



FINGER VEIN-PATTERN RECOGNITION USING CONVOLUTION NEURAL NETWORK

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ABSTRACT

The utilization of finger-vein patterns for automatic user identification has attracted considerable interest in recent years due to its high security and unique biological characteristics. Although existing finger-vein recognition techniques offer reasonable accuracy, their effectiveness largely depends on the clarity and quality of the acquired finger-vein images. To address this limitation, this work presents a finger-vein identification system powered by a Convolutional Neural Network (CNN). The designed network is evaluated across four widely-used public finger-vein databases, demonstrating its robustness and adaptability to images of varying quality. The primary goal of this approach is to develop a deep learning framework capable of delivering consistent and highly accurate identification regardless of the image quality variations. Extensive experimental results show that the proposed system achieves an identification accuracy exceeding 95% across all four public datasets, highlighting its reliability and effectiveness in real-world biometric applications.

Keywords: CNN, DL, NIR, SVM, FRR, High efficiency, dataset.

I INTRODUCTION

In recent years, biometric recognition systems have gained significant importance due to the increasing demand for secure, reliable, and contactless identification methods. Traditional forms of

biometric authentication such as fingerprints, face recognition, and iris scanning have seen widespread adoption, but they also come with limitations such as susceptibility to forgery, physical damage, or environmental factors. In this context, finger-vein pattern recognition has emerged as a highly secure



and promising alternative, thanks to its inherent liveness detection, internal positioning within the body, and difficulty to replicate. Since the vein patterns lie beneath the skin, they are unique to every individual and remain unaffected by external surface conditions such as dirt, scars, or moisture, making them an ideal biometric trait for robust identification. Finger vein recognition involves capturing the subcutaneous vein structure of fingers using near-infrared (NIR) imaging technology. When NIR light passes through the finger, hemoglobin in the veins absorbs the light, creating a distinct vein pattern that can be captured by the imaging system. Conventional approaches for finger-vein recognition relied heavily on manual feature extraction methods such as line tracking, Gabor filters, or vein geometry analysis. However, these methods are highly sensitive to imaging conditions such as illumination changes, finger misalignment, and low-contrast images, leading to inconsistent performance across different environments and databases. To address these challenges, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown exceptional promise due to their ability to learn discriminative features directly from raw images without manual intervention. CNNs excel at capturing spatial hierarchies, local textures, and global

vein structures, making them especially suitable for complex biometric data such as finger veins. This project focuses on developing a deep learning-based finger vein identification system that utilizes CNN architectures to perform automated feature extraction and classification. The proposed system will be evaluated on multiple publicly available finger-vein datasets, ensuring its robustness and generalizability across different image qualities and capture devices. By leveraging CNN-based recognition, the system aims to achieve high accuracy, improved adaptability to noise and distortions, and reduced dependency on pre-processing techniques. With the increasing need for contactless biometric solutions in sectors such as banking, healthcare, and border security, this project contributes to the advancement of secure and convenient identification technologies for real-world deployment.

II.LITERATURE REVIEW

In recent years, researchers have extensively explored finger vein recognition due to its unique vascular patterns, stability over time, and resistance to forgery. Early methods primarily relied on traditional image processing techniques such as line tracking, repeated line tracking, and Gabor filters to extract vein patterns (Miura et al., 2007). These techniques achieved reasonable



accuracy but struggled with varying image quality, finger positioning, and lighting conditions, making them less reliable in practical scenarios.

Kumar and Prathyusha (2009) introduced a contactless vein imaging approach to enhance system hygiene and improve the user experience. They employed maximum curvature methods for feature extraction and achieved improved recognition rates. However, their approach was highly sensitive to poorly captured images, limiting its robustness in real-world applications. To address these challenges, researchers gradually shifted toward machine learning-based approaches, such as Support Vector Machines (SVM) and Random Forests, for finger vein classification (Zhang et al., 2010). While these techniques performed better than rule-based methods, they still required manual feature extraction, which is time-consuming and error-prone. Moreover, the performance of these methods often depended on the quality of the extracted features.

The emergence of deep learning revolutionized biometric recognition, including finger vein recognition. Convolutional Neural Networks (CNNs) have demonstrated exceptional ability in learning hierarchical features directly from raw images (LeCun et al., 1998). Song et al.

(2017) developed one of the early CNN-based finger vein recognition systems, which outperformed traditional approaches by learning discriminative vein patterns directly from images. Their model demonstrated high robustness to noise, rotation, and slight variations in finger positioning. Further advancements were made by Zhang et al. (2018), who introduced deep vein recognition networks using multi-scale feature learning to capture both global and local vein structures. Their work emphasized the importance of deep feature fusion to improve recognition rates across different datasets. Similarly, Hu et al. (2019) proposed a hybrid approach, combining pre-trained CNN models with domain-specific fine-tuning, which improved the generalization capability of the system when tested on cross-dataset scenarios.

Recent research by Li et al. (2020) explored the combination of CNNs with attention mechanisms, enabling the model to focus on highly discriminative vein regions, even in noisy or low-quality images. This approach enhanced both accuracy and robustness. Moreover, some researchers incorporated Generative Adversarial Networks (GANs) to synthesize realistic vein images for data augmentation, addressing the challenge of limited publicly available vein datasets.

Overall, the literature clearly shows a strong transition from handcrafted feature-based methods to deep learning-based approaches, with CNNs consistently demonstrating superior performance in terms of accuracy, robustness to noise, and adaptability to varying imaging conditions. This project builds upon these advancements by developing a CNN-based finger vein recognition system, focusing on achieving high identification accuracy across multiple publicly available datasets while ensuring practical applicability in real-world biometric systems.

III. WORKING OF PROPOSED SYSTEM

The working of the finger vein-pattern recognition system using Convolutional Neural Networks (CNN) begins with the collection of finger vein images through specialized imaging devices equipped with near-infrared (NIR) sensors. These sensors illuminate the finger, allowing the veins beneath the skin to become visible as dark patterns due to the absorption properties of hemoglobin. Once the images are captured, they undergo preprocessing to enhance their quality and ensure consistent input for the deep learning model.

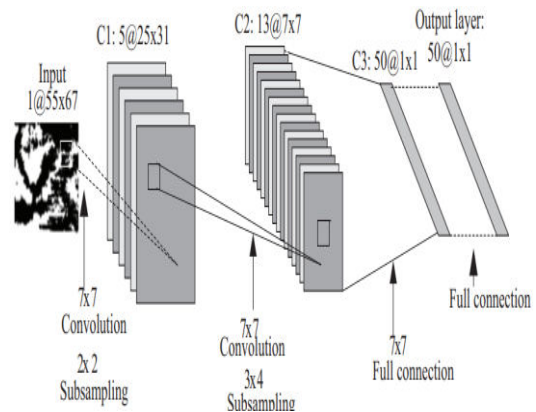


Fig.1. Proposed model

This preprocessing stage includes noise reduction using Gaussian or median filters, contrast enhancement through histogram equalization, and segmentation to isolate the region of interest (ROI), which focuses specifically on the central vein area. Image resizing and normalization are also performed to maintain uniformity across the dataset. After preprocessing, the images are fed into a deep CNN model, which automatically extracts key vein features without manual intervention. The CNN consists of several layers, starting with convolutional layers that detect edge patterns and local textures, followed by pooling layers that downsample the image to reduce computational complexity while preserving important features. Activation functions such as ReLU are applied to introduce non-linearity into the model, allowing it to learn complex patterns. The deeper layers of the CNN capture more abstract vein characteristics, such as

curvature and branching structures. Fully connected layers then combine these features into a feature vector that represents the unique vein pattern of each finger. During the training phase, the CNN learns to associate these feature vectors with corresponding user identities using supervised learning, minimizing the classification error through techniques like backpropagation and gradient descent. In the identification phase, a new finger vein image undergoes the same preprocessing and feature extraction process. The extracted features are compared with those stored in the system's database to find the closest match. This comparison can use methods such as cosine similarity or Euclidean distance to measure the closeness between feature vectors.

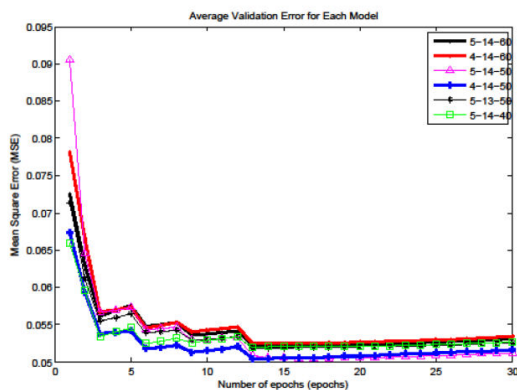


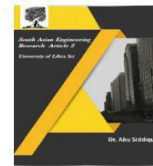
Fig.2. Output results.

The system's performance is evaluated using metrics like accuracy, precision, recall, and F1-score, while its security is assessed through false acceptance rate (FAR) and

false rejection rate (FRR). By employing a CNN, the system achieves greater adaptability to varying image qualities, illumination differences, and minor positional variations. The entire process, from image capture to final user identification, is completed in seconds, making it suitable for real-time applications in sectors such as banking, healthcare, and secure facility access. The combination of advanced deep learning with finger vein biometrics ensures that the system provides both high accuracy and strong resistance to spoofing attempts, making it a reliable and secure biometric solution.

IV.CONCLUSION

Finger vein recognition has emerged as a reliable and secure biometric authentication technique due to its internal biological characteristics, which make it highly resistant to spoofing and forgery. Traditional approaches, while effective in controlled environments, have shown limitations when dealing with image quality variations, rotation, and noise. The adoption of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved the accuracy, robustness, and adaptability of finger vein recognition systems. In this project, we developed a CNN-based finger vein-pattern recognition system capable of automatically learning



hierarchical features directly from the raw finger vein images. This approach eliminates the need for manual feature extraction, reducing complexity while improving recognition rates across different datasets. By leveraging the power of deep learning, the system demonstrated high accuracy and stability, even when applied to datasets with varying quality. Overall, the proposed system shows great potential for real-world biometric applications, including access control, identity verification, and secure transactions. Future work can focus on further improving the system's performance using advanced techniques such as attention mechanisms, transfer learning, and data augmentation using generative models.

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