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MULTI SCALE DEEP REPRESENTATION AGGREGATION FOR VEIN RECOGNITION

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Abstract

Deep Convolutional Neural Networks (DCNNs) have demonstrated strong performance in image recognition due to their robust feature extraction capabilities. However, in vein recognition tasks—where training datasets are often limited in size—DCNNs tend to underperform due to over-reliance on large-scale data. To address this challenge, we propose a novel Multi-Scale Deep Representation Aggregation (MSDRA) framework built upon a pre-trained DCNN. The method begins by extracting multi-scale feature maps from the pre-trained model. These feature maps are refined using a local mean thresholding approach to suppress noise and highlight relevant features. Subsequently, an Unsupervised Vein Information Mining (UVIM) technique is introduced to generate a binary mask that localizes vein structures within the feature maps. This mask is then employed to filter out background data while retaining discriminative vein information. The enhanced multi-scale features are aggregated and concatenated into compact feature vectors, which are finally classified using a Support Vector Machine (SVM). Experiments conducted on two benchmark vein datasets confirm the superior accuracy of the proposed method over existing approaches. Additionally, validation on the PolyU Palmprint dataset underscores the model's robustness and generalization capacity.

Keywords: Pre-trained DCNN, vein recognition, MSDRA, local mean threshold, UVIM, SVM.

I. INTRODUCTION

With the increasing emphasis on secure and reliable authentication systems, **hand-dorsa vein recognition** has emerged as a promising biometric identification technique in recent years.

Compared to traditional biometric modalities such as face, palmprint, fingerprint, and iris recognition, hand-dorsa vein recognition offers three distinct advantages: **enhanced security**, **inherent liveness detection**, and **user convenience**. These characteristics position it as a highly effective and robust biometric solution, especially for applications demanding high levels of authentication assurance.A typical hand-dorsa vein recognition system comprises four key stages: **vein image acquisition**, **image preprocessing**, **feature extraction**, and **feature**

matching. Among these, feature extraction plays a critical role in determining the system's accuracy and robustness. Existing approaches to feature extraction for hand-dorsa vein recognition can be broadly categorized into three groups: **shape-based**, **texture-based**, and **deep learning-based** methods.

Shape-based methods primarily rely on extracting geometrical or structural vein information through vein segmentation or mathematical modeling. While such methods are intuitive, they often suffer from inaccuracies due to poor segmentation or low image contrast, which can significantly impact recognition performance. In contrast, **texture-based methods** such as Scale-Invariant Feature Transform (SIFT) and Local Binary Patterns (LBP) aim to encode the local textural variations within vein images. However, these approaches face challenges in handling sparse vascular structures and are sensitive to image preprocessing techniques like contrast enhancement, which can result in keypoint mismatches and unreliable identification outcomes.

The recent success of **Deep Convolutional Neural Networks (DCNNs)** in various computer vision tasks has inspired their application in vein recognition. DCNNs are capable of learning hierarchical and discriminative features directly from data, making them particularly well-suited for complex pattern recognition tasks. In vein images, they can capture anatomical properties such as the number, location, angle, and curvature of vein branches. These structural patterns are critical for uniquely identifying individuals.

Despite their potential, DCNN-based methods are often constrained by the limited size of available vein datasets, which can affect their generalization capability. Additionally, some prior work, such as anatomical analysis-based vein recognition, has utilized structural characteristics like continuity, solidity, and directionality to refine the vein patterns. However, these characteristics were used primarily for correcting segmentation defects rather than being directly employed as discriminative features.

To address these limitations, the present work proposes a **multi-scale deep representation aggregation framework** that integrates anatomical insights with deep feature extraction. The aim is to enhance the model's ability to extract robust and discriminative vein features while mitigating the effects of small dataset sizes and preprocessing artifacts. The effectiveness of the proposed method is substantiated through comprehensive experiments, as detailed in the subsequent sections.

II LITERATURE SURVEY

Liu et al. proposed **MMRAN**, a deep learning model that incorporates a residual attention mechanism to enhance vein recognition performance. The model exhibits strong results during training. However, as noted by **Krishnan**

and Thomas, MMRAN's effectiveness decreases when tested on images involving rotation or scaling transformations that were not present in the training data, indicating limitations in generalization.

Shaheed et al. introduced **DS-CNN**, a vein recognition model based on the Xception architecture and utilizing depth-wise separable convolutions. This model demonstrates high accuracy when applied to large and well-annotated datasets. Nonetheless, **Krishnan and Thomas** highlight its vulnerability to variations in image quality and pose, especially when test samples deviate from the training distribution.

Zhang and Wang presented a vein recognition approach based on **partitioned Local Binary Patterns (LBP)**. By dividing vein images into multiple regions and extracting features locally, the method aims to improve discriminative power. Despite this, **Krishnan and Thomas** assert that the model remains sensitive to spatial transformations such as translation and rotation, thus limiting its robustness in real-world scenarios.

Das et al. proposed **CNN-FVR**, a convolutional neural network designed specifically for finger vein recognition. The network is trained on raw finger vein images without extensive preprocessing. According to **Krishnan and Thomas**, this model risks learning features from non-venous image regions, potentially increasing false positive rates. Additionally, image resizing, often required for uniform input dimensions, can impair recognition accuracy.

Qin and El-Yacoubi developed **Deep-FV**, a deep learning model leveraging feature extraction and reconstruction techniques for finger vein verification. While effective in theory, **Krishnan and Thomas** emphasize that Deep-FV demands extensive training data to perform well, a common limitation in biometric systems where annotated vein datasets are scarce.

Yang et al. implemented an **anatomy-based analysis** strategy to enhance the clarity and accuracy of extracted vein patterns. Their method uses anatomical features—such as vein continuity, solidness, and directionality—to correct structural artifacts like burrs and gaps. However, **Krishnan and Thomas** criticize this approach for not integrating these anatomical traits directly into the vein recognition process as input features, which could have improved recognition accuracy.

III EXISTING SYSTEM

Current finger vein recognition techniques can broadly be categorized into **shape-based**, **texture-based**, and **deep learning-based** approaches. Each of these has distinct mechanisms and limitations that impact their effectiveness under varying conditions.

Shape-based methods rely heavily on the precise segmentation of vein patterns from the background. While they can provide accurate recognition under ideal imaging conditions, their performance significantly deteriorates when dealing with low-quality or poorly segmented images. Inconsistent lighting, noise, and finger placement variations further complicate the segmentation process, making these methods less reliable in practical deployments.

Texture-based methods, such as those using **Scale-Invariant Feature Transform (SIFT)** and **Local Binary Patterns (LBP)**, attempt to characterize vein patterns by capturing local textural variations. These descriptors offer some robustness to minor changes in lighting or orientation. However, finger vein images typically possess sparse and low-contrast structures, which limits the ability of texture-based methods to extract stable and distinctive features. Additionally, these methods are **highly sensitive to preprocessing steps** like filtering, enhancement, and normalization. Any inconsistencies in these stages can lead to significant variability in the extracted features, thereby degrading overall system performance and reliability.

IV PROBLEM STATEMENT

Traditional finger vein recognition systems continue to face significant challenges that hinder their effectiveness in real-world applications. **Shape-based** and **texture-based** methods often suffer from **poor feature extraction capabilities**, relying on handcrafted features that are **highly sensitive to noise**, skin condition, image quality, and illumination. These methods struggle particularly in low-contrast and noisy environments, which are common in real-life biometric scenarios. While **deep learning-based models** such as **Deep Convolutional Neural Networks (DCNNs)** offer improved feature extraction through automated learning, they require **large-scale, high-quality labeled datasets** for training. Unfortunately, such datasets are scarce in the vein recognition domain, which significantly limits their practical deployment.To address these limitations, the **Multi-Scale Deep Representation Aggregation (MSDRA)** model has been proposed. This model leverages a **pre-trained DCNN** to extract **multi-scale feature maps**, thereby capturing rich and hierarchical vein features. Additionally, it integrates a **Local Mean Thresholding** method to effectively **suppress background noise**, which enhances the clarity and usability of the extracted vein patterns.The goal of MSDRA is to **improve the accuracy, robustness, and generalization** of vein recognition systems, especially under challenging conditions. By focusing on **multi-scale representation** and **noise elimination**, MSDRA represents a significant advancement in biometric identification. It directly addresses the **unique challenges** of finger vein recognition—such as low image contrast, uneven illumination, and limited data availability—making it a **more practical and secure solution** for real-world biometric security applications.

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V PROPOSED SYSTEM

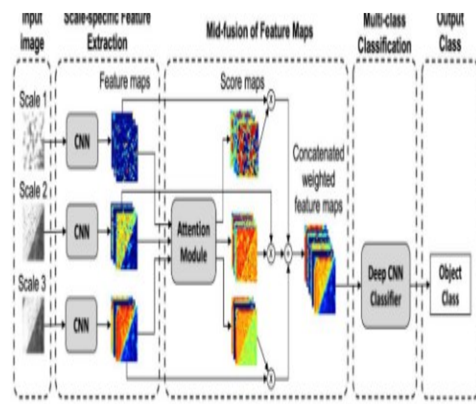
The proposed system introduces the **Multi-Scale Deep Representation Aggregation (MSDRA)** model, designed to overcome the limitations of traditional finger vein recognition methods by improving feature extraction, noise suppression, and generalization. The system is built with a strong emphasis on **accuracy, robustness across datasets**, and **computational efficiency**, making it highly suitable for deployment in real-world biometric security applications.

The MSDRA model begins by extracting **multi-scale feature maps** from input images using a **pre-trained Deep Convolutional Neural Network (DCNN)**. This enables the system to capture both **coarse-level vein structures** and **fine-grained details**, which are essential for accurate finger vein identification. By incorporating multiple scales, the model ensures that even subtle vein features are effectively detected.

To refine these features and eliminate noise, the system employs a **Local Mean Thresholding** technique. This adaptive method dynamically adjusts to **local intensity variations** within the image, effectively isolating relevant vein patterns while suppressing irrelevant background regions. This enhances the clarity and usability of the extracted vein features, even under challenging lighting or image quality conditions.

Furthermore, the system introduces an innovative component called **Unsupervised Vein Information Mining (UVIM)**. UVIM addresses the problem of limited labeled data by learning to highlight **vein-specific features** in an **unsupervised manner**. It automatically identifies and emphasizes consistent patterns across different samples, improving the **discriminative power** of the feature representations without relying on manual annotations.

VI SYSTEM ARCHITECTURE



VII IMPLEMENTATION

a comprehensive vein recognition system is designed by combining shape-based, texture-based, and deep feature-based techniques to extract distinctive features from finger vein patterns. Shape-based methods analyze the geometric structure and branching of veins, while texture-based methods capture local surface variations and pixel intensity distributions. Deep feature-based approaches utilize convolutional neural networks to learn high-level abstractions of vein patterns, making the system more resilient to variations in lighting, orientation, and scale. A

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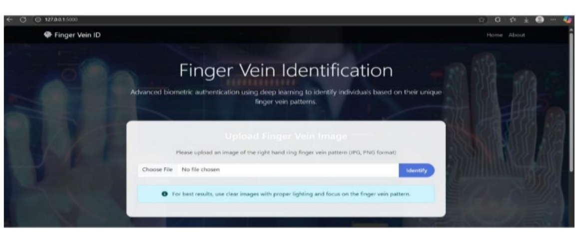
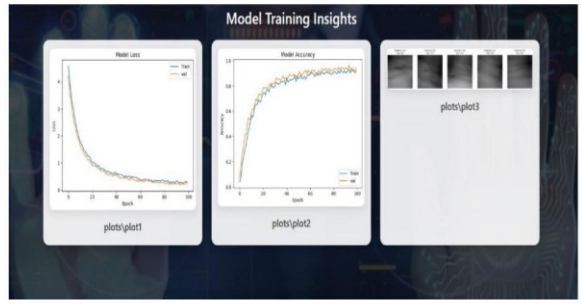
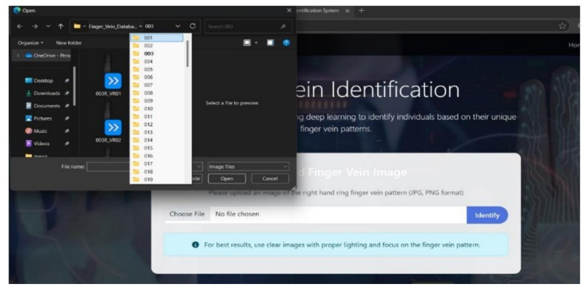
critical component of the system is the **Selected Feature Maps Generation Module**, which refines and selects multi-scale features from a pre-trained deep learning model. This module ensures that only the most discriminative and relevant vein features are retained for further processing, significantly improving the accuracy and robustness of the recognition system.

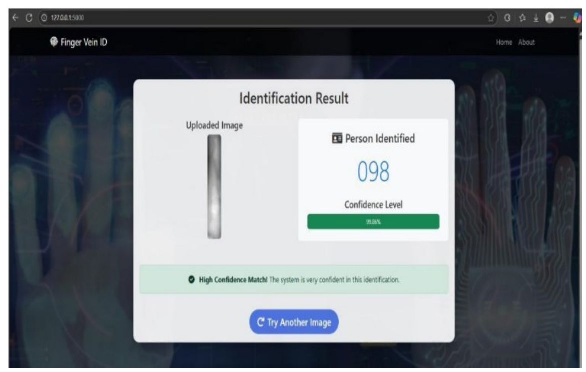
The system includes a web-based interface that provides an intuitive platform for users to upload their finger vein images. Once an image is submitted, it undergoes preprocessing operations such as resizing and normalization to prepare it for model input. The preprocessed image is then forwarded to the trained deep learning model, which extracts feature vectors and generates a feature matrix. This matrix is used to predict the user's identity with high precision. The implementation ensures seamless communication between the front-end and back-end components, allowing for real-time processing and immediate feedback. By integrating advanced deep learning techniques with an easy-to-use interface, the system achieves high recognition accuracy, user convenience, and practical applicability in biometric authentication scenarios.

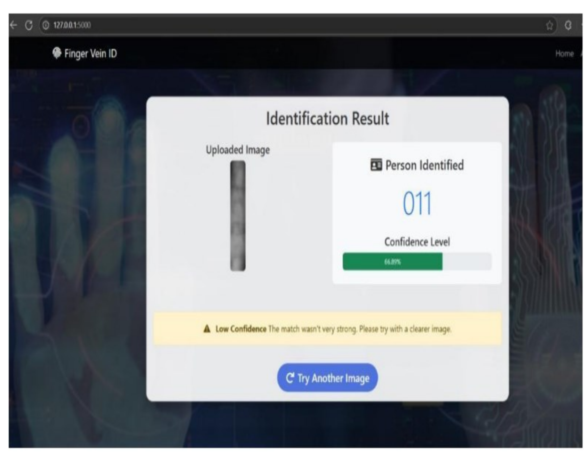
RESULTS











The system performed effectively under standard conditions, with successful image preprocessing (resizing and normalization), accurate multi-scale feature extraction from the conv5_1 and pool5 layers, and high-confidence classification using the SVM model, confirming that the core modules are functioning as intended. The Streamlit interface enabled smooth, real-time image uploads and predictions, making the system user-friendly and suitable for deployment. However, limitations were observed in handling edge cases—blank or white images were misclassified with high confidence instead of being rejected, and cropped finger images with incomplete vein patterns resulted in incorrect predictions. These issues highlight the need for improved input validation, uncertainty handling, and robustness to ensure consistent performance in real-world applications.

CONCLUSION

This vein recognition project effectively enhances the accuracy of personal identification by leveraging distinctive hand vein patterns through a deep learning-based approach. The system intelligently combines multi-layered feature extraction and background noise reduction to focus on the most relevant vein structures, ensuring robust recognition performance. With a user-friendly Streamlit interface, it enables real-time image uploads and immediate results, making it practical for real-world applications. While the system performs reliably with clear and complete images, future improvements are needed to handle challenging cases such as blank, low-quality, or cropped images more effectively. Overall, the project demonstrates significant potential for deployment in secure authentication systems across domains like healthcare, security, and identity verification, with room for further enhancement in robustness and adaptability.

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