorsal hand vein images and generate discriminative biometric features for reliable identity verification. The overall architecture consists of multiple processing stages that transform raw infrared images into compact feature embeddings used for authentication.

A. System Overview

The overall system architecture follows a sequential processing pipeline. Initially, dorsal hand images are captured using a near-infrared imaging setup. These images are then processed through a preprocessing module that removes irrelevant regions and enhances the visibility of vascular structures. The enhanced vein images are then passed to a deep learning model that extracts discriminative features representing the unique vascular pattern of each individual.

The extracted features are stored as template embeddings in a database during the enrollment stage. During authentication, the feature embedding of a newly captured image is compared with stored templates using a similarity measure. Based on the similarity score, the system determines whether the presented biometric sample matches the stored identity.

B. Preprocessing Pipeline Architecture

The preprocessing stage is designed to improve the visibility of vein structures and remove non-informative regions from the captured images. The pipeline consists of ten sequential stages applied before feature extraction.

The process begins with Gaussian filtering to reduce noise in the captured infrared images. Otsu-based automatic hand region detection then crops and centers the hand, removing unnecessary background areas. Wrist removal is performed by analyzing the distance-transform thickness profile of the hand region to detect the transition between the palm and wrist. Finger removal is achieved using convex hull-based techniques that identify the valleys between fingers and isolate the central metacarpal region. Otsu segmentation is then applied to generate a clean binary hand mask. CLAHE enhances local contrast to highlight subtle vascular patterns before the Sato vesselness filter is applied to amplify tubular vein structures. A feathered mask with soft boundary fading is then applied to suppress edge artifacts introduced by the Sato filter near the hand boundary. Finally, a tight crop and resize to 224×224 pixels is performed, followed by Z-score normalization to prepare the image for CNN input.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 15, Issue 3, March 2026

DOI: 10.17148/IJARCCE.2026.15372

C. Deep Learning Model Architecture

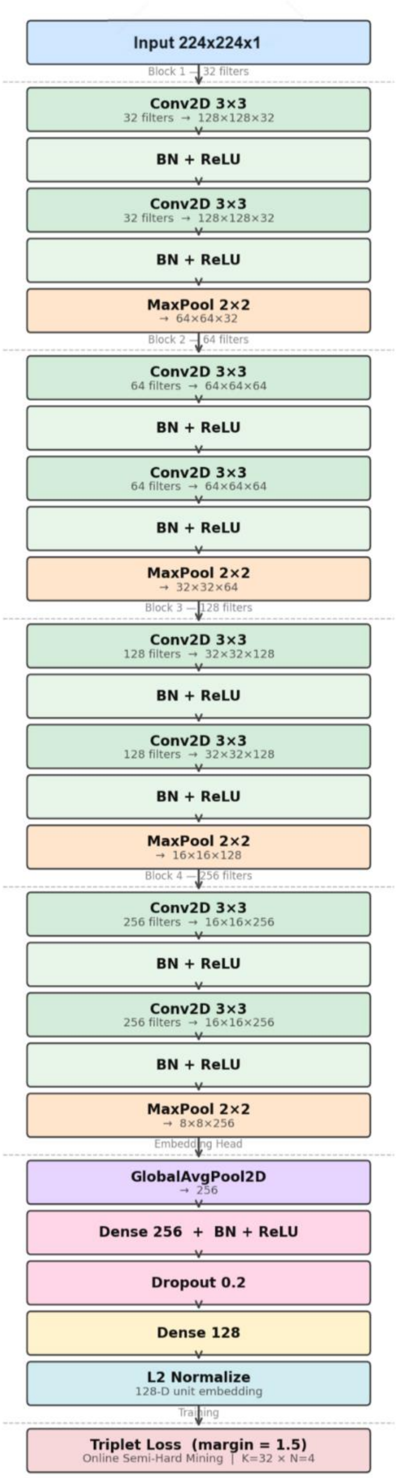

Fig. 2 Proposed CNN architecture for dorsal hand vein feature extraction and embedding generation using triplet loss training.

After preprocessing, the enhanced vein images are used as input to a convolutional neural network designed to extract discriminative vascular features. Convolutional layers are used to learn hierarchical features from the vein patterns

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 15, Issue 3, March 2026
DOI: 10.17148/IJARCCE.2026.15372

present in the images. These layers capture spatial structures and texture patterns that represent the vascular network of the hand.
The CNN backbone consists of four convolutional blocks with filter depths of 32, 64, 128, and 256. Each block contains two 3×3 convolutional layers with batch normalization and ReLU activation, followed by 2×2 max pooling. Global Average Pooling then reduces the spatial dimensions, followed by a Dense (256) layer with batch normalization, ReLU, and Dropout (0.2) for regularization. A final Dense (128) layer produces the raw embedding, which is L2-normalized to a unit-length vector, yielding a 128-dimensional embedding.

D. Training Strategy
The deep learning model is trained using a metric learning approach with online semi-hard triplet mining. For each anchor sample, the hardest positive (same identity, maximum distance) and a semi-hard negative (different identity, farther than the positive but within the margin) are selected within each batch. When no semi-hard negative exists for a given anchor, the hardest negative is used as a fallback. Instead of performing direct classification, the model learns a feature space where images belonging to the same individual are closer together while images belonging to different individuals are separated. The trained embeddings are L2-normalized so that all feature vectors lie on a unit hypersphere, enabling consistent distance-based matching using Euclidean distance in the range [0, 2].

During training, augmented images are used to increase dataset variability and improve model generalization. Data augmentation was applied during training using the following techniques: spatial rotation (±12°) and translation (±7%) to simulate hand placement variation; Gaussian noise addition to simulate sensor noise; random sharpening or blurring to simulate focus variation and motion blur; grid distortion to simulate skin deformation; and random rectangular patch erasing to prevent over-reliance on any single vein segment.

E. Embedded Implementation on Raspberry Pi
The final system is designed to operate on an embedded platform to enable practical real-world deployment. A Raspberry Pi 4 Model B is used as the processing unit for executing the biometric authentication pipeline. The device processes captured images, performs preprocessing operations, and runs the trained deep learning model for feature extraction.

Deploying the system on an embedded platform enables local processing of biometric data without requiring continuous connectivity to cloud services. This approach reduces system latency, enhances privacy, and allows low-cost deployment in real-world authentication scenarios. The Raspberry Pi-based implementation demonstrates that the proposed biometric recognition framework can operate efficiently on edge computing devices while maintaining reliable authentication performance.

VI. EXPERIMENTAL SETUP AND EVALUATION

This section describes the experimental setup used to train and evaluate the proposed hand vein biometric authentication system. The experiments were conducted using the collected dorsal hand vein dataset and a deep learning–based recognition framework. The objective of the evaluation is to measure the effectiveness of the proposed preprocessing pipeline and feature extraction model in identifying unique vascular patterns.

A. Dataset Preparation
The collected dataset consists of 261 individuals contributing 522 unique hand identities, with 10 images captured per hand identity, resulting in a total of 5220 images. Left and right hands are treated as independent biometric identities throughout training and evaluation. Before training the recognition model, the images were processed using the proposed preprocessing pipeline which includes noise reduction, region of interest extraction, finger and wrist removal, and vein enhancement.

The processed images were resized to a fixed spatial resolution suitable for input to the deep learning model. Let $I(x,y)$ represent the original grayscale image and $I_p(x,y)$ represent the preprocessed image obtained after enhancement and normalization. The normalization step ensures consistent intensity distribution across the dataset and can be expressed as

$$I_{norm} = \frac{I_p - \mu}{\sigma}$$

where μ represents the mean intensity and σ represents the standard deviation of the image.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 3, March 2026

DOI: 10.17148/IJARCCE.2026.15372

The dataset was split at the identity level into training (75%), validation (15%), and test (10%) subsets, resulting in approximately 391 training identities, 78 validation identities, and 53 test identities. Identity-level splitting ensures that images of the same individual never appear in both training and evaluation sets, preventing data leakage. The validation set was used for threshold calibration and early stopping, while the test set was used for final performance evaluation.

B. Training Configuration

The deep learning model was trained using the enhanced vein images produced by the preprocessing pipeline. The neural network learns discriminative feature representations that capture the unique vascular patterns of each individual.

Data augmentation techniques were applied during training to improve the generalization capability of the model. These techniques include spatial rotation (±12°), translation (±7%), Gaussian noise addition, random sharpening or blurring, grid distortion, and random rectangular patch erasing. Augmentation increases the effective size of the training dataset and improves robustness to variations in hand placement.

During training, the model generates embedding vectors that represent the biometric features of each image. The similarity between two embeddings can be measured using the Euclidean distance defined as

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

where x and y represent two embedding vectors and n represents the embedding dimension.

The model was trained using the Adam optimizer with an initial learning rate of 1×10^{-4}, decaying to a minimum of 1×10^{-6} using a cosine annealing schedule with 5-epoch linear warm-up and restarts every 20 epochs. The triplet loss margin was set to 1.5. Training ran for a maximum of 50 epochs with early stopping patience of 15 epochs. The batch size was 128 (K=32 identities × N=4 images). The embedding dimension was 128 and input image size was 224×224 pixels. The training and validation loss convergence is shown in Fig. 3.

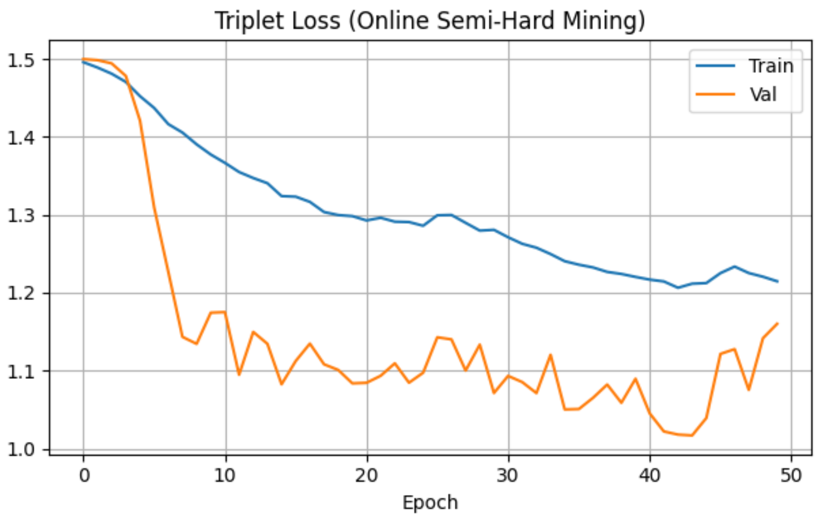

Fig. 3 Training and validation triplet loss over 50 epochs using online semi-hard mining.

C. Evaluation Metrics

The performance of the biometric authentication system was evaluated using commonly used biometric evaluation metrics. These metrics measure the ability of the system to correctly verify genuine users while rejecting unauthorized individuals.

The overall recognition accuracy is defined as

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 3, March 2026
DOI: 10.17148/IJARCCE.2026.15372

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

Another important metric is the False Acceptance Rate (FAR), which measures the probability that an unauthorized user is incorrectly accepted by the system. It can be defined as

$$FAR = \frac{FP}{FP + TN}$$

Similarly, the False Rejection Rate (FRR) represents the probability that a legitimate user is incorrectly rejected during authentication and is defined as

$$FRR = \frac{FN}{TP + FN}$$

An important performance indicator for biometric systems is the Equal Error Rate (EER). The EER corresponds to the operating point where the FAR and FRR are equal. Lower EER values indicate better system performance and higher reliability.

D. Hardware Setup

The final authentication system was implemented on a Raspberry Pi 4 Model B platform to enable edge-based biometric authentication. The device performs image preprocessing, feature extraction, and identity verification using the trained deep learning model. Image acquisition is carried out using an Arducam Noir Camera (OV5647 5MP), while 850 nm near-infrared LEDs are used to illuminate the hand and enhance vein visibility. An MLX90614 infrared temperature sensor is integrated to measure hand temperature for liveness verification.

Deploying the system on an embedded platform enables local biometric authentication without requiring continuous connectivity to a remote server. This reduces system latency, improves data privacy, and enables cost-effective deployment in real-world authentication scenarios.

VII. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed hand vein biometric authentication system. The evaluation focuses on assessing the effectiveness of the preprocessing pipeline, deep learning-based feature extraction, and embedded deployment in identifying unique vascular patterns.

The preprocessing pipeline significantly improves the visibility of dorsal hand vein structures before feature extraction. Techniques such as Gaussian smoothing, automatic hand region detection, wrist and finger removal, contrast enhancement using CLAHE, and vessel enhancement filtering help highlight the vascular structures while removing irrelevant regions and background noise. As a result, the deep learning model is able to focus on the discriminative vein patterns that are unique to each individual.

After preprocessing, the enhanced images are processed by the deep learning model to generate feature embeddings that represent the vascular patterns of the hand. During authentication, the similarity between the embedding vectors of the input image and stored templates is calculated using a distance-based metric. Images belonging to the same individual produce smaller distance values, while images belonging to different individuals produce larger distances. This separation of embeddings in the feature space allows reliable identity verification.

The performance of the proposed system was evaluated using the collected hand vein dataset. Experimental results demonstrate that the model achieves a recognition accuracy of 99.12% at a threshold of 0.5371. The Equal Error Rate (EER) was observed to be 1.32% at a threshold of 0.6052, as illustrated in Fig. 4. At the EER operating point, the system achieved a FAR of 1.32% and an FRR of 1.32%. These results indicate that the system is capable of accurately distinguishing between genuine users and impostors while maintaining a very low error rate.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁐ Peer-reviewed & Refereed journal ⁐ Vol. 15, Issue 3, March 2026

DOI: 10.17148/IJARCCE.2026.15372

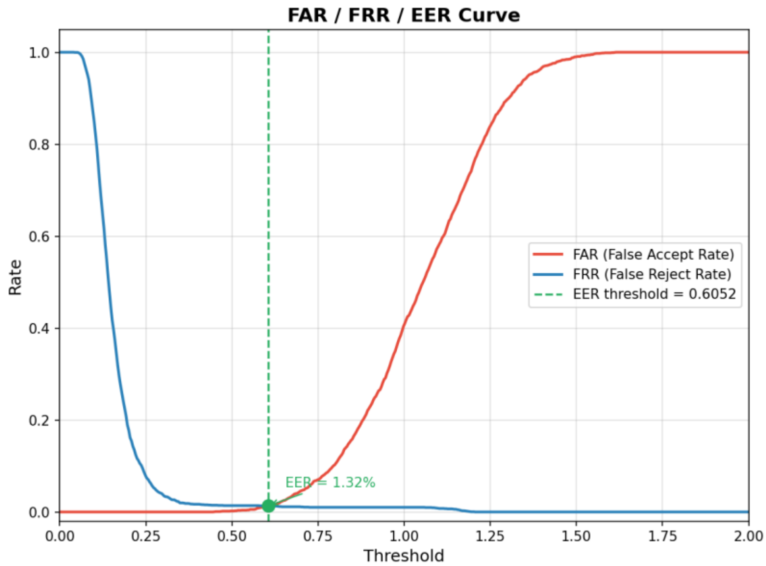

Fig. 4 FAR and FRR curves with EER = 1.32% at threshold = 0.6052.

Table I summarizes the performance metrics obtained during the evaluation of the proposed biometric authentication system.

TABLE I PERFORMANCE METRICS OF THE PROPOSED SYSTEM

METRICS	Value
Accuracy	99.12% (threshold = 0.5371)
Equal Error Rate (EER)	1.32% (threshold = 0.6052)
False Acceptance Rate (FAR)	1.32% @EER
False Rejection Rate (FRR)	1.32% @EER

The experimental results demonstrate that the proposed approach provides reliable biometric recognition using dorsal hand vein patterns. The use of data augmentation during training improves the robustness of the model and enables it to handle variations in hand positioning and imaging conditions.

In addition to recognition performance, the embedded implementation on a Raspberry Pi 4 Model B demonstrates the feasibility of deploying the system on low-power edge computing hardware. The device is capable of performing image preprocessing, feature extraction, and identity verification efficiently, enabling real-time authentication without requiring continuous connectivity to cloud services. The complete authentication pipeline runs in under 1 second per query on the Raspberry Pi 4B, with TFLite INT8 inference completing in under 200ms and preprocessing completing in under 1800ms.

Furthermore, the integration of a thermal sensing mechanism improves the security of the system by verifying that the presented biometric sample originates from a live subject. The MLX90614 infrared temperature sensor measures the surface temperature of the hand and rejects samples that fall outside the expected range for living tissue (32°C–37°C). This ensures that spoofing attempts using printed images, prosthetics, or artificial replicas are rejected before biometric matching is performed.

Overall, the experimental results confirm that the combination of advanced preprocessing techniques, deep learning-based feature extraction, and embedded system deployment provides an effective and practical solution for secure hand vein biometric authentication.

VIII. CONCLUSION

This paper presented a hand vein biometric authentication system that combines advanced image preprocessing techniques with deep learning–based feature extraction. The proposed framework utilizes near-infrared imaging to

DOI: 10.17148/IJARCCE.2026.15372

capture dorsal hand vein patterns and applies a structured preprocessing pipeline to enhance vascular structures and isolate the region of interest for reliable recognition.

A convolutional neural network was employed to learn discriminative feature representations of the vein patterns, enabling accurate biometric matching between individuals. The system was trained and evaluated using a manually collected dataset consisting of 261 individuals contributing 522 hand identities with 5220 images. Experimental results demonstrate that the proposed system achieves high recognition performance with an accuracy of 99.12% and an Equal Error Rate of 1.32% at a threshold of 0.6052.

In addition, the system was implemented on a Raspberry Pi 4 Model B platform to demonstrate the feasibility of edge-based biometric authentication. The embedded implementation enables real-time authentication while maintaining low computational requirements. A thermal sensing mechanism using an MLX90614 infrared temperature sensor was also integrated to provide liveness verification and improve system security.

Overall, the proposed framework demonstrates that combining robust preprocessing methods, deep learning–based feature extraction, and embedded system deployment can provide an effective and practical solution for secure hand vein biometric authentication. Future work may focus on expanding the dataset, improving model efficiency, and exploring additional liveness detection mechanisms to further enhance system robustness.

REFERENCES

[1]. P. Tome and S. Marcel, “Palm Vein Database and Experimental Framework for Reproducible Research,” 2015 International Conference of the Biometrics Special Interest Group (BIOSIG), 2015.

[2]. M. H. A. Sater, H. Kanaan, and M. Ayache, “Promising Database for Palm Vein Classification,” International Journal of Biology and Biomedical Engineering, vol. 13, pp. 149–160, 2019.

[3]. Z. Khan et al., “Multispectral Palmprint Encoding and Recognition,” arXiv preprint arXiv:1402.2941, 2014.

[4]. S. Minaee and A. Abdolrashidi, “Multispectral Palmprint Recognition Using Textural Features,” 2014 IEEE Signal Processing in Medicine and Biology Symposium (SPMB), IEEE, 2014.

[5]. S. Minaee and A. Abdolrashidi, “Highly Accurate Multispectral Palmprint Recognition Using Statistical and Wavelet Features,” arXiv preprint arXiv:1408.3772, 2014.

[6]. S. Minaee and A. Abdolrashidi, “On the Power of Joint Wavelet-DCT Features for Multispectral Palmprint Recognition,” 2015 49th Asilomar Conference on Signals, Systems and Computers, IEEE, 2015.

[7]. Thamri, K. Aloui, and M. S. Naceur, “Improving Palmprint Based Biometric System Performance Using Novel Multispectral Image Fusion Scheme,” International Journal of Advanced Computer Science and Applications, vol. 11, no. 8, 2020.

[8]. P. Tome and S. Marcel, “On the Vulnerability of Palm Vein Recognition to Spoofing Attacks,” 2015 International Conference on Biometrics (ICB), IEEE, 2015.

a. Gumaei et al., “An Improved Multispectral Palmprint Recognition System Using Autoencoder with Regularized Extreme Learning Machine,” Computational Intelligence and Neuroscience, 2018.

[9]. M. I. Obayya, M. El-Ghandour, and F. Alrowais, “Contactless Palm Vein Authentication Using Deep Learning with Bayesian Optimization,” IEEE Access, vol. 9, pp. 1940–1957, 2020.

[10]. Marattukalam et al., “Deep Learning-Based Wrist Vascular Biometric Recognition,” Sensors, vol. 23, no. 6, 2023.

[11]. Marattukalam, W. H. Abdulla, and A. Swain, “N-Shot Palm Vein Verification Using Siamese Networks,” 2021 International Conference of the Biometrics Special Interest Group (BIOSIG), IEEE, 2021.

[12]. N. Miura, A. Nagasaka, and T. Miyatake, “Feature Extraction of Finger-Vein Patterns Based on Repeated Line Tracking and Its Application to Personal Identification,” Machine Vision and Applications, vol. 15, no. 4, pp. 194–203, 2004.

a. Kumar and K. V. Prathyusha, “Personal Authentication Using Hand Vein Triangulation and Knuckle Shape,” IEEE Transactions on Image Processing, vol. 18, no. 9, pp. 2127–2136, 2009.

[13]. L. Wang, G. Leedham, and S. Y. Cho, “Infrared Imaging of Hand Vein Patterns for Biometric Purposes,” IET Computer Vision, vol. 1, no. 3–4, pp. 113–122, 2007.

[14]. D. Thapar, G. Jaswal, and V. Kanhangad, "PVSNet: Palm Vein Authentication Siamese Network Trained Using Triplet Loss and Adaptive Hard Mining," 2018 IEEE 4th International Conference on Identity, Security and Behavior Analysis (ISBA), pp. 1–8, 2018.

[15]. J. Zhong, X. Zhu, and Y. Zhang, “Binarized Dual ResNet for Palmprint Recognition with Siamese Learning,” IEEE Signal Processing Letters, vol. 28, pp. 319–323, 2021.

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⨳ Peer-reviewed & Refereed journal ⨳ Vol. 15, Issue 3, March 2026
DOI: 10.17148/IJARCCE.2026.15372

[16]. Jaswal, A. Kaushik, and R. Vig, "A Deep Siamese Network for Contactless Palm Vein Identification with Semi-Hard Triplet Mining," Journal of Ambient Intelligence and Humanized Computing, vol. 13, no. 5, pp. 2645–2662, 2022.
[17]. S. Zhao, B. Zhang, and C. P. Chen, "Joint Siamese Network and Online Hard Example Mining for Palmprint and Palm Vein Fusion," Information Sciences, vol. 546, pp. 835–850, 2021.
[18]. Marattukalam, W. H. Abdulla, and A. Swain, "Efficient Multi-Finger Vein Recognition Using a Dense-Head Probabilistic Siamese Network," Scientific Reports, vol. 14, no. 1, 2024.

