# Deep Learning for Finger Vein Recognition: A Brief Survey of Recent Trend

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***Abstract*—Finger vein recognition technology plays an important role in biometric recognition and has been successfully applied in many fields. Because veins are buried beneath the skin tissue, finger vein recognition has an unparalleled advantage, which is not easily disturbed by external factors, and it has excellent performance over other surface biometric features. At the same time, the similarity between different fingers of the same person is also worth exploring. Our state-of-the-art survey summarizes 46 papers about deep learning for finger vein image recognition from 2017 to 2022. To understand finger vein recognition technology, our survey analyzes related works according to different tasks of deep neural networks. Additionally, we point out the challenges and potential development directions of finger vein recognition. All in all, our contribution is providing a comprehensive sight for deep learning-based finger vein recognition technology.**

***Index Terms*—Finger vein recognition, Deep learning, Deep neural network**

## I. Introduction

Biometric recognition aims to identify a person based on physical features, such as fingerprint, voice, and iris [1]. With the growing requirement of digital security verification systems, biometric recognition plays a vital role in many fields, such as online payment, security, and other fields. The recent popular trend of *Deep Learning* (DL) techniques is to employ deep neural networks for various tasks. Compared to the traditional secure identification process, biometric recognition technology is more efficient due to its convenience and steady security. Unfortunately, several representative biometric identification technologies are struck in some bottlenecks. For instance, the fingerprint recognition rate is significantly affected by the finger surface. Besides, the fingerprints inadvertently left on things may lead to security risks. Voice recognition usually requires a relatively quiet environment. The recognition rate of iris systems is outstanding, but it requires expensive sensors. Different from the above technologies, the *Finger Vein Recognition* (FVR) is efficient and low-cost. The finger vein is buried beneath the skin of the finger and is unique to each individual. It can be recognized through the *Near Infra-Red* (NIR) light [2], not the visible light which is vulnerable to external factors. A comparison of these different biometric recognition methods is shown in Tab. I.

TABLE I
Several biometric recognition technologies. **N** represents non-contact. **C** represents contact. **RF** represents radio frequency. **NIR** represents near-infrared.

| Feature | Security | Obstruction | Data | Contact | Cost |
|---|---|---|---|---|---|
| Face | Normal | Illumination | Image | N | Low |
| Voice | Normal | Noise | Audio | N | Low |
| Fingerprint | Good | Skin surface | Image | C | Low |
| Iris | Superior | Glasses | Image | N | High |
| Retina | Good | Glasses | Image | N | Middle |
| Gait | Normal | Personal appearance<br>Filming angle | Video<br>Foot pressure<br>Velocity<br>Frequency | N | Low |
| Signature | Normal | Randomness of writing | Image<br>Writing pressure<br>Writing posture | N | Low |
| Finger vein | Superior | Few | Image | N | Low |

FVR, as an identification technology, is contingent upon the utilization of finger vein images captured from the human body. Since finger veins are concealed beneath the skin's surface, the acquisition of finger vein images typically involves the use of an NIR sensor and a *Charge-Coupled Device* (CCD) camera, as illustrated in Fig. 1. Upon a person placing their finger onto the finger vein capture device, the NIR sensor emits NIR light across the entire finger. Hemoglobin in the blood exhibits a higher absorption rate of NIR light compared to other biological tissues. Consequently, when illuminated

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978-1-6654-6837-4/22/$31.00 © 2022 IEEE

by the CCD camera, the vascular tissue within the finger manifests a darker brightness compared to surrounding areas, thereby enabling the capture of the finger vein image.

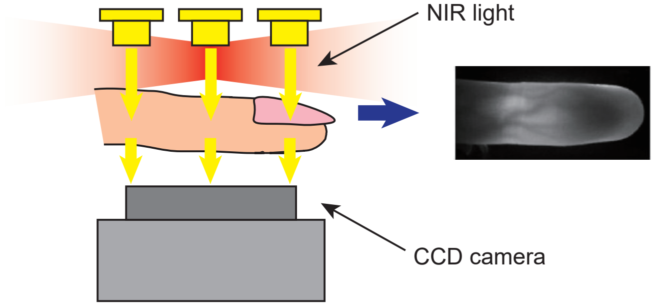


Fig. 1. Image acquisition step obtained in FVR [3]. On the left is the procedure for capturing the finger vein images utilizing a NIR sensor coupled with a CCD camera. On the right is the resultant captured finger vein image.

Artificial intelligence technology, especially DL technology, has developed rapidly in recent years, and DL has dominated the recent research in the field of AI. The recent popular trend in DL is to use deep neural networks to perform a wide variety of tasks, including image processing. Compared with transitional image processing methods, DL achieves overwhelming performance in many tasks of computer vision, such as biometric recognition [1], biomedical image analysis [4], and autonomous driving [5]. DL-based methods are widely used in FVR tasks. The traditional FVR process usually includes image capture, image data pre-processing, feature extraction, and classification or other analysis tasks. In the registration phase, images undergo initial pre-processing operations to attain elevated quality and adhere to uniform standards. Subsequently, vein features are extracted from the processed finger vein images and securely stored in a dedicated database. During the matching stage, the input finger vein image undergoes pre-processing in a manner consistent with the registration process. Features are extracted from this processed image and subsequently compared with the stored data in the database to ascertain the correct affiliation. The overall flow of FVR is depicted in Fig. 2.

The application of DL-based methods, especially *Convolutional Neural Networks* (CNNs), greatly changes the manual feature extraction process. The performance of conventional machine learning approaches is significantly influenced by feature engineering, in which the feature selection is based on human domain knowledge. Nevertheless, CNNs can extract abstract but efficient features by supervised or semi-supervised learning. The recognition process has been extremely simplified by DL-based methods. The advent of DL injects fresh vigor into the field of FVR. Leveraging its capability to autonomously learn feature extraction capability, DL automatically extracts vein features from finger vein image data. Subsequently, it employs the fully connected layer and Softmax function to effectively execute the classification task. With the extraordinary advantages pf DL, FVR no longer requires human experts to manually design templates for feature extraction, greatly saving the cost of recognition.

To illustrate the recent trend and potential direction of DL-based FVR, we conduct this brief survey. We summarize 46 related papers from 2017 to 2022, which cover different finger vein image analysis tasks, including classification, feature extraction, image enhancement, image segmentation, and encryption. These papers are collected from popular academic datasets or searching engines, which mainly include IEEE, Springer, Elsevier, MDPI, ACM, World Scientific, and Google Scholar. We use "finger vein image analysis" AND ("deep learning" OR "neural network" OR "ANN" OR "CNN" OR "GAN" OR "RNN" OR "LSTM") as the search keywords. The structure of this paper is as follows: In Sec. II, We present our work related to this thesis, existing FVR surveys, and analyze the intricacies and sophistication inherent in our research. Sec. III summarize publicly available datasets commonly utilized in FVR tasks, presenting detailed information about each dataset and providing summary tables for clarity. In Sec. IV, we introduce the deep neural network structure commonly employed in FVR. In Sec. V, we organize the application of DL to FVR into five tasks, offering a detailed exploration of each task. This includes presenting representative approaches and providing a comprehensive summarizing table for clarity. In Sec. VI, the challenges and potential directions of FVR are talked about. Finally, in Sec. VII, the conclusion and future work of this paper is provided.

## II. Related Work

FVR, as an emerging biometric technology, garners widespread attention. To underscore the uniqueness of our contribution, this section presents a comparative analysis between our work and existing FVR-related surveys. [6]–[9] provide a summary of the entire FVR process, encompassing pre-processing, feature extraction, and matching. In terms of critical algorithms for recognition, these papers concentrate on traditional machine learning algorithms. [10], [11] exclusively concentrate on feature extraction algorithms for FVR. These works still emphasize the application of traditional machine learning methods for feature extraction in FVR, neglecting the significant contribution of DL to the field. [12] discusses the application of CNNs in FVR, encompassing common classification tasks and segmentation tasks. Nevertheless, the discussion is constrained to specific network structures characterized by shallow layers of structural components, and it lacks research on the broader application of DL in FVR. In contrast to preceding surveys, [13], [14] emphasizes focus on the application of DL technology in FVR. [13] summarizes a limited number of papers and lacks a comprehensive analysis of DL to FVR from an algorithmic perspective. The discussion of [14] spans various classical deep neural network architectures, yet the summary of related FVR work lacks coherence and does not systematically organize the task of applying DL to FVR. We comprehensively and systematically summarize the various application tasks of FVR using DL technology, detailing the specific DL algorithms and elucidating related values in FVR. Additionally, we offer an introduction to commonly utilized

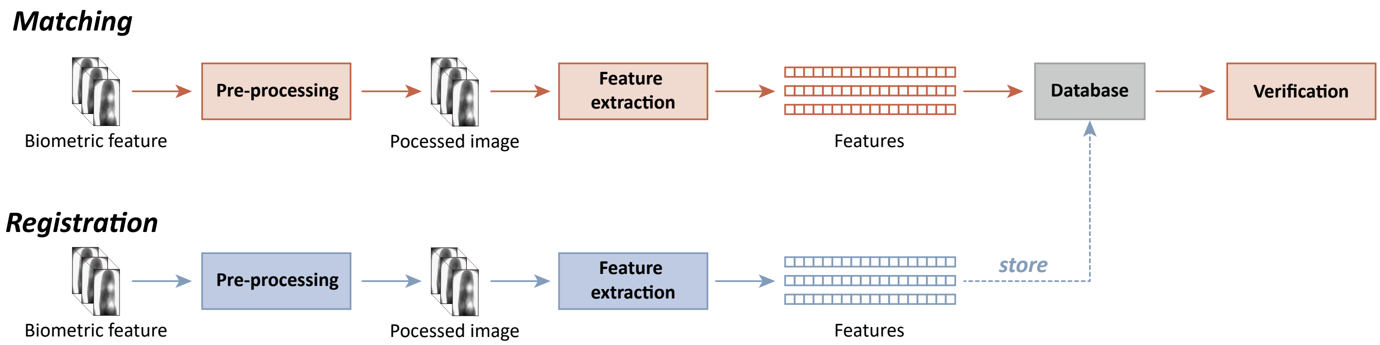


Fig. 2. The general workflow of biometric identity verification system on FVR. These essential steps encompass preprocessing, feature extraction, and matching. During the enrollment phase, the extracted vein feature data is meticulously stored in a dedicated database. In the subsequent matching phase, the feature data extracted from the input image is systematically compared with the information already stored in the database to facilitate identification.

correlation datasets and classical deep neural networks and propose challenging potential directions for the advancement of FVR.

## III. Dataset

As DL relies on extensive data resources for automatic learning, the dataset exerts a significant influence on the ultimate performance of the DL model. The size of the dataset directly determines the extent to which the trained DL model possesses sufficient generalization ability. The quality of image data also impacts the quality of features extracted by DL. Through the investigation of relevant papers, the most widely used datasets are FV-USM [15], HKPU [16], MMCBNU-6000 [17], SDUMLA-HMT [18], UTFVP [19], and THU-FVFDT. The base information of these datasets is provided in Tab. III.

### A. FV-USM

FV-USM contains 5904 images obtained from 123 volunteers, including 93 males and 40 females, ranging in age from 20 to 50. The image collection process was divided into two stages. The time gap between these two stages is more than two weeks. Each person provided four fingers for image capture. For each image collection stage, six images were taken for each finger.

### B. HKPU

HKPU contains 6264 images acquired from 156 subjects. Half of these images are finger vein images, and the rest are finger texture images. 93% of the subjects are younger than 30 years old. Images were acquired in two separate sessions with a minimum interval of one month and a maximum interval of six months. The average interval is 66.8 days. In each session, every subject provided six samples. Each sample contains one vein image and one finger texture image.

### C. MMCBNU-6000

MMCBNU-6000 contains 6000 finger vein images collected from 100 volunteers from 20 different countries. These volunteers have different skin tones. Each subject provided their index finger, middle finger, and ring finger, and each finger was photographed ten times in an office environment (rather than a dark environment).

### D. SDUMLA-HMT

SDUMLA-HMT is a homologous multi-modal traits database containing multiple biometric features such as face, finger veins, gait, iris, and fingerprints. The finger vein part of SDUMLA-HMT is the first publicly available finger vein dataset, consisting of 3816 images. These images were collected from each of the six fingers of 106 people, and six images were collected from each finger.

### E. UTFVP

UTFVP contains 1440 vascular pattern images obtained from 60 volunteers. These images were captured in two sessions. The average time gap between these sessions is 15 days. The vascular pattern of the six fingers from each subject was taken two times.

### F. THU-FVFDT

THU-FVFDT contains two versions. The first version, THU-FVFDT1, contains 440 finger vein images from 220 subjects. The second version, THU-FVFDT2, contains 2440 finger vein and finger dorsal texture images from 610 subjects. Both datasets were acquired with only one finger of each subject, and their image acquisition process was finished in two sessions.

## IV. Deep Neural Networks

One [ivotal factor, integral to the significant breakthroughs facilitated by DL technology across various domains, is the utilization of deeply structured artificial neural networks, especially CNNs. This is indispensable in conjunction with extensive data-driven training processes. In contrast to the uncomplicated neuron structure of multi-layer perceptions, deep neural networks have a substantial number of parameters. This abundance of parameters enables them to extract high-level semantic information from intricate images, thereby exhibiting satisfactory generalization capabilities, particularly when provided with ample data. Numerous network structures have been devised in the field of DL, demonstrating performance

TABLE II
DETAIL OF PUBLIC DATASETS THAT ARE WIDELY USED IN FVR. **NO. SUB.** REPRESENTS THE NUMBER OF SUBJECTS. **NO. IMG** REPRESENTS THE TOTAL NUMBER OF IMAGES ON THE DATASET. **NO. F.** REPRESENTS THE NUMBER OF FINGERS ENGAGED IN THE GESTURE WITHIN A SINGLE SUBJECT.

| Dataset | No. Sub. | No. Img. | No. F. | Year | Resolution | Highlight | URL |
|---|---|---|---|---|---|---|---|
| FV-USM | 123 | 5904 | 4 | 2014 | $640 \times 480$ | Both; Middle, index; Two sessions ROI; Finger vein and geometry | [15] |
| HKPU | 156 | 6264 | 2 | 2011 | $513 \times 256$ | Left; Middle, right; Finger vein and finger surface texture | [16] |
| MMCBNU-6000 | 100 | 6000 | 6 | 2013 | $640 \times 480$ | Both; Middle, index, right; The subject are from 20 different countries. | [17] |
| SDUMLA-HMT | 106 | 3816 | 6 | 2010 | $320 \times 240$ | Both; Middle, index, right; The earliest FVR public dataset | [18] |
| UTFVP | 60 | 1440 | 6 | 2013 | $672 \times 380$ | Both; Middle, index, right; Two sessions; High resolution | [19] |
| THU-FVFDT1 | 220 | 440 | 1 | 2014 | $200 \times 100$ | Left; Index; Two sessions; Finger vein and finger dorsal texture | [20] |
| THU-FVFDT2 | 610 | 2440 | 1 | 2014 | $200 \times 100$ | Left; Index; Two sessions; Finger vein and finger dorsal texture; ROI | [21] |

across various tasks. Consequently, these structures have found widespread adoption in many research studies within the realm of computer vision. These classical deep neural networks are more capable of achieving guaranteed performance results than structures of their own design. There are also many deep classical deep neural networks that are frequently used in DL studies related to FVR, and they can accurately extract finger vein features from finger vein images. In this section, we introduce the classical deep neural network models that are frequently employed in FVR to enhance the clarity of our overview These are AlexNet [22], ResNet [23], and GAN [24]. The base characteristics of them are provided as follows.

### A. AlexNet

AlexNet is a milestone in DL technology. Before it, the development of neural network technology was at a low ebb for many years. It is the first CNN to win the ILSVRC 2012. After AlexNet, DL starts to be the mainstream technology in many computer vision tasks [25]. The structure of AlexNet contains five convolutional layers and three max-pooling layers. Additionally, it has three fully connected layers with 4096, 4096, and 1000 neurons, respectively. Its structure is provided in Fig. 3. This network adopts ReLU as the activate function, and Dropout and data augmentation are applied to prevent over-fitting.

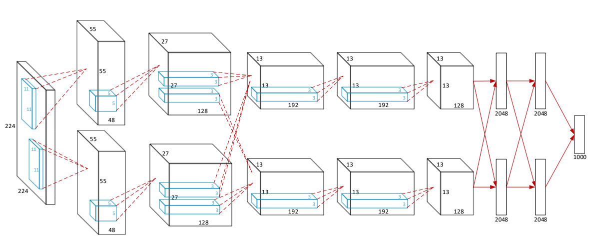

Fig. 3. The structure of AlexNet

### B. ResNet

ResNet is a deep neural network composed of several residual units connected in series. As shown in Fig. 4, the residual unit is made up of convolution layers and a shortcut connection. The shortcut connection can effectively guarantee the backpropagation of the gradient. Additionally, ResNet does not contain any fully connected layer, except for the output layer. This design dramatically reduces the number of network parameters. Owing to the excellent structure of ResNet, it is widely used as the backbone of many computer vision tasks.

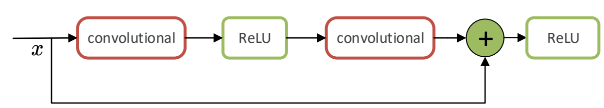


Fig. 4. The residual unit structure.

### C. GAN

GAN is commonly used in the finger vein image restoration task. Its structure is shown in Fig. 5. Different from the neural networks used for classification, GAN is composed of the generator and discriminator. The task of the generator is to generate fake samples that can fool the discriminator. The discriminator aims to distinguish between true and false samples. This generative adversarial process can be modeled in the form of (1). $V$ is the objective function of the entire model. $D$ is the discriminator, $G$ is the generator, $E_{x \sim P_{data}}$ represents the true data distribution, $E_{z \sim P_z(z)}$ represents random noise distribution The entire formula reveals the GAN optimization process. As shown in Fig. 5, the generator network receives the noisy random input, while the discriminator network receives the true sample. The output of the generator network is then fed into the discriminator, which verifies if it is a genuine sample.

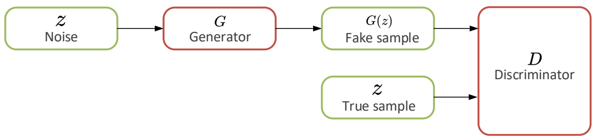


Fig. 5. The basic theory of GAN

$$\min_{Gener}\max_{Discr} V(Gener, Discr) = E_{x\sim P_{data}}[logDiscr(x)]+ E_{z\sim P_z(z)}[log[1 - Discr(Gener(z))]] \quad (1)$$

## V. Finger vein recognition based on deep learning

An overview of FVR based on DL is presented in this section. According to the tasks of neural networks, the papers are divided into five parts. The tasks that we thoroughly discuss include classification, feature extraction, image enhancement, image segmentation, and encryption. Classification stands as the central task in FVR, commonly employing an end-to-end approach to execute identity-matching tasks with the utilization of finger vein images. The feature extraction task focuses on the quality of features extracted from finger vein images through the utilization of DL methods. The quality of finger vein images is often suboptimal due to variations in imaging environments. Image enhancement techniques play a crucial role in enhancing the quality of finger vein images, thereby improving the overall recognition performances of DL models. Image segmentation techniques have the capability to isolate the pattern of vein lines from the original finger vein images. Encryption is a pivotal technology that warrants discussion in FVR because ensuring privacy and security is imperative for any biometric recognition technology. In each task, the representative methods are introduced. In the end, we provide a summary table in Tab. III.

### A. *Classification*

Classification is the main task in FVR. Compared with traditional machine learning methods, DL technology shows overwhelming performance in finger vein image classification tasks. The flow of the classification task is shown in Fig. 6.

A substantial portion of research in this domain directly employs CNNs for end-to-end FVR tasks, encompassing both feature extraction and classification. [26]–[53] focus on the finger vein classification task based on DL. Among them, most papers adopt a similar CNN-based workflow to classify the finger vein data. For example, ResNet is directly applied to the image data to perform the classification task in [30]. Similar workflows are used in [32], [41], [46], [52]. It is worth noting that [48] imports a joint attention module to improve the contribution of vein patterns in feature extraction. The attention mechanism plays a crucial role in enabling the model to concentrate on key regions in the finger vein images, thereby improving its capability to capture essential semantic features.

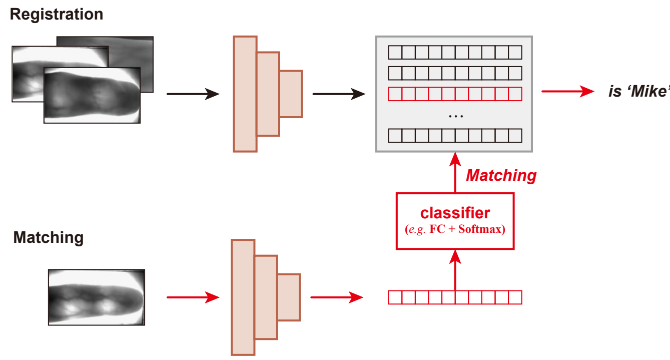


Fig. 6. The flow of classification in FVR. In the registration phase, the feature vectors extracted by the deep neural network are stored in the database. During the log in phase, feature vectors extracted from the input images are compared with the data in the database, completing the identification process.

This enhancement contributes to an overall improvement in the classification performance of the model.

Besides CNNs, there are some papers adopting different neural networks, such as [33] use *Graph Neural Network* (GNN) to perform the classification. The intricate vein texture can be described as a graph structure. Hence, GNN can quickly distinguish different finger vein images from limited data. Additionally, [35] uses bias filed correction and spatial attention to optimize the CNN-based FVR task. The module of [38] had better rotation invariance than normal CNN by using the capsule network. Ordinary CNNs face challenges in effectively learning spatial location relationships within images. In contrast, capsule networks encode both spatial information and the probability of an object's presence as capsule vectors. The magnitude of the vector represents the probability of the feature's presence, and the direction of the vector represents the pose information of the feature. The utilization of capsule networks in FVR is able to learn effectively the positional relationships between various vein lines in finger vein images. [40] proposes a novel approach based on GAN. This method learns the joint distribution of finger vein images and pattern maps, which enhance the capacity for feature representation. [49] employs the triplet loss with a hard triplet online mining approach to explore the similarity between different fingers of a person. The objective of the triplet loss function is to facilitate effective feature learning by minimizing the distance between samples of the same class in the embedding space, while simultaneously maximizing the distance between samples of different classes.

### B. *Feature Extraction*

Feature extraction stands out as one of the critical steps in applying DL to FVR. Moreover, it represents a fundamental departure point where DL diverges significantly from traditional machine learning methods. FVR methods based on manual feature extraction necessitate dependence on expensive manual template design. In contrast, DL excels by automatically extracting features from finger vein images in a data-driven manner. Several studies concentrate on enhancing the model's methodology for vein feature extraction, particularly in the context of DL algorithms [54]–[60]. Some research [54], [56], [58] adopt the analogous workflow, which usually uses CNN structure to extract features, and then adopts a traditional machine learning algorithm to analyze these features. Additionally, some studies use novel approaches to extract features, such as [57] uses the *Convolutional Auto-Encoder* (CAE) to learn the feature codes from finger vein images. CAE is a network that employs a backpropagation algorithm to minimize the discrepancy between its inputs and outputs. The core algorithm of CAE involves compressing the inputs into latent spatial representations. [59] proposes a capsule neural network-based region of interest extraction approach for finger veins, which can represent the relationship between the part and the whole image. [55] designs a lightweight two-channel network that has only three convolution layers to extract image features with an acceptable computation cost, and then a support vector machine is adopted to perform the verification task. Networks with substantial parameter sizes can indeed attain superior performance in FVR. However, the drawback is that they often lead to prolonged inference times, making them less practical for deployment in real-world applications. Lightweight CNNs compress the network size while ensuring satisfactory performance, enhancing inference speed, and facilitating easier deployment of mobile terminals. [60] proposes a deep fusion of electrocardiogram and finger vein image data-based multi-modal biometric authentication system. This method reaches a very high recognition accuracy.

### C. Image Enhancement

Different finger vein image collection devices and user habits often lead to noisy image data in real scenarios [54], which seriously influences the performance of the DL model. To obtain high-quality images sometimes, the original finger vein images must be enhanced. Image enhancement of finger vein images involves the removal of unwanted impurities from the entire image, thereby emphasizing essential vein features more prominently. The effect of image enhancement is shown schematically in Fig.

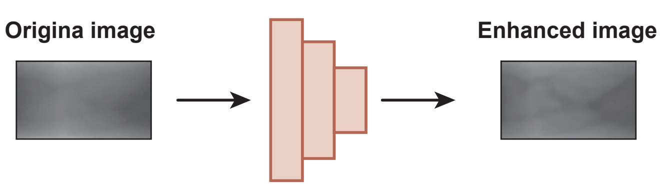


Fig. 7. The flow of image enhancement in FVR. The original finger vein image undergoes enhancement to accentuate the visibility of vein lines.

[61]–[67] introduce the application of DL technology in finger vein image enhancement. Among these papers, GAN has a wide range of applications. For instance, GAN is used to recover the missed vein patterns that are generated in the image capture process owing to various factors in [63]. To recover the severely damaged finger vein images, [64] proposes a modified GAN based on neighbors-based binary patterns texture loss. [65] proposes a modified DeblurGAN to increase identification performance by restoring motion-blurred finger vein images to solve the problem of motion blur in FVR. In addition to GANs, some other modules are applied in image restoration for FVR. [61] proposes a finger vein image denoising method based on the deep CNN, the deconvolution sub-net recovers the original image based on the features, and the modified linear unit extract finger vein texture details. [62] uses a CAE to restore the venous networks of the finger vein images, thereby effectively extracting features. [66] proposes a new network architecture based on the pulse-coupled neural network to improved the finger vein image quality and increase the practicality of FVR.

### D. Image Segmentation

Finger vein image segmentation is an important stage in FVR technology. The quality of segmentation has a direct impact on feature extraction and recognition. The effect of image segmentation is schematically shown in Fig. [68] proposes a finger vein segmentation algorithm based on LadderNet, it can obtain abundant semantic information from vein images by concatenating the feature channels of the expanding path and contracting path in the network. Additionally, the parameters of normal finger vein segmentation networks are overabundant, which makes they are challenging to use in mobile terminals. To overcome this problem, [69] proposes a lightweight real-time segmentation network in FVR based on the embedded terminal. The performance of this network is not inferior to more complex networks and satisfies the needs of embedded mobile terminals.

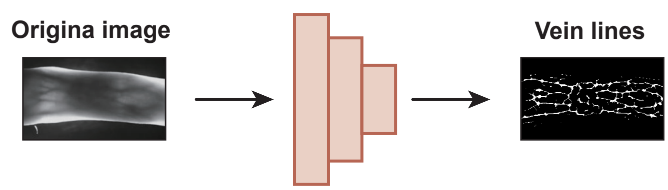


Fig. 8. The flow of image enhancement in FVR. The image segmentation technique directly isolates the vein line pattern from the captured finger vein images.

### E. Encryption

Since biometric information is irreplaceable and unique for everyone, once the original biometric information is stolen, it may cause irreversible loss. To protect the privacy of users more effectively, encryption methods are used in FVR. This technology masks the biometric information in the image by encrypting the original image. Even if the finger vein image is stolen, criminals cannot obtain valid information from it. However, the biggest challenge of encryption is how to keep the performance of the recognition system while protecting biometric data. The overall of the encrypted FVR is shown in Fig. 9.

To address this issue, [70] presented a novel FVR algorithm by using a secure biometric template scheme based on DL

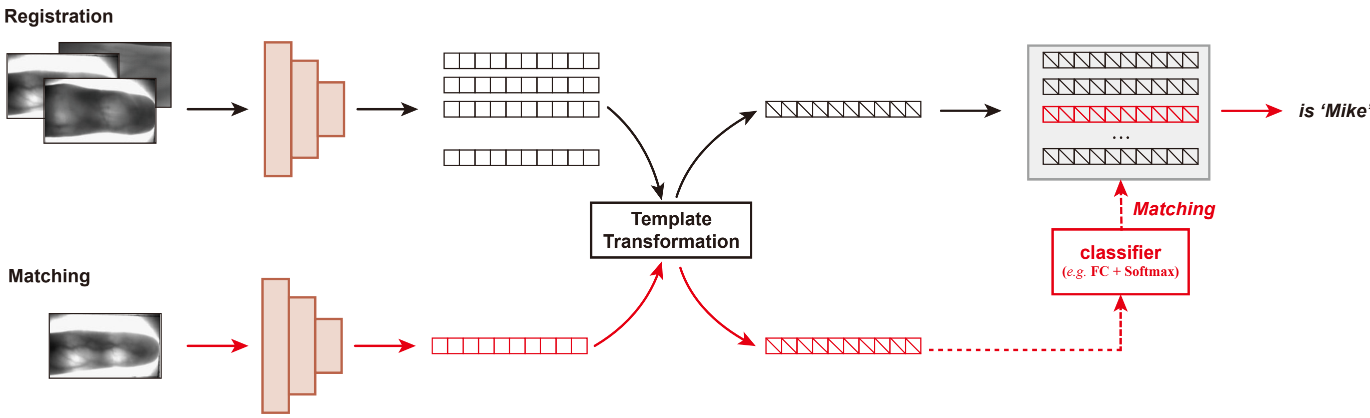


Fig. 9. The flow of encryption in FVR. In contrast to typical classification tasks, following the extraction of feature vectors by the deep neural network, these vectors require additional processing using specialized encryption algorithms.

and random projections. This algorithm randomly generates a secured template for the original biometric message by random projections. In [31], a supervised hashing algorithm is applied to finger vein templates stored in the database. This implementation not only enhances the matching rate but also incorporates encryption measures, thereby fortifying the security of the stored templates. [71] proposes a deep CAE structure to reduce the dimension of the feature space and introduces the Biohashing algorithm to generate protected templates based on the features that were extracted at the CAE.

## VI. Challenge and potential direction

Compared with traditional biometric technology, FVR has unparalleled advantages but it still faces some challenges, especially during image capture [64], [72], [45], which contains uneven illumination, light scattering in finger tissue, inappropriate ambient temperature, image displacement, presentation attacks, shading, etc. All of the aforementioned challenges have varying degrees of impact on the performance of FVR. To overcome these challenges, [26], [29], [45], [56], [63], [64], [66], [67] try to propose solutions from different aspects. However, these technical difficulties have not been completely solved, and they will remain the focus of FVR in the future.

Besides, FVR also has some potential directions. For instance, FVR generally needs to be implemented on lightweight portable mobile terminals. However, most of the deep neural networks are not suitable for this kind of device. Therefore, DL-based FVR faces some difficulties in practice. Knowledge distillation [73] can be utilized to overcome this challenge. Knowledge distillation can greatly condense complicated networks by teaching a small student model from a large model. This technology can greatly improve the application ability of FVR in reality.

Furthermore, one of the conveniences of FVR is that even if one finger is in an accident, the other fingers can still be used for identification. But registering ten fingers simultaneously in an identification system is a hassle for users. Therefore, it is necessary to explore whether the finger veins of the ten fingers of the same individual are similar in future FVR research work. If there is some connections between different finger veins of the same person and they can be identified by FVR systems, it will take the convenience of FVR systems to a new level. Although [41], [49] focus on this problem, they still have some limitations. [41] considers the connection between the veins of different fingers of the same person is too weak to perform the recognition. [49] utilizes the triplet loss with hard triplet online mining for FVR. This strategy successfully verified that symmetric fingers (the same sort of finger but from opposite hands in the same individual) have enough similarities to be recognized. The similarities of other asymmetric fingers is also proved in [49], but the proposed recognition system is still unable to effectively identify these asymmetric finger veins. Therefore, related work can still be further explored in the future.

## VII. Conclusion and future work

In this brief survey, we summarize the DL technology for FVR. First, we introduce the base information of widely used public datasets and some popular CNN structures. After that, we summarize 46 related research literature of FVR based on DL from 2017 to 2021, and classify them according to the tasks of neural networks, which includes classification, feature extraction, image enhancement, image segmentation, encryption. Finally, we discuss the current challenges and development directions of FVR. From this review, it can be found that the tasks of neural networks are diverse in FVR, and compared to other biometric recognition systems, FVR has unique advantages. In the future, we will investigate more literature and DL techniques in FVR to propose a comprehensive review.

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TABLE III

THE SUMMARY TABLE OF SURVEYED PAPERS. FOR SHORT, TASK, DATASET, REFERENCE, NETWORK, PERFORMANCE, CLASSIFICATION, FEATURE EXTRACTION, IMAGE ENHANCEMENT, IMAGE SEGMENTATION, ENCRYPTION, SDUMLA-HMT, HKPU, MMCBNU-6000, FV-USM, UTFVP, THU-FVFDT2, SCUT, IDIAP, PLUSVEIN-FV3, PRIVATE, VEINECG, ISPR, ACCURACY, EQUAL ERROR RATE, PEAK SIGNAL-TO-NOISE RATIO, STRUCTURAL SIMILARITY, PRESENTATION CLASSIFICATION ERROR RATE, BONA-FIDE PRESENTATION CLASSIFICATION ERROR RATE, AND REFERENCE ARE ABBREVIATED TO T, D, REF, NET, PERF, C*, F*, IE*, S*, E*, SD*, HK*, MM*, US*, UT*, TH*, SC*, ID*, PL*, PR*, VE*, IS*, ACC, EER, PSNR, SSIM, APCER, BPCER, AND REF.

| Task | Ref | Network | Datasets | Performance |
|---|---|---|---|---|
| C | [30] | ResNet-101 | SDUMLA-HMT<br>HKPU | EER = 3.3653%<br>EER = 1.0799% |
| C | [38] | Capsule Network | SDUMLA-HMT<br>HKPU | ACC = 100%<br>ACC = 88% |
| C | [31] | Light CNN | SDUMLA-HMT | EER = 0.1497% |
| C | [37] | RefineNet | SDUMLA-HMT<br>UTFVP | EER = 2.46%<br>EER = 0.64% |
| C | [40] | GAN | SDUMLA-HMT<br>THU-FVFDT2 | EER = 0.94%<br>EER = 1.12% |
| C | [33] | GNN | SDUMLA-HMT<br>MMCBNU-6000 | ACC = 99.98%<br>ACC = 99.98% |
| C | [41] | DenseNet-201 | SDUMLA-HMT | EER = 0.54% |
| C | [42] | DenseNet-161 | SDUMLA-HMT<br>HKPU | EER = 2.35%<br>EER = 0.33% |
| C | [43] | DenseNet-161 | SDUMLA-HMT<br>HKPU | EER = 1.65%<br>EER = 0.05% |
| C | [35] | ResNet-50 | SDUMLA-HMT<br>THU-FVFDT2 | ACC = 99.53%<br>ACC = 98.64% |
| C | [47] | ResNet | SDUMLA-HMT<br>HKPU<br>MMCBNU-6000<br>FV-USM | EER = 2.137%<br>EER = 0.277%<br>EER = 0.090%<br>EER = 0.091% |
| C | [48] | JAFVNet | SDUMLA-HMT<br>MMCBNU-6000<br>FV-USM<br>SCUT | EER = 1.18%<br>EER = 0.23%<br>EER = 0.49%<br>EER = 0.86% |
| C | [49] | SqueezeNet | SDUMLA-HMT<br>HKPU<br>UTFVP<br>PLUSVEIN-FV3 | EER = 2.7%<br>EER = 3.7%<br>EER = 2.5%<br>EER = 2.4% |
| C | [52] | GoogLeNet | SDUMLA-HMT | ACC = 92.22% |
| C | [51] | Two-branch CNN | SDUMLA-HMT<br>MMCBNU-6000 | EER = 0.94%<br>EER = 0.17% |
| C | [28] | Self-designed CNN | HKPU<br>FV-USM | EER = 2.70%<br>EER = 1.42% |
| C | [39] | LSTM | HKPU | EER = 0.95% |
| C | [53] | Self-designed CNN | HKPU | ACC = 91.19% |
| C | [46] | Self-designed CNN | MMCBNU-6000<br>FV-USM | EER = 0.503%<br>EER = 1.070% |
| C | [32] | DBN | FV-USM<br>Private | ACC = 97.4%<br>ACC = 97.8% |
| C | [44] | Self-designed CNN | FV-USM | ACC = 95.1% |
| C | [36] | NASNet | FV-USM | ACC = 98.89% |
| C | [26] | FPNet | SCUT<br>IDIAP | EER = 0.00%<br>EER = 0.25% |

TABLE 2

CONTINUED: THE SUMMARY TABLE OF SURVEYED PAPERS.

| Task | Ref | Network | Datasets | Performance |
|---|---|---|---|---|
| C | [45] | FVRASNet | SCUT<br>IDIAP | EER = 2.02%<br>EER = 4.26% |
| C | [50] | SqueezeNet | PLUSVEIN-FV3 | EER = 3.00% |
| C | [29] | AlexNet | Ptivate | APCER = 0.00% |
| C | [34] | LSTM | Private | ACC = 99.13% |
| F | [55] | Two-branch CNN | SDUMLA-HMT<br>MMCBNU-6000 | EER = 0.47%<br>EER = 0.10% |
| F | [58] | PCANet | SDUMLA-HMT<br>FV-USM<br>THU-FVFDT2 | ACC = 98.19%<br>ACC = 99.49%<br>ACC = 100.00% |
| F | [59] | Capsule Network | SDUMLA-HMT<br>FV-USM | ACC = 97.5%<br>ACC = 99.7% |
| F | [54] | Self-designed CNN | HKPU | ACC = 87.08% |
| F | [57] | CAE | FV-USM | EER = 0.16% |
| F | [32] | VGG-16 | IDIAP<br>ISPR | EER = 0.0000%<br>EER = 0.0311% |
| F | [60] | Self-designed CNN | VeinECG | EER = 0.12% |
| IE | [65] | GAN | SDUMLA-HMT<br>HKPU | EER = 5.270%<br>EER = 4.536% |
| IE | [67] | GAN | SDUMLA-HMT | EER = 0.87% |
| IE | [61] | Self-designed CNN | HKPU | PSNR 29.638 |
| IE | [63] | GAN | MMCBNU-6000<br>USPS | EER = 5.66%<br>EER = 2.37% |
| IE | [62] | CAE | Private | EER = 0.16% |
| IE | [64] | GAN | Private | PSNR = 30.42% |
| S | [68] | LadderNet | SDUMLA-HMT<br>MMCBNU-6000 | ACC = 92.44%<br>ACC = 93.93% |
| S | [69] | DintyNet | SDUMLA-HMT<br>MMCBNU-6000 | ACC = 91.93%<br>ACC = 90.90% |
| E | [71] | CAE | UTFVP | EER = 0.7% |
| E | [70] | CAE | Private | FAR = 1.5% |


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