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A Survey of Finger-vein Recognition using Deep Learning: Concepts, Challenges, and Opportunities

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Abstract

In recent years, convolutional neural networks have been frequently used for finger-vein biometrics. Various methodologies have been proposed to improve the recognition performance on available datasets. Deep learning-based approaches have a promising performance, and they have been an effective solution for feature learning. Nevertheless, some problems in the literature need to be solved, such as the lack of test protocol and comparability. In this study, a review of deep learning-based studies on finger-vein biometrics has been presented in two categories: identification and verification. This review contains 68 publications from reputable databases published between 2016 and 2025. The contents of the articles have been discussed in detail. The pros and cons of the proposed algorithms have been stated critically. The arising confusion due to the usage of the term recognition for identification and verification has been removed. The role of the experimental protocol and metrics in performance results on reviewed papers has been stated. The need for comparing the results against the existing results in the literature on the same finger-vein datasets using totally the same test protocol has been highlighted. Lastly, foreseen opportunities have been listed to draw the researcher's attention.

Keywords: Authentication, Finger-vein, Identification, Recognition, Verification.

1. INTRODUCTION

Biometric systems are intended to recognize the innate physical characteristics and the embraced behaviors of individuals. Fingerprint, face, signature, and finger-vein are some of the biometrics traits that are widely in use in today's world. Like other biometric traits, finger-vein offers a variety of expected advantages such as being unique, universal, collectible, permanent, and user-friendly [1]. Thus, it has been regarded as a reliable and preferable trait for biometric applications. However, vein images have low contrast due to the scattering effect of near-infrared light, and finger-vein biometric systems suffer from this characteristic [2]. Since vein images are not so clear and there is not any accurate mathematical model to detect finger-vein patterns, various conventional feature extraction methods have been proposed in the literature [3]. As known, convolutional neural networks (CNNs) provide more effective generalization than conventional feature extraction methods [4]. Therefore, with the advances in deep learning, CNNs have started to be widely used for finger-vein biometrics. Since CNNs provide feature learning rather than feature extraction, deep learning-based studies have started to replace conventional feature extraction-based studies [5].

The finger-vein studies in the literature can be examined in roughly several main categories. Therefore, these studies can be searched using some keywords: Image enhancement and preprocessing oriented, data augmentation and synthetic data generation oriented, spoofing attack oriented, imaging platform design oriented, region of interest extraction oriented, multimodal biometrics oriented, cross finger and cross-database oriented, the effect of hyperparameter oriented, identification oriented and verification oriented studies. Each study in these categories aims either to contribute or improve the best obtained performance rates for identification and verification in the literature on used datasets. However, some of the published studies in the literature do not use a common test protocol with the previous studies and just aim to obtain the best performance rates on certain publicly available datasets. Without sharing the crucial details about hyperparameter selections and experimental protocols, these studies report the obtained results and compare findings against the ones published in the literature on the same database, although scientifically unacceptable [6]. Therefore, rather than focusing on only the reported quantitative performance results, this study highlights the methodology and original contributions of manuscripts published in identification and verification categories.

1.1. Related Works

Deep learning provides effective end-to-end solutions in recognition systems [7]. The importance of review articles is rising in biometrics gradually since the number of publications increased with the help of deep learning-based methodologies. However, there are few review articles on finger-vein using deep learning in the literature because review articles mostly focus on studies using conventional methods.

In 2018, [8] published one of these review papers. This paper provides a thorough analysis of finger-vein biometrics. With its comprehensive content, it introduces publicly available datasets and characteristics of finger-vein biometrics. It lists preprocessing algorithms, ROI extraction methods, and image enhancement methods. This review paper mainly focuses on conventional feature extraction methods such as vein-based methods, local binary-based methods, dimensionality-based, and minutiae-based methods. Additionally, it provides a brief review of various deep learning-based studies.

In 2018, [9] provided a systematic review of finger-vein biometric verification systems. They stated challenges and motivations collected from various studies on finger-vein verification. In this review, they provided an extensive literature review from hand-crafted methods to deep learning-based methods. They analyzed the distribution of published articles in certain categories. They presented the details of publicly available datasets, and they provided the advantages of using finger-vein as a biometric trait in terms of security and accuracy. They listed faced challenges related to finger-vein such as low image quality and template protection needs. They also provided some recommendations to developers, researchers, and companies.

In 2021, [10] released a review on physiological biometric trait systems. They presented recent advances in biometrics based on some physiological biometric traits such as finger-vein, palm vein, fingerprint, and iris. In this study, they summarized studies that use deep learning-based or conventional techniques for each biometric modality. By revisiting and analyzing biometric steps of recognition, they tried to focus on challenges and future trends for biometric systems.

In 2021, [5] published a comprehensive review of feature extraction methods for finger-vein. They listed publicly available datasets and provided the download links of these datasets. They examined the advantages and disadvantages of feature extraction algorithms. They focused on mainly feature extraction methods. They reviewed publications that use mostly conventional methods, but they still listed some feature learning methodologies with CNN. They presented the pros and cons of proposed architectures in terms of performance evaluation criteria. Moreover, they shared the distribution of publications related to finger-vein.

In 2022, [11] released a detailed analysis of finger-vein recognition. With a deep content, they introduced the characteristics of finger-vein biometrics. They listed the usage of artificial neural networks for finger-vein biometrics via 149 related papers, where these papers are related to artificial neural networks and deep neural networks. These papers were grouped by several topics such as verification, image enhancement, and segmentation. Lastly, they discussed the challenges and potential directions of finger-vein biometrics for the future.

In 2022, [12] published a comprehensive analysis of finger-vein biometrics. With detailed content, they introduced the characteristics of finger-vein biometrics. They listed conventional feature extraction methods for finger-vein. They roughly compiled deep learning-based methods. They mainly intended to provide an overview of finger-vein imaging, vein image preprocessing, feature learning, and feature matching.

In 2022, [13] published a review article that focuses on manuscripts related to finger-vein authentication, presentation attack detection, and multi-modal biometric finger-vein authentication. In this review, paper selection criteria and selection processes were illustrated. Performance analysis of selected papers was presented, and promising research articles were indicated. They subdivided deep learning-based finger-vein authentication into preprocessing, feature extraction, and recognition categories. They listed deep learning-based feature extraction, recognition, and quality assessment approaches. Besides, they shared the state-of-the-art performances of the existing deep learning-based methods.

Lastly, [14] published a comprehensive analysis of finger-vein biometrics in 2023. With detailed content, they introduced the characteristics of finger-vein biometrics. They focused on details of image acquisition, image enhancement, and feature extraction for finger-vein. They discussed the advances and shortcomings of the literature on finger-vein image enhancement and feature extraction for identification by compiling conventional method-based papers.

1.2. Contributions

Our contributions can be listed as follows: There is no need to go through topics that have previously been covered in review papers on finger-vein biometrics, such as hand-crafted feature extraction methods and image acquisition techniques. Thus, this study focuses on only deep learning-based recognition studies in finger-vein biometrics. Firstly, a detailed keyword-guided search was conducted on the publications. These publications are journal papers and conference papers indexed by Google Scholar. The keywords used were related to "finger-vein", "recognition", "verification", "identification", "authentication", and "deep learning". In this study, distinguished publications available in the literature about deep learning-based finger-vein biometrics have been listed and reviewed. The inevitable ambiguity arising from the common use of the term recognition for identification and verification has been removed by referring to ISO standards that locate these two terms under the umbrella of 'biometric recognition'. The necessity of the common experimental protocol usage to compare obtained performance results against the results on reviewed papers has been stated and highlighted. Most of the publications do not have any mechanism to promote interpretability and explainability in their model. Thus, there is an urgent need for Explainable Artificial Intelligence (XAI) methods in finger-vein systems as future work. This study proposes to use XAI for finger-vein biometrics for the first time. Lastly, existing opportunities other than XAI usage in finger-vein biometrics have been listed for future works in this area for researchers.

The rest of the paper is organized as follows: Section 2 introduces some of the popular publicly available finger-vein datasets. Section 3 presents the definitions of performance metrics for identification and verification in detail. Section 3 presents the definitions, protocols, and performance metrics for identification and verification in detail. Moreover, this section explains open-set and closed-set scenarios with computational examples to encourage reproducible works in the literature. Section 4 presents a comprehensive analysis of the deep learning-based finger-vein recognition literature in 2 categories, namely identification and verification. Section 5 lists flaws of finger-vein recognition analyses in the literature. Section 6 presents the existing challenges and opportunities in finger-vein biometrics to help researchers. Lastly, Section 7 discusses the contributions of this study to the literature and concludes the conducted study with an outlook on future works.

2. DATASETS

There are a few publicly available finger-vein datasets in the literature commonly used for biometric recognition. With a comprehensive search and analysis, the details about these datasets are given in this section. Moreover, information about the suitability of the datasets for identification or verification applications is also given. Although feature learning based on deep learning is considered more robust compared to conventional feature extraction methods while building an efficient recognition system, the limited image amount of publicly available finger-vein datasets is an indisputable challenge since those systems are mostly data-driven [13]. The main disadvantage of deep learning-based approaches is the lack of huge, and publicly available datasets [5]. This handicap is managed by using data augmentation methods and transfer learning strategies.

SDUMLA is the first publicly available finger-vein dataset, collecting data from multiple fingers of each subject [15]. It was collected from 106 different individuals in total. Vein images were captured from individuals' (his/her) index fingers, ring fingers, and middle fingers of both hands. Images were taken from each finger 6 times. The images in the dataset contain information through 3 channels. In total, the dataset contains 3816 finger-vein images [16]. It could be used in identification and verification applications due to the diversity of the dataset and the fact that the dataset contains sufficient samples for each finger.

HKPU dataset was created by collecting finger-vein images from 156 volunteers for 11 months. 93% of the subjects of the dataset were individuals under the age of 30. Data was collected in 2 sessions. Samples were taken from the index finger and middle finger of the left hand of each subject. For data collection, 105 of 156 volunteers attended both sessions. In total, 6 finger-vein images were obtained from each finger in each session. Thus, 3132 finger-vein images were collected for the dataset [17]. Considering the diversity of the dataset and the number of samples, it seems to be suitable for identification and verification applications.

UTFVP dataset was collected from a total of 60 volunteers in an academic year. 82% of the subjects of the dataset were between the ages of 19-30. Images were taken from the ring, index, and middle fingers of both hands of the subjects in two different sessions. In total, 4 finger-vein images were obtained from each finger of each subject. Thus, the dataset consists of 1440 images in total [18]. These images have high quality [15]. The dataset has a structure suitable for open-set and closed-set protocols. Thus, it can be used in both identification and verification applications.

Images of the MMCBNU dataset were collected almost in a month from 100 subjects consisting of university students and professors who are from 20 different countries. 10 samples were taken from the index, ring, and middle fingers of both hands of each subject [19]. The dataset consists of 6000 images in total. Due to the diversity of the dataset and the abundance of finger-vein data, it seems to be suitable for identification and verification applications.

FVUSM dataset was collected from the index and middle fingers of both hands of 123 subjects in two different sessions, where 83 subjects were male, and 40 subjects were female [20]. Six samples were collected in each session. Thus, 2952 images were collected in total in each session. As the authors stated, images of the first session were aimed to be used for registration, while images of the second session were planned to be used for test. Due to the diversity of the dataset and its sample amount, it is suitable for both identification and verification studies. Details about these 5 most commonly used datasets are given in Table 1.

Table 1. The overview of popular publicly available finger-vein datasets

Dataset	Total Image	Total Subjects	Image number per finger	Image Format	Image Resolution
SDUMLA [16]	3816	106	6	.bmp	320x240
HKPU [17]	6264	156	6	.bmp	513x256
UTFVP [18]	1440	60	4	.png	672x380
MMMCBNU [19]	6000	100	6	.bmp	640x480
FVUSM [20]	5904	123	6	.jpg	640x480

3. CONCEPTS

In biometrics, systems may operate in two recognition modes, depending on the application context: either identification mode or verification mode [7]. Although these modes are similar to each other, they differ depending on their place of use and the intended security level. Moreover, the generic term recognition is used commonly for both due to not wishing to make a distinction between verification and identification [1]. In this section, the details of these two recognition modes will be examined to eliminate the inevitable ambiguity due to the joint usage of recognition terms for identification and verification in finger-vein biometrics literature. Furthermore, the protocols for verifying and identifying finger-vein datasets as well as performance evaluation metrics employed in the literature will be described.

3.1. Identification

A biometric system operates in either identification mode or verification mode, depending on the context of the performed application [21]. The identification mode compares the image of the enrolled individual with the images stored in the database to find his identity. The recognition process is accomplished by finding a match after searching the whole database. Using a one-to-many (1:N) comparison, the identification mode establishes the enrolled individual's identity. In identification mode, the system searches for the closest match among the other data stored in the system. Therefore, the finger-vein data of someone who is not registered in the system is assigned to the closest compatible finger-vein data [22]. Thus, some decision errors can be made in the recognition process. The formation and operation of the identification mode on finger-vein data is given in Figure 1.

In this figure, the identification process consists of two stages, which are the Enrollment Phase and the Query Phase. Finger-vein data are taken from the developed imaging platform and transmitted to the first step for quality control. After the quality assessment of the created dataset, the first part of the enrollment process is completed. In the second part, the data is preprocessed to extract biometric templates for storage. Thus, the enrollment process does not inherently involve learning. Since the identification structure can be evaluated as a multi-class classification problem, the dataset is split according to the applied protocol. Then, the used or proposed deep learning model is trained with this data. The deep learning model is ready to be used for the identification system and its performance is tested with the remaining finger-vein data allocated for test. In the query or test phase, the prediction result is obtained after 1:N matching by following these sequential steps: taking a query finger-vein image, performing quality control, applying preprocessing operations, and decision making using the developed model. The identification makes predictions based on the trained data belonging to individuals.

3.2. Verification

The verification mode matches the image of the enrolled individual with a template of his name to adopt if the requested identity by the individual is true or false, using a one-to-one (1:1) comparison [14]. The trained models extract the attributes representing the identity of each subject and record them in the system. Thus, each individual registered in the system is kept in the system with the vein's attributes and his/her preliminary information such as identification number (ID) and username in the enrollment phase. When a new user wants to log in to the system, they first enter the required preliminary information like ID or username. Then, they provide their finger-vein data with a finger-vein imaging tool. The system uses this preliminary information to retrieve the biometric data from the database of the registered user who is trying to log in. Finally, the system compares the new finger-vein data with the retrieved data. The diagram scheme explaining the working principle of verification systems is given in Figure 2.

In this figure, the verification process consists of three stages, which are the Enrollment Phase and the Query Phase. Firstly, the system takes images from a finger-vein imaging device. Then, it is checked whether the resulting finger-vein image is suitable for enrollment. Finger-vein images are preprocessed to be used by deep learning models or traditional methods. With the open-set protocol structure used for verification systems, finger-vein data are used to train the deep learning model. With the trained model, features of finger-vein classes are extracted and recorded in the database. In the verification section, the qualified finger-vein data coming from the imaging system is pre-processed. Feature extraction is accomplished by using the deep learning model. During the login operation, the preliminary information requested from the new user and his/her finger-vein attributes are compared by the system, and the distance to the new attribute data is calculated. Reliability is ensured by acceptance or rejection according to the threshold value given to the system, where the threshold assigns the security level of the application.

3.3. Protocols

Biometric studies use different finger-vein datasets in the literature. Depending on the problem definition, different protocols are used to determine training and testing data on these datasets. There are two protocols used in the literature: closed-set protocol and open-set protocol. Due to the lack of huge, and publicly available finger-vein datasets, each finger sometimes can be considered a different class, as if it represents a different individual rather than a subject by these protocols.

The closed-set protocol specifies how to split the dataset into training and testing datasets. In this protocol, no other classes come to the system other than the classes in the training dataset. Therefore, it is assumed that the identities of all classes are known for the designed system and the system is trained accordingly during the training phase. Therefore, it is expected that there will be no data other than the training class in the test dataset [23]. Thus, the closed-set protocol is widely needed in closed environments like factories and enterprises [24]. Therefore, the closed-set protocol can predict the identity of only classes that were used in the training phase.

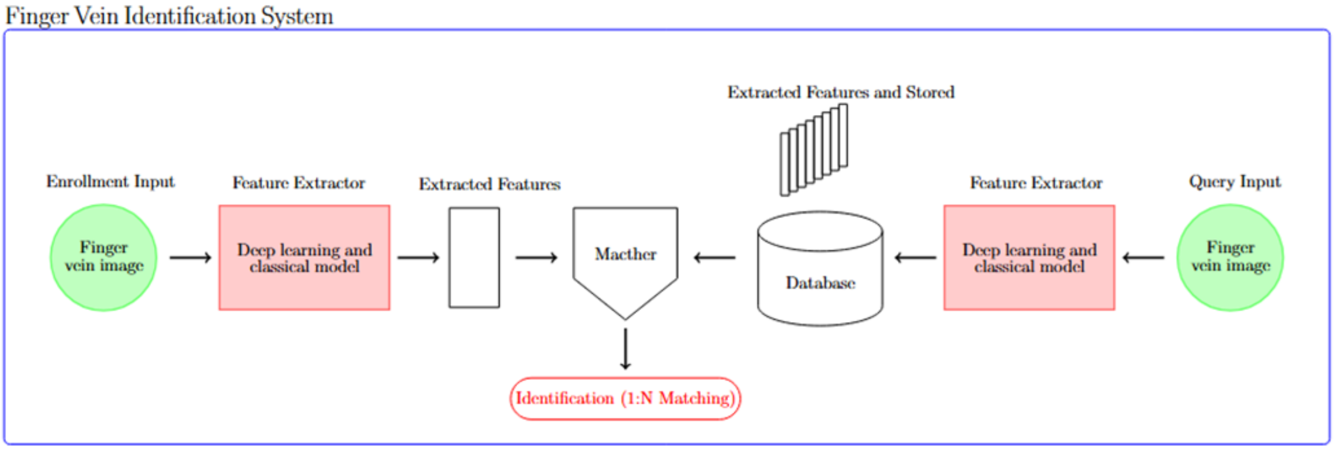

Figure 1. Finger-vein identification system summary

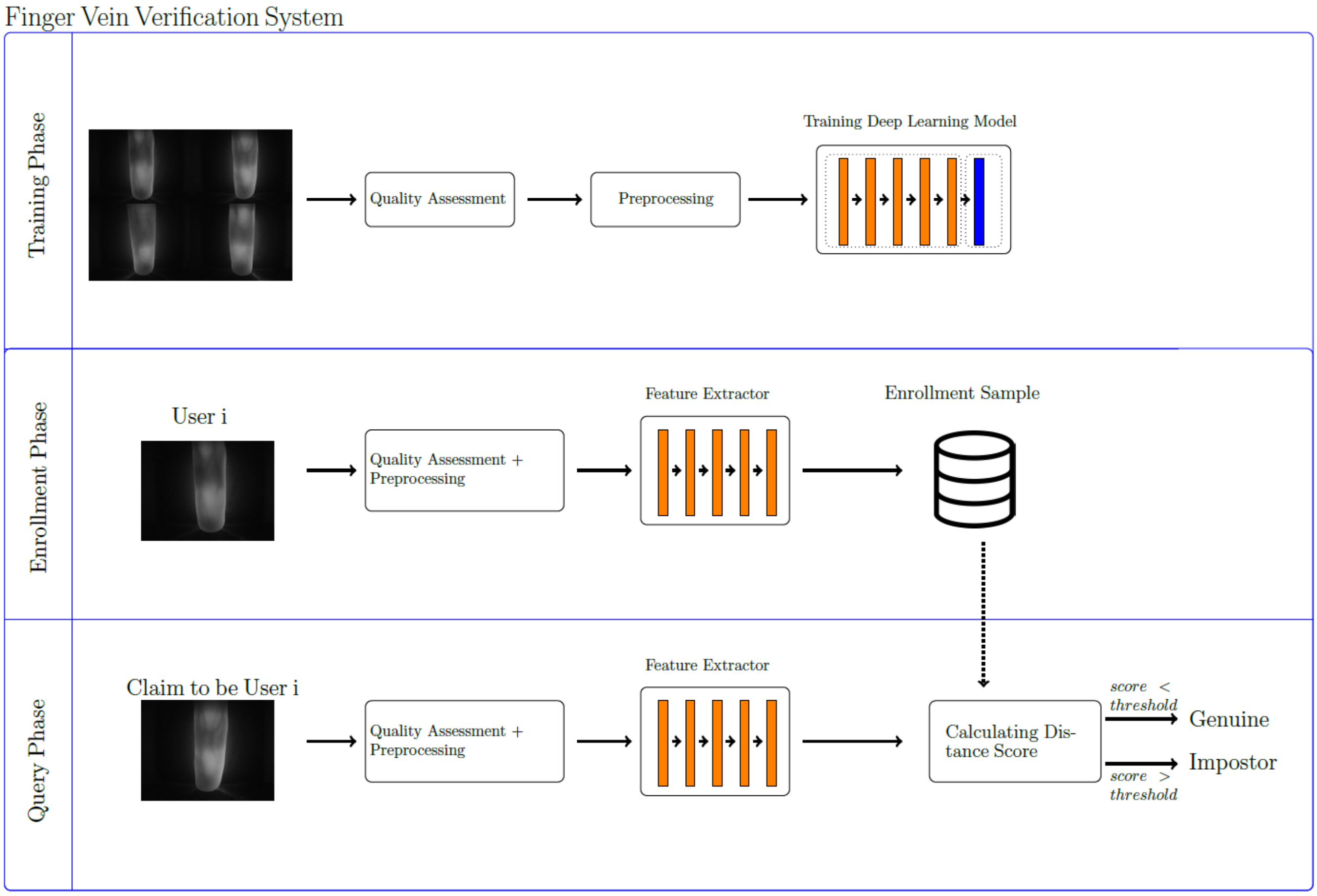

Figure 2. Finger-vein verification system summary

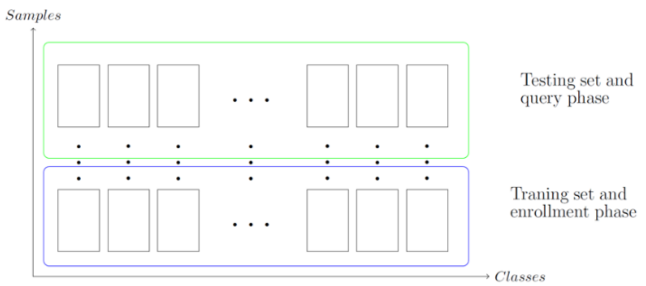

Figure 3. Closed-set Protocol summary [23]

The structure of the closed-set protocol is shown in Figure 3. For any finger-vein dataset, data belonging to each class should be reserved for being used in the training and testing phases for the closed-set protocol, since this protocol requires knowing whole class knowledge at the training time [25]. In the literature, various train and test data split rates are used for the sake of obtaining the best recognition performance. Thus, details about split rates and used samples among the whole dataset for training and testing phases should be reported in detail for reproducibility and fair comparisons.

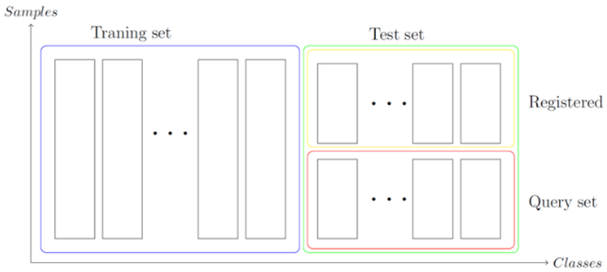

Figure 4. Open-set Protocol summary [65].

The open-set protocol is widely used for real-world problems because of poor image quality or the possibility of intrusion attempts [24]. The open-set protocol specifies how to split the dataset into training and testing datasets. In this protocol, it is essential to accept the classes learned during the training phase and to reject classes other than trained ones. Shortly, it is assumed that the identities of all classes are not known for the designed system. The system is trained accordingly during the training phase, and some data other than the trained classes can be encountered in the test dataset for this protocol. With this acceptance, the success of the models in the literature is tested and compared [65].

The structure of the open-set protocol is shown in Figure 4. In the literature, various train and test data split rates are used for the sake of obtaining the best recognition performance. Thus, details about split rates and used samples among the whole dataset for training and testing phases should be reported in detail for reproducibility and fair comparisons. However, the employed protocol's details are often not provided [6]. Thus, it is generally not easy to compare the findings against the results in the literature, also it is even not easy to perform the same tests on the same data using the designated protocol.

3.4. Performance Metrics

To evaluate the performance of any biometric system, it is important to define and use metrics. Thus, users can have a better user experience and judgment about the quality of the system. The performance of biometric systems is measured using different parameters and metrics depending on the operation mode. Depending on various purposes in different domains, biometric systems use identification or verification modes. These modes use closed-set or open-set protocols for the learning and evaluation phases.

In the literature, datasets used in identification studies are divided into training and test datasets, and they are processed generally using a closed-set protocol. For these problems, it is important how accurately the system predicts the classes. Therefore, Accuracy is used as a performance metric, where it can be described as a ratio of correct predictions of the proposed deep learning model to the total number of predictions in the test dataset. The equation for the Accuracy metric is given in Equation 1. In addition, Correct Identification Rate (CIR) and Accuracy are used interchangeably for the performance evaluation of identification studies in the literature.

$$Accuracy = \frac{Number\ of\ True\ Predictions}{Number\ of\ all\ predictions} \tag{1}$$

Likewise, in studies on verification problems, datasets are divided into training and test sets and processed using generally an open-set protocol. The open-set protocol offers a compatible structure with real-world problems. With this structure, the system's responses, as a "YES" or "positive class" and "NO" or "negative class", are examined and the number of acceptances or rejections is used for performance metrics. Therefore, verification can be described as a binary classification problem and is evaluated with metrics that compare the predictions made with the proposed models with the actual values. These metrics are derived from True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). In the literature, model performance evaluations are made based on the Equal Error Rate (EER) value and the Detection Error Tradeoff (DET) curve calculated from these 4 base metrics.

The DET curve shows the effectiveness of the models and the balance between false acceptance rates (FAR) and false rejection rates (FRR). The EER point is determined by the diagonal line drawn on this graph. Thus, the behavior of the system is examined in detail using different threshold values from the distance between vectors of the estimated and real values.

Definitions of False Acceptance Rate (FAR) and False Rejection Rate (FRR) values to calculate EER are given in Equations 2 and Equation 3, respectively. FRR denotes the robustness of the matching algorithm and FAR denotes the strength of the matching algorithm. Depending on the security expectations of the application, FRR and FAR values can be regularized. For instance, the higher value of the FRR makes the application less convenient because more subjects are recognized incorrectly. To calculate these values, the distance or similarity between feature vectors is used. This similarity estimation is done over distance terms such as Euclidean Distance and Cosine Distance. The calculated distance value determines the status of the two vectors according to the determined threshold value. Vector values belonging to the same class are expected to be close and determined as genuine. On the contrary, vector values belonging to the different classes are expected to be far as much as possible and determined as impostors. These measurements are made for all vector pairs.

$$FAR(t) = \frac{Number\ of\ False\ Acceptances}{Number\ of\ Imposter\ Attempts} = \frac{FP}{FP+TN} \tag{2}$$

$$FFR(t) = \frac{Number\ of\ False\ Rejections}{Number\ of\ Geniune\ Attempts} = \frac{FN}{FN+TP} \tag{3}$$

The FAR(t) and FRR(t) values as shown in Equations 2 and Equation 3 are calculated depending on the values of the determined threshold value t. The DET curve is drawn with these pairs obtained according to different threshold values. In these equations, FAR and FRR are represented as a function of t. Figure 5 shows the graph corresponding to the FAR and FRR pair obtained according to different threshold values. The intersection point with the drawn diagonal line indicates the Equal Error Rate (EER) value of the system.

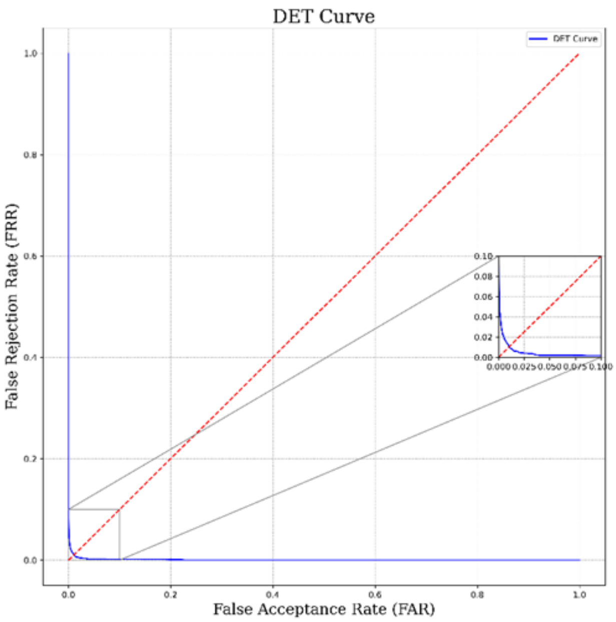

Figure 5. DET Curve and EER point summary

As a result of vector operations performed on the test dataset, distance values between vectors are calculated, and genuine/imposter decisions associated with these distances are made. In this process, a sample from each class in the test dataset is selected as a constant template data and compared with examples from the same class and other classes within the scope of intra-class and inter-class comparisons. These comparisons generate two types of similarity scores: Genuine Match Scores (GMS), derived from intra-class comparisons, and Impostor Match Scores (IMS), obtained from inter-class comparisons. Threshold values are selected at specified sensitivity levels, and genuine/imposter values are calculated for each threshold value. The distributions of genuine and impostor scores are computed based on the comparison results. Threshold values are applied to these distributions to determine decision boundaries, which affect the error rates such as FAR and FRR. The intersection amounts of these distributions contain information about the performance of the verification system. The number of necessary vector distance comparison operations for the calculation of GMS and IMS on a test set is given in Equation 4 and Equation 5, respectively. In these equations, NoGS represents the number of genuine scores and NoIS represents the number of imposter scores. Lastly, NoC in both equations denotes the number of classes, and NoI shows the number of images in a class.

$$NoGS = NoC \times (NoI - 1) \tag{4}$$

$$NoIS = NoC \times (NoC - 1) \times (NoI - 1) \tag{5}$$

4. LITERATURE ANALYSIS

Technological advances in computer graphics processing units (GPUs) have stimulated an increase in publications of deep learning-based finger-vein biometrics. However, most of these publications used different performance indices and did not have a common protocol [5]. Since used datasets are not large and comprehensive enough in terms of the number of subjects and samples, these studies conducted experiments on a different number of datasets, and they reported the best performances. In these studies, different experimental protocols have been used to achieve state-of-the-art results. Moreover, disparate preprocessing and data augmentation methods have been utilized to achieve their best performance in these manuscripts without giving the details about the implementation [6]. However, while the same classification method is used, it is possible to obtain different performance results even using different hyperparameters [26]. Therefore, we focused on mostly the proposed methodologies and content of the reviewed articles, without denying their contributions to the literature by their achieved performance results in terms of benchmarking.

Moreover, we have noticed that there is some confusion about the use of the definitions of recognition, identification, and verification interchangeably. As known, a biometric system essentially can operate in two modes [13]. These modes are namely verification and identification. Identification and verification, in other words, authentication, are the subsets of recognition. However, the generic term recognition can be used not to make a distinction between verification and identification modes [1]. The stated usage of recognition confuses the finger-vein literature. Manuscripts entitled as recognition may or may not suggest experiments related to either identification mode or verification mode. Thus, we searched for and reviewed manuscripts in the literature by considering this nuance.

For identification, we reviewed 34 deep learning-based publications that use accuracy as a performance metric. In addition, Correct Identification Rate (CIR) and Accuracy are used interchangeably with the definitions made in the literature. For verification, we reviewed 29 deep learning-based publications that evaluate obtained performance results using an Equal Error Rate (EER). For identification and verification, we reviewed performance measures from ISO/IEC 19795-1 [27]. Besides these performance measures, we gave also definitions of other measures that are defined to evaluate the performance of biometric systems more accurately for identification and verification.

This section introduces the finger-vein recognition papers chronologically. In the summarized papers, neural networks for verification and identification are used just for classification. Some of these papers utilized shallow neural networks and have experienced the limited capability to extract venous features. Most of these papers suffered from a deficiency of the sufficient number of samples and subjects in publicly available finger-vein datasets. A comprehensive analysis of each paper has been given in detail by using performance metrics with critical discussions.

4.1. Identification

In identification applications, a biometric system searches the stored templates of all the subjects in the system database to recognize a subject's identity. Therefore, the system compares acquired sensor data using one-to-many matching, where CIR is used as an evaluation metric [28].

In 2016, [29] explored the use of convolutional neural networks for finger-vein identification with a theoretical background of CNNs. This novel approach was the first attempt to apply CNN for finger-vein recognition. They proposed a four-layer CNN with fused convolutional-subsampling architecture to achieve high accuracy on a custom dataset. They aimed to reduce preprocessing operations owing to the proposed structure. Furthermore, they experimented with different combinations of normalization and weight initialization methods to find the best average accuracy. They achieved 100% and 99.38% accuracy for different numbers of subjects and samples. They compared the performance of the proposed CNN method with existing solutions in recognition accuracy, and they demonstrated viability for finger-vein identification. Although the proposed approach enabled high performance with minimal preprocessing operations owing robustness of the CNN to noise and misalignment, this study has potential generalizability problem. Since they determined the optimal network architecture, input size and parameter settings empirically, it is hard to adapt these empirical settings to diverse finger-vein datasets without requiring similar optimization settings.

In 2018, [30] proposed a finger-vein image quality assessment method using a lightweight CNN to reduce the errors and costs of manual annotation. They introduced an automatic labeling method to label vein images based on traditional image processing methods. By training 2 networks, they evaluated the quality of the images of MMCBNU and SDUMLA datasets. They explained the process of finding the optimal CNN model by comparing the performance of different architectures. With the proposed lightweight model, they accurately identified low and high-quality images and outperformed existing methods in distinguishing vein characteristics in terms of classification accuracy. Despite notable strength of automation of the labelling process with supporting superior performance, this study encounters critical limitations on test set's quality assessment where around 71-74% accuracy was achieved on the test sets of MMCBNU and SDUMLA datasets.

In 2018, [31] presented a deep learning-based method using a convolutional autoencoder (CAE) with a convolutional neural network. They applied a series of filters for preprocessing and trained a CAE to extract features from finger-vein images. They used extracted features to train a support vector machine classifier, and they explored the application of an autoencoder to efficiently compress data. Using convolutional autoencoders to learn features, they classified finger-vein images using convolutional neural networks. They achieved 99.16% recognition rate on FVUSM dataset. They highlighted the importance of the proposed methodology over other methods. However, the proposed method is computationally expensive and this study has concerns about the potential computational expense for large-scale applications.

In 2018, [32] proposed a methodology that involves training a CNN on a large dataset to learn the discriminative features of the dataset's subjects. They analyzed the effect of training strategies and image enhancement techniques on obtained accuracy on 4 different datasets namely SDUMLA, HKPU, UTFVP, and FVUSM. They also compared the accuracy of the CNN-based identification system with conventional methods such as Maximum Curvature (MC) and Repeated Line Tracking (RLT). They discussed the potential benefits of image enhancement methods in improving identification performance. They investigated the performance of the designed network across datasets, and they demonstrated high accuracy values exceeding 95% in 4 datasets. Using different training strategies, they achieved higher accuracy values compared to state-of-the-art comparison methods using SDUMLA and UTFVP datasets. This study emphasizes the limitations of existing recognition methods regarding low-quality finger-vein images. Moreover, it denotes the effect of finger rotation and translation on recognition performance. However, this study achieves stable and highly accurate performance despite variations in image quality and acquisition conditions across 4 datasets. In this study, the dependency of the network's optimal performance on the availability of a sufficient number of training samples per subject is encountered as a limitation inherent to the CNN approach.

In 2019, [33] presented a study on the use of CNNs for finger-vein-based identification. They designed four different CNN models empirically and compared model performances on SDUMLA, HKPU, FVUSM, and MMCBNU datasets. They provided insights into the behavior of designed models for each dataset based on loss versus number of epochs and accuracy versus number of epochs graphs. Without using any preprocessing operations or data augmentation, they avoided overfitting problems despite the limited number of samples per subject on these datasets using batch normalization and dropout mechanisms on their model architectures. On the HKPU dataset, they achieved 99.61% as the highest accuracy among all these datasets, and they noted that datasets with more classes require more training samples to achieve satisfactory performance. They used closed-set protocol, and they demonstrated the efficiency of CNN designs despite limited data. However, they have a limitation of translating the obtained high-performance results to real-world scenarios using open-set protocol.

In 2019, [34] proposed a new filter generation method designed for finger-vein recognition on FVUSM, SDUMLA, and THU-FV2 datasets. They proposed a novel filter generation in the Principal Component Analysis Network (PCANet) using Canonical Correlation Analysis (CCA). They generated a novel filter to find the unique characteristics of vein images via the combination of the original image and vein line features. In this study, they analyzed the effect of the number of filters and the filter size on the obtained performance. Furthermore, they showed the robustness of the proposed method by variations in the number of training images per class and obtained higher accuracy values compared to PCANet and CCANet on each dataset. Lastly, compared their performances with the ones achieved for SDUMLA and FVUSM datasets in the literature. They demonstrated higher accuracy values by exceeding 97% for 2 datasets. Despite having a notable robustness to variations in the number of training images, the proposed model depends on the successful extraction of vein lines in the preprocessing step.

In 2019, [35] proposed a recognition scheme based on CNN using the curvature of finger-vein images. By using a 2-dimensional Gaussian template, they calculated the curvature of finger-vein images, and they benefitted from the curvature gray images to recognize the identity of input images by training improved CNN. By utilizing curvature gray images as input, they trained an improved convolutional neural network to recognize the identity of the curvature image. They used an improved activation function to increase the network discrimination ability, and they adopted the intermediate value pooling method in the pooling layer. 96.7% recognition rate using closed-set protocol and the experimental results on the used dataset using 5 different scenarios shows that the proposed scheme is effective and slightly better than existing schemes.

In 2019, [36] presented a novel approach for finger-vein extraction and recognition using generative adversarial networks (GANs). With this approach, they improved the feature representation and generalization capacity of CNN. They addressed challenges related to feature extraction from low-contrast finger-vein images. By using joint distribution of vein images and pattern maps, they learned from the whole dataset as combined data rather than direct mapping. They conducted experiments on SDUMLA and THU-FVFDT2 datasets and compared the results of their methodology with several conventional approaches such as Repeated Line Tracking (RLT), Maximum Curvature (MC), and Wide Line Detector (WLD). They achieved robust feature extraction and 98.52% recognition performance. However, they encountered instability associated with training GANs.

In 2019, [37] explored the use of Capsule Network for finger-vein identification and the feature extraction capability of this network. They utilized Capsule Network for automatic feature extraction on UTFVP, MMCBNU, HKPU, and SDUMLA benchmark datasets, and they compared the proposed approach with CNN-based and LeNet-5 models in terms of accuracy. They proposed to use the Capsule Network to capture hierarchical relationships between features in an image. As a preprocessing operation, they used the Repeated Line Tracking algorithm to extract the edges of veins to improve recognition accuracy. They highlighted the challenges posed by limited finger-vein image samples. They achieved an average 95.5% accuracy on the benchmark sub-databases at 32x32 resolutions by utilizing the capability of ensuring translational and rotational invariance of the Capsule Network. With this study, they highlighted the importance of achieving high accuracy despite low image samples and image resolution for practical purposes. Rather than including evaluations against modern CNN backbones trained from scratch, the usage of specific custom models and LeNet-5 can be evaluated as a critical limitation for this study.

In 2020, [38] presented a methodology for finger-vein identification using Merge CNN on FVUSM, SDUMLA, and THUFVDT2 datasets. By combining multiple identical CNNs with different input image qualities, Merge CNN unifies the outputs of these CNNs into a single layer. They evaluated the performance of the proposed system using accuracy on SDUMLA and FVUSM datasets, and their method outperformed other deep networks. They achieved 96.75% for the FVUSM and 99.48% for the SDUMLA datasets using six and five images for training, respectively. They achieved 99.56% for the THU-FVFDT2 dataset. They proved the potential of Merge CNN in the field of biometrics for high-security personal recognition. However, the obtained performance significantly depended on the number of training images.

In 2021, [39] proposed a novel image enhancement method for finger-vein recognition using convolutional neural networks (CNNs). Utilizing Contrast Limited Histogram Equalization (CLAHE), image sharpening, and gamma correction as preprocessing operations, they proposed to use of a convolutional neural network for feature extraction and classification on SDUMLA, FVUSM, UTFVP, and THU-FVFDT datasets. They used transfer learning by modifying 13 convolutional layers of VGG-16. They compared the performance of the proposed light-weight method with two commonly used finger-vein identification methods, RLT and MC, in terms of accuracy. They showed that their proposed approach outperforms both of them. Furthermore, they compared their method with other state-of-the-art methods in the literature and showed that their proposed method achieved better results in terms of accuracy by achieving 99% on the experimented dataset. However, the obtained performance suffered from high variability and uncontrolled acquisition conditions radically.

In 2021, [40] presented a deep neural network using bidirectional feature extraction and transfer learning for recognition on the FVUSM dataset. They captured finger-vein features by constructing a new finger-vein dataset using opposite position information and adjusting the unidirectional dataset parameters. By concatenating the extracted features to form bidirectional features, they trained and classified Support Vector Machines (SVM) for recognition. They reached an accuracy of 99.67% for FVUSM and this is higher than the unidirectional recognition. In this study, they compared the obtained recognition performances of experiments on the 2 finger-vein dataset, and they showed the proposed algorithm with bidirectional feature extraction achieves higher accuracy compared to unidirectional recognition. However, they need to process images in 2 orientations which cause additional computational costs compared to many state-of-the-art methods.

In 2021, [41] proposed a lightweight recognition method based on Multi-Receptive Field Bilinear (MRFB) CNN with a Dimensional Interactive Attention Mechanism (DIAM). They used an attention mechanism to improve the network’s feature extraction capability. They evaluated the proposed model’s performance on FVUSM and SDUMLA datasets using accuracy and time. With the proposed approach, they reduced the number of parameters and calculations with the help of the MRFB CNN structure where depth-wise separable convolution separates the spatial and channel-wise convolutions. They enhanced the correlation between channels and spaces. They used this structure to obtain the second-order features of veins, which better distinguish veins with small differences between classifications. They demonstrated high accuracy values exceeding 99% in 2 datasets. The proposed method seems suitable for practical finger-vein recognition applications since it provides reduction in computational costs.

In 2021, [42] proposed a new algorithm to address the challenges of traditional finger-vein recognition systems, which are related to robustness and generalization. They used a deep neural network to extract feature maps and used these maps to train a classifier. They utilized an advanced Mask-RCNN-based mask extraction algorithm to obtain accurate masks. Furthermore, they used a bidirectional traversing and center diffusion method for ROI extraction. They developed a Deep Generalization Label Finger-Vein (DGLFV) model, and they evaluated the performance of the proposed model on the SDUMLA dataset in terms of accuracy. They achieved an accuracy of 99.08% and their model outperformed existing state-of-the-art methods. The most notable strength of the proposed method can be the highly efficient recognition time since it is appropriate for practical real-world deployment.

In 2021, [43] presented a new loss function for finger-vein verification on FVUSM, SDUMLA, and HKPU datasets. They combined softmax loss and arccosine center loss function to improve the discriminative ability of CNNs. They improved the recognition accuracy and reduced the inference time. They improved the feature learning ability, and their discriminative approach outperformed other state-of-the-art methods on both open-set and closed-set protocols. With the proposed loss function respectively for these datasets, they achieved accuracy performance as utmost 99.99%, 99.56%, and 99.60% for closed set and 99.79%, 99.25%, and 99.44% for open-set protocol. Despite having notable performance results, the proposed method is sensitive to finding the optimal weighting between the arccosine center loss and softmax loss.

In 2022, [44] proposed a methodology to extract biometric features from finger-vein images using CNNs. They utilized preprocessing operations to enhance the edge of finger-vein images, and they used CNN to extract biometric information. They achieved a high accuracy rate of 99.10% and 98.10% for FVUSM and SDUMLA datasets, respectively. They highlighted the importance of the development of contactless recognition systems with stable and accurate performance for finger-vein-based applications. Despite robust performance even with environmental interference, the proposed method suffers from the complexity introduced by the multi-stage preprocessing pipeline for real-world applications.

In 2022, [45] presented a new approach by dividing the finger-vein image into blocks and calculating a matrix after blocking and averaging for recognition. They discussed the need for larger datasets to improve recognition performance, and they utilized publicly available FVUSM and HKPU datasets for performance evaluation and comparison. They validated the robustness of the proposed method to noise and image rotation through experiments. They achieved the correct identification rate greater than 98% for both datasets. The notable strengths of the proposed method could be listed as its computational simplicity and computational efficiency.

In 2022, [46] presented a new approach to finger-vein biometrics using deep learning and generative adversarial networks. Their approach combines a triplet loss function with a classifier GAN to improve the obtained performance on SDUMLA, HKPU, and FVUSM datasets. They aimed to expand the training data and improve the feature extraction ability of the CNN. They introduced a new loss function to prevent collapse during the training process. They also introduced a new distance metric that uses cosine distance instead of Euclidean distance to improve the feature extraction capability. Using open-set and closed-set protocols with different loss functions, they compared the performance of traditional data augmentation methods and the proposed generative adversarial network-based method. They achieved accuracy performance as utmost 99.66%, 99.53%, and 99.29% using closed set protocol and 99.49%, 94.10%, and 98.65% using open-set protocol for FVUSM, SDUMLA, and HKPU, respectively. However, the proposed method faces challenges in the open-set environment since it suffers from the current database sizes radically.

In 2022, [47] presented a novel vision transformer-based capsule network on FVUSM, SDUMLA, MMCBNU, and HKPU datasets. The proposed method combines global and local attention to selectively focus on important finger-vein features. They processed finger-vein images by linearly embedding patches, and they used a transformer encoder to extract vein features. They used a capsule network for further training. With this study, they presented a more effective and more interpretable approach to understanding finger-vein images. By combining capsule network with the vision transformer architecture, they tried to avoid accuracy performance degradation due to low image quality, finger position deviation, and ambient lighting. They achieved utmost 98.68%,94.97%, 97.52%, and 95.61% accuracy for FVUSM, SDUMLA, MMCBNU, and HKPU, respectively. Lastly, a notable strength of the proposed method was the model's ability to perform well even with limited training data.

In 2022, [48] explored the use of synthetic finger-vein images for network training to improve recognition accuracy. By synthesizing virtual finger-vein images and creating a dataset larger than real ones, they aimed to show the use of real and synthetic vein images for pre-training. They generated a virtual dataset with a larger number of subjects and samples. With the help of synthetic data, they reduced the required number of epochs and improved recognition accuracy for MMCBNU dataset. They evaluated the generated dataset's effectiveness in pre-training a VGG16 model for recognition. With this study, they reflected the need for sufficient datasets by improving the recognition efficiency of the pre-trained model from 97.58% to 98.50%. However, this method suffers from data limitations despite using the synthesized data for pre-training.

In 2022, [49] proposed a deep learning tool for finger-vein recognition on the SDUMLA dataset where this tool includes several stages such as image acquisition, preprocessing, feature extraction, and parameter tuning. Firstly, they applied preprocessing operations to detect the region of interest. Then, they extracted features using the Deep

Stacked Auto Encoder (DSAE) classifier. Finally, they used the LSTM-DM tool, which is an LSTM-based decision-making tool, to train the model and evaluate the recognition system. With the proposed model, they aimed to address challenges such as temperature differences and image quality variations. They compared the results of the proposed model with existing models in terms of accuracy, equal error rate (EER), and computation time (CT), and demonstrated their model's superiority in terms of these 3 metrics on SDUMLA dataset. They achieved an effective outcome with 98.95% accuracy.

In 2022, [50] proposed a novel approach using a convolutional neural network with a hybrid pooling mechanism. They used preprocessing operations to discard noise, shadows, and low-contrast before ROI extraction. The proposed network uses a hybrid pooling mechanism that combines max pooling and average pooling to extract discrete features from inter-class image samples. They presented a way of extracting discrete features despite low visual quality, and they evaluated the model on HKPU and FVUSM datasets using good and poor-quality images. They achieved utmost 93.18% accuracy on the HKPU and utmost 97.84% accuracy on the FVUSM. However, the evaluation is limited to a closed-set scenario. Thus, it does not fully reflect the requirements of real-world open-set biometric verification systems.

In 2022, [51] proposed a lightweight model with a Convolutional Block Attention Module (CBAM) for finger-vein recognition. They embedded the module in the original network to infer the attention mapping according to independent dimensions where these two dimensions are channel and spatial order. They multiplied attention mapping into the input feature mapping with adaptive feature refinement. Furthermore, they evaluated model performance on HKPU and FVUSM datasets, and they achieved 100% recognition accuracy on both datasets. They achieved better performance than other methods in terms of accuracy and computational efficiency, owing to enhancing the flow of information in channels and spaces with minimal computation and without performance degradation.

In 2022, [52] presented a shape-driven CNN with a light-weight structure on 3 publicly available datasets. With the proposed approach, they achieved high accuracy with minimum memory consumption and minimum algorithm complexity. They highlighted the advantages of using rectangular filters and the effectiveness of the proposed networks for FVUSM, SDUMLA, and HKPU datasets. They emphasized the weaknesses of current deep learning models for finger-vein biometrics, and they proposed the use of rectangular filters to address these limitations with the proposed networks Rec-FFVN and Semi-PFVN. Notably, with the superior performance of Semi-PFVN, they achieved 94.67%, 96.61%, and 93.05% identification performances for the listed datasets respectively.

In 2023, [53] proposed to use multistage and multiscale residual attention networks (MMRAN) for finger-vein recognition on 5 different finger-vein datasets. Their model combines a fusion of residual attention block (FRAB) and multistage residual attention connection (MRAC) to adapt to the flaws of finger-vein images, such as low-resolution and low-image quality. The proposed model achieved 99.83%, 99.75%, 99.29% recognition accuracy on MMCBNU, FVUSM, and HKPU datasets, respectively. Due to the low image quality and limited number of samples, the proposed approach could not outperform other models but still achieved high accuracy scores with fewer required parameters and faster recognition. Achieving high accuracy with significantly fewer parameters is the key strength of MMRAN.

In 2023, [54] proposed a recognition network FGL-Net that fuses global and local features to improve recognition accuracy under changing displacement of finger poses. They presented a multi-branch network structure to learn finger-vein features of FVUSM finger-vein dataset. They also provided a lightweight version of this network that uses knowledge distillation and feature map loss to improve generalization capacity. Experimental results show that proposed networks outperform conventional methods and existing networks such as VGGNet, InceptionResNet, and MobileNetv3 on FVUSM. They achieved utmost 99.90% accuracy on FVUSM after completing extensive experiments such as ablation analysis using different networks and loss functions. The difficulty of aligning local features during extreme finger movements and the optimal weighting of different features are identified as main concerns for the obtained performance.

In 2023, [55] presented a deep ensemble learning method for finger-vein identification. They combined multiple deep neural networks to improve the accuracy of identification performance on HKPU and FVUSM datasets using a single sample. They proposed to use a combination of CNNs and long short-term memory (LSTM) networks for feature extraction. The proposed method outperformed the existing state-of-the-art methods in terms of accuracy and demonstrated robustness to variations in finger-vein images due to factors such as rotation and translation. They focused on intrinsic characteristics of vein patterns for identification applications. They generated multiple feature maps from input images and trained multiple convolutional neural networks in parallel to obtain weak classifiers. By designing a shared learning scheme to enhance feature representation and learning speed, they proposed an outperforming solution for the single sample per person (SSPP) finger-vein recognition problem. They achieved 94.17% and 92.11% accuracy for FVUSM and HKPU datasets. The critical limitations of the proposed method can be listed as the computational complexity and resource demands.

In 2023, [56] proposed a finger-vein recognition system using a CNN based on multi-directional local feature coding. They integrated manual feature extraction with automatic extraction to create a lightweight model with enhanced feature discrimination and improved recognition accuracy. They presented a lightweight model (LModel) and a feature integration model (FIModel) to extract shallow features and reduce network parameters. Using FVUSM and HKPU datasets, they evaluated system performance with accuracy. They achieved 99.13% and 99.38% accuracy for LModel and FIModel on FVUSM. They achieved 98.22% and 98.58% accuracy for LModel and FIModel on HKPU. They provided ablation experiments to analyze the impact of different components of their approach on recognition performance. They achieved satisfactory recognition performance with low hardware requirements. With this study, they provided a robust and efficient solution for finger-vein recognition where the proposed model has less computational intensity and stronger anti-noise resilience. A critical limitation noted for the proposed method is the lack of adaptability to varying input image dimensions.

In 2023, [57] presented a novel multiscale feature bilinear fusion network (MSFBF-Net) to achieve high accuracy and address the shortcomings of previous methods in the literature. They proposed a lightweight network with multiple attention mechanisms (MAM) for recognition. They used a multiscale feature bilinear fusion network to extract features from different scales, and they fused them using a bilinear pooling layer. Bilinear pooling was used to capture interactions between different features and improve the discriminative power of the features. Multiple attention mechanisms were used to improve the discriminative power of the features. They achieved state-of-the-art performance on FVUSM and SDUMLA public finger-vein datasets, with a high recognition accuracy of 99.90% and 99.82%, respectively. The proposed method addresses the problems of large models, many parameters, and long computation time in existing finger-vein recognition methods. It achieves significant accuracy despite reductions in computational complexity and recognition time.

In 2023, [58] proposed a new approach to improve the accuracy of recognition while reducing the computation and training time. They used the attention mechanism to extract representative features of finger-vein images of FVUSM and HKPU datasets. The proposed lightweight convolutional attention model (LCAModel) consists of two main components: an attentional model (AModel) and a convolutional model (CModel). The AModel is implemented by a lightweight convolutional network (LCN) and a convolutional block attention module (CBAM) block. The LCN is used to extract features from the input image, and the CBAM block is used to enhance the important features. They compared the performance of the proposed method with existing neural network-based schemes in terms of accuracy and loss. Among the proposed modules, they achieved utmost 99.21% and 99.52% for HKPU and FVUSM, respectively. Their approach outperformed and achieved state-of-the-art accuracy levels since the attention mechanism improves generalization ability and feature representation capability with adaptive matching. However, separating the feature extraction network from the final classification layer adds additional complexity to the overall pipeline.

In 2023, [59] presented a novel approach to capture long-distance topology and local texture information for finger-vein recognition. The proposed method involves using axially enhanced local attention blocks for feature amplification with a low-cost group convolution. They developed a lightweight model that achieves high accuracy at lower parameter scales on SDUMLA and HKPU datasets. They ensured recognition accuracy while generating more feature maps with fewer parameters. They achieved 94.50% accuracy on the SDUMLA and 97.86% accuracy on the HKPU dataset.

In 2023, [60] presented a new method using a vision transformer model with a modified architecture and data augmentation techniques on SDUMLA and FVUSM datasets. They proposed this model to achieve comparable performance to fine-tuning pre-trained models despite small finger-vein datasets. They compared the performance of the vision transformer model trained from scratch with the corresponding pre-trained models. They also acknowledged some limitations of closed-set protocol, and they emphasized the need for the usage of open-set protocol.

In 2023, [61] proposed a lightweight model architecture with a reduced number of model parameters and execution time. They transformed the model architecture into a simplified version via a function using an attention mechanism and residual model. They enhanced the model’s subtle vein feature extraction ability, and also they ensured consistency in feature extraction for translated vein images. They minimized intra-class differences, and they maximized inter-class differences on FVUSM dataset. They achieved an accuracy of 99.82%. In this study, they highlighted the robustness of the proposed method against translation.

In 2024, [62] introduced the Let-Net to overcome the limitations of CNN-based finger-vein identification. By using large kernels with an attention mechanism, Let-Net model captures both local and global features effectively, where this model utilizes hybrid depthwise convolution and residual connections. With a low cost of training time and low parameter number, they minimized intra-class differences, and they maximized inter-class differences on FVUSM dataset. They achieved an accuracy of 99.77%. Using ablation analysis, they confirmed the importance of an attention mechanism and large kernels for the proposed model to achieve effective identification performance. Since the proposed Let-Net model has a lightweight structure, they suggested deploying it on edge devices with limited memory and computational capacity.

In 2024, [98] utilized image preprocessing techniques and deep learning models for finger-vein recognition. They used a closed-set identification protocol by evaluating the performance of various deep learning models on a fixed dataset where all individuals are known during training and testing. Their methodological contribution involves a suite of image preprocessing techniques, data augmentation, and evaluation of a diverse set of pre-trained CNN architectures including VGG16, VGG19, and ResNet101 through transfer learning. Performance was assessed using standard classification metrics such as accuracy, precision, recall, and F1-score. A notable strength of this approach is the usage of preprocessing variations and a wide range of modern CNN models, demonstrating the impact of data augmentation on generalization and achieving very high recognition accuracies. They achieved an accuracy of 99.9% with VGG16. However, a critical limitation highlighted by the study is computation cost for models like VGG16, VGG19, and ResNet101.

In 2024, [99] proposed a lightweight recognition algorithm that modifies the VGG19 architecture by reducing convolutional and fully connected layers, replacing some activation functions with Leaky ReLU, and introducing a multi-attention mechanism. The proposed algorithm is designed for small sample sizes, evaluating its performance on the FVUSM, and SDUMLA datasets. The methodological novelty lies in modifying the VGG19 network and using a multi-attention. The system was evaluated using a closed-set protocol. The primary evaluation metric reported was recognition accuracy. However, reliance on a single accuracy metric for performance evaluation is evaluated as a notable limitation.

In 2024, [100] introduced a multiscale convolutional neural network (MCNet) for finger-vein recognition, evaluating its performance on the FVUSM, SDUMLA, and HKPU datasets. The methodological novelty of their work lies in the MFE module, which employs both rectangular and square convolution kernels. They used these kernels to enhance longer texture feature extraction, and also they used the CFA block, a cross-information fusion attention mechanism designed to combine spatial and channel information for improved local detail extraction. They used a closed-set protocol with evaluation metrics including recognition rates (accuracy), F1 score, and Equal Error Rate (EER). They achieved recognition rates of 99.86% on FVUSM, 99.11% on SDUMLA, and 99.15% on HKPU. Strengths of the MCNet include its ability to simultaneously enhance longer texture features and incorporate an attention mechanism in shallow layers to thoroughly explore local textual features. A potential limitation is high computation cost due to the complexity of the network architecture.

Table 2. The best results obtained in studies conducted in the field of identification on publicly available finger-vein datasets

Paper	Dataset	Performance (Accuracy)	Year
[63]	FVUSM	98.10%	2021
[32]	HKPU	95.32%	2019
[37]	MMCBNU	100%	2019
[37]	SDUMLA	100%	2019
[64]	THU-FVFDT2	90%	2022
[32]	UTFVP	98.33%	2019

4.2. Verification

In verification applications, a biometric system validates the subject's identity by comparing the acquired sensor data with stored data belonging to the subject in the system's database. Therefore, the system compares biometric data using one-to-one matching [28].

In 2017, [3] proposed a verification model that can extract and recover finger-vein features using limited a priori knowledge. This model uses a convolutional neural network to predict the probability of each pixel being background or foreground, and then uses this prediction to extract finger-vein features. The proposed model exploits pixel-level correlations and nonlinear statistical dependencies through a hierarchical feature representation learned by a deep neural network. Additionally, it recovers missing finger-vein patterns in binary images using a fully convolutional network (FCN) structure trained on artificially corrupted image pairs and their ground truth counterparts. Verification was performed on newly generated images obtained by patches taken from the FVUSM and HKPU datasets. The evaluation was conducted under an open-set verification protocol, although the specific implementation details of the protocol are not clearly explained in the paper. EER performance values of 3.02% and 1.69% were obtained on these datasets. A key novelty of this approach lies in its automatic patch-level labeling scheme based on the fusion of multiple segmentation methods, which eliminates the need for manual annotation. However, a potential weakness is the reliance on baseline segmentation performance, particularly in ambiguous regions, which may lead to inaccuracies in CNN training and false vein recovery in the FCN stage. Nevertheless, this novel approach was one of the first attempts to apply CNN s for finger-vein recognition and demonstrated significant improvement in handling noise and corrupted data compared to traditional methods.

In 2018, [23] proposed to expand the limited training data of MMCBNU, FVUSM, and SDUMLA datasets by using augmentation strategies. They used pre-trained models to improve model generalization on these publicly available datasets, rather than training a network from scratch. They built the FV-Net model by transplanting some layers from the VGGFace-Net model. Using open-set and closed-set protocols to assess the proposed model, they demonstrated the effectiveness of the model by comparing it with state-of-the-art approaches. Using the closed-set protocol, they achieved 0.04%, 0.06%, and 0.46% EER for the MMCBNU, FVUSM, and SDUMLA datasets. For the open-set protocol, they achieved 0.30%, 0.76%, and 1.20% EER, respectively. A key methodological contribution is the design of the FV-Net architecture, which leverages transfer learning and preserves spatial information from convolutional layers, coupled with a novel template-like matching strategy specifically designed to address the significant challenges posed by translation and rotation misalignment during acquisition. The study reports EER as the evaluation metric, which is appropriate for the verification task, and demonstrates state-of-the-art performance across all evaluated datasets compared to existing approaches.

In 2018, [65] presented a lightweight two-stream convolutional network learning framework for verification on SDUMLA and MMCBNU datasets. This network integrated the original image and ROI to obtain higher and superior performance results. They used extracted ROI images to address the displacement problem in the finger-vein images. With the proposed end-to-end framework, they solved the lack of finger-vein data, and they achieved high recognition performance. Even with the two-channel network, they showed the strong ability of the proposed network for inter-class feature extraction. By analyzing a two-channel network, two-stream network, and the joint network performances, they achieved 0.1% and 0.47% EER on MMCBNU and SDUMLA datasets, respectively. The study evaluated the system's performance using a pair-wise comparison verification protocol and reported the EER, a standard and appropriate metric for the verification task. A key contribution is the use of a two-channel network and mini-ROI extraction to mitigate displacement effects, along with a selective two-stream architecture that dynamically adapts to the subject's data characteristics.

In 2018, [66] introduced a finger-vein recognition method using semantic segmentation networks, which are U-Net, RefineNet, and SegNet, on the SDUMLA and UTFVP datasets. They released human-annotated ground-truth labels, and they presented semantic segmentation experiments on automatically generated labels and cross-dataset training. They tried to investigate the minimal number of image samples needed to train the proposed networks. By comparing network performances, they emphasized the significance of network architectures in influencing the obtained EER value. Using varying numbers of generated vein image labels by the Maximum Curvature Method, they reported EER scores obtained for these 3 networks on SDUMLA and UTFVP. They also analyzed the scores of cross-dataset training and improved the obtained performances for these datasets. The performance was evaluated using a standard verification protocol, following the FVC2004 guidelines, and key metrics including EER, FMR1000 (FMR), and ZeroFMR (ZFMR) were reported. A notable strength was that training networks with automatically generated labels significantly improved recognition accuracy compared to manual labels, while also eliminating the need for time-consuming manual annotation. The best CNN configurations also outperformed several traditional finger-vein recognition methods.

In 2019, [67] proposed finger-vein verification based on stacked CNN and LSTM networks. The proposed method involves labeling image pixels as background and foreground pixels, generating sequences along different directions, and training stacked networks to form a complementary representation. With the proposed model, they tried to handle the spatial dependencies of finger-veins. They predicted the probability of each image pixel being a vein pixel or not. By using the proposed networks with supervised and unsupervised encoding, they achieved 0.58% and 0.62% EER scores respectively on the HKPU dataset. The evaluation was conducted under what effectively constitutes a closed-set verification protocol, as all test subjects were part of the original dataset, with training and validation subsets derived from the same population. A key novelty of the method is the combination of CNNs for local texture extraction and LSTMs for modeling long-range spatial dependencies by learning from directional sequences, followed by a supervised thresholding scheme to enhance inter-class separability. Strengths of the approach include its ability to capture complex spatial patterns beyond local regions, and the use of supervised encoding optimized directly for verification accuracy. However, a notable limitation is the reliance on initial pixel labeling generated by handcrafted segmentation techniques, which may introduce bias and affect downstream performance.

In 2019, [68] presented an authentication method using CNN architectures and supervised discrete hashing. Using the triplet-based loss function and supervised discrete hashing, they achieved reputable performance while reducing the template size and enhancing matching speed. By comparing the performances of different CNN architectures such as VGG-16 and Siamese on the HKPU dataset, they highlighted the contribution and the superiority of the discrete hashing approach in terms of matching accuracy. They achieved as low as 0.0887% EER using independent test subjects for finger-vein matching. The method was evaluated on a two-session public database using a standard verification protocol, generating genuine and impostor scores, and employing appropriate metrics such as ROC curves and EER. A methodological contribution lies in combining CNN-based feature learning—enhanced by triplet similarity loss and preprocessing methods like Gabor filters—with supervised discrete hashing (SDH) to reduce template size without sacrificing accuracy. A major strength of the method is its ability to shrink template size significantly (to 2000 bits), providing practical advantages for storage and matching speed. However, a notable limitation is that their best-performing architecture, which outputs direct scores, could not be integrated with the hashing scheme, preventing template size reduction for that specific model.

In 2019, [69] proposed a novel method to extract discriminative vein features. By using data augmentation in conjunction with a pre-trained-weights-based CNN, they tried to enhance the performance of the Siamese structure. Since an insufficient number of training data is a big issue for finger-vein verification, they adopted a heavy augmentation strategy, and they developed a pre-trained-weights-based CNN architecture. They combined this structure with a modified contrastive loss function to achieve state-of-the-art performance in verification on MMCBNU, FVUSM, and SDUMLA. They achieved 0.08%, 0.11%, and 0.75% EER scores on these datasets, respectively. The approach was evaluated using open-set experiments, and EER was reported as the primary performance metric, which is appropriate for the verification task. A key contribution was the design of a modified contrastive loss within the Siamese framework, paired with heavy data augmentation and pre-trained weights to address data scarcity and enhance discriminative learning. Additionally, a lightweight CNN was developed using knowledge distillation from the pretrained model to reduce model size and inference time for practical deployment. A limitation of the method is the reliance on manual ROI extraction, which the authors acknowledge.

In 2019, [70] proposed a lightweight architecture for finger-vein classification. They used fully convolutional generative adversarial network architectures for augmentation. The augmented synthetic images were used to improve the classification accuracy of the CNN. They designed a network to classify the images of the SDUMLA dataset. They compared the performance of different GAN-based augmentation methods, and they demonstrated the reliability and generalization ability of their method. In addition to classification, they evaluated the robustness of the CNN's feature extraction capability using a one-to-many verification protocol on the SDUMLA and HKPU datasets, reporting EER, GAR, and ROC curves. They addressed the challenges faced by deep learning-based methods due to the lack of a sufficient amount of data, and they achieved 0.87% EER. The method also achieved 0.52% EER on the HKPU dataset, demonstrating improved generalization even to unseen data. A key strength of their approach is the significant performance boost obtained by integrating FCGAN-generated images into training. However, a notable limitation is the high training complexity, as a separate GAN instance must be trained for each finger-vein category.

In 2019, [71] introduced a DenseNet-based finger-vein recognition method to address the issues caused by the misalignment of fingers on the imaging platform. Using densely connected convolutional networks with composite images, they proposed a method with high performance and robustness against noise owing to composite image usage. They highlighted the limitations of existing CNN-based approaches and hand-crafted feature-based methods. They obtained composite images by adding Gaussian random noise, and they obtained difference images by subtracting pixel values. They confirmed the robustness of composite images against noise using the SDUMLA and HKPU datasets. By using the shift matching method with a fine-tuned DenseNet-161 model, they improved recognition performance. They achieved 0.33% and 2.35% EER on the HKPU and SDUMLA datasets, respectively. The experiments were conducted under an open-set evaluation protocol, where training and testing classes were disjoint, which is suitable for the verification task. A primary novelty of the study is the design of a 3-channel composite image that combines enrolled and input ROI images, enabling deeper network layers to contribute to verification, unlike earlier distance-based approaches. The integration of a shift matching technique further enhanced robustness against misalignment. While the method showed high accuracy and potential for embedded system deployment, a key limitation was its sensitivity to conditions such as severe shading, low brightness, or highly similar vein patterns.

In 2019, [72] presented a method using a pre-trained CNN model and fine-tuning it on two different datasets. They used a CNN-based local descriptor to exploit learnable convolutional filters to overcome problems arising from the limited finger-vein images. They achieved competitive performance compared to state-of-the-art models. They selected learnable CNN filters using their appearances and responses, which resemble Gabor filters, based on observations and analysis. They used selected CNN filters to build a histogram while generating a competitive order image. Using the MMCBNU and SDUMLA datasets, they achieved 0.74% and 2.37% EER, respectively. The evaluation was conducted using a closed-set verification protocol on both datasets, and the performance was reported using EER and ROC curves. A key novelty of the approach is the design of the CNN competitive order (CNN-CO) descriptor, which applies a winner-take-all rule on selected convolutional filter responses, followed by a pyramidal histogram representation. A major strength of the method is its ability to extract discriminative features effectively in limited data environments, showing improvement over traditional local descriptors.

In 2019, [73] presented an integration of a convolutional autoencoder with a support vector machine (SVM) for verification using the FVUSM and SDUMLA datasets. They used autoencoders to extract and learn vein features from images. They utilized SVM to classify the finger-vein based on the learned features. They achieved 0.12% and 0.21% EER for these datasets, respectively. The method was evaluated using a ten-fold cross-validation under an open-set verification protocol, reporting metrics including EER, FAR, FRR, and RR. Moreover, they analyzed the computational cost of the proposed method in terms of time, and they demonstrated the efficiency of the proposed approach. A major contribution is the use of a convolutional autoencoder (CAE) for unsupervised feature learning, enabling the extraction of compact and robust representations from finger-vein images, which are then classified by an SVM. A significant strength of the method is its ability to learn low-dimensional, effective features even with limited training data, enhanced by data augmentation, leading to superior performance compared to many existing methods. They highlighted the success of the proposed method in finger-vein verification.

In 2020, [74] proposed a model using a modified conditional generative adversarial network to restore optically blurred finger-vein images. They tried to recognize the restored finger-vein images using a deep convolutional neural network. The proposed network maintains features by actively using residual blocks and feature concatenation. A key methodological contribution is the removal of dropout from the generator in the conditional GAN to ensure deterministic outputs, which is important for consistent biometric pattern restoration. Using the SDUMLA and HKPU datasets, they compared recognition error rates with and without optical and motion blur. The evaluation was conducted using an open-set, subject-disjoint two-fold cross-validation protocol, and performance was measured using standard metrics including EER and ROC curves, which are appropriate for the verification task. They achieved up to 4.290% and 2.465% EER for these datasets, respectively. They also compared the required number of parameters and processing time for the models. A notable strength of their approach is its effectiveness in restoring optically blurred images and improving recognition accuracy across various CNN architectures, even under different blur intensities.

In 2020, [75] tried to improve recognition performance using a deep convolutional neural network via texture images and shape images. They analyzed class activation maps from shape and texture images, and they demonstrated the effect of extracted features on recognition. They proposed to enhance recognition performance by using score-level fusion of simultaneous texture images and shape images. They extracted vein regions using shape images, but they realized that texture images include background regions besides vein regions. Furthermore, they compared the performance of different CNN architectures and found that DenseNet-161 provides higher recognition performance. They used the SDUMLA and HKPU datasets. They achieved 1.65% and 0.05% EER for these datasets, respectively. The evaluation was conducted under an open-set protocol with subject-disjoint training and testing sets, and performance was assessed using EER and ROC curves, which are appropriate metrics for the verification task. A key methodological contribution is the score-level fusion of two DenseNet-161 networks to leverage the complementary strengths of each modality. The proposed approach demonstrates state-of-the-art performance on both datasets.

In 2020, [76] proposed a vein verification system using a CNN in combination with an autoencoder. They investigated the effectiveness of a cascaded network to discriminate inter-class features using a supervised CNN and an unsupervised autoencoder structure. They used DenseNet-161 as the backbone CNN and trained it using the SDUMLA and HKPU datasets. They achieved 0.009% and 0.189% EER for these datasets, respectively. They also used ResNeXt-101 as the backbone CNN and trained it using these datasets. They achieved 0.085% and 0.439% EER for these datasets, respectively. The evaluation was performed under an open-set verification protocol, using standard metrics such as ROC, EER, which are appropriate for the verification task. A key novelty of the study is the proposed cascaded architecture, which integrates a supervised CNN for feature extraction with an unsupervised densely-connected convolutional autoencoder (DCCAE) to refine representations. A major strength of the method is its significant performance improvement over baseline CNNs and prior state-of-the-art methods across various vein modalities, including finger, palm, and dorsal veins

In 2020, [77] investigated the use of transfer learning for vein verification while addressing limitations arising from an insufficient number of vein images. By using different training strategies while utilizing transfer learning via the Densenet-161 architecture, they achieved high-performance results and demonstrated potential advancements for vein recognition. They used the SDUMLA and HKPU datasets. They achieved 0.41% and 0.006% EER for these datasets, respectively. They confirmed the advantage of modifying state-of-the-art CNN models rather than training from scratch by building custom models to boost the obtained recognition performance. The evaluation was conducted under an open-set verification protocol with subject-disjoint training and testing, using standard metrics such as EER and ROC, which are suitable for the verification task. A key methodological contribution is the addition of a custom embedder layer to the Densenet-161 architecture, and Siamese network training strategies to be explored for learning discriminative vein features. A major strength of the approach is demonstrating significantly improves performance, outperforming prior deep learning methods on finger, palm, and dorsal vein datasets.

In 2020, [78] proposed to integrate a fully convolutional neural network with a conditional random field to segment finger-vein texture accurately. They used residual recurrent convolution to capture complex vein structures without any missing. Due to environmental factors and user behavior, they faced some problems in image quality for segmentation. They explored different segmentation methods using conventional techniques and deep learning-based approaches on the SDUMLA, MMCBNU, and HKPU datasets. They compared the performance of the proposed model with U-Net and its variants. They achieved 0.085%, 5.827%, and 0.364% EER for these datasets, respectively. The evaluation was conducted using a closed-set verification protocol, and results were reported using EER, which are appropriate for the task. A notable strength of the proposed method is its ability to connect discontinuous veins and detect weak vessels, resulting in superior segmentation and verification performance across all datasets.

In 2020, [79] presented a new finger-vein recognition approach using a lightweight CNN with a center loss function and dynamic regularization. This approach was evaluated on the MMCBNU and FVUSM datasets and outperformed other popular loss functions. The proposed loss function avoided overfitting and tried to improve EER performance. They achieved 0.586% and 1.417% EER for these datasets, respectively. They used the center loss function to distinguish inter-class and intra-class distances. They used dynamic regularization to avoid overfitting problems and to optimize convergence. The evaluation was conducted under a closed-set protocol, and performance was assessed using multiple metrics including EER, Area Under the Curve (AUC), Precision-Recall (PR) curves, and Cumulative Match Characteristic (CMC) curves, which are suitable for both verification and identification tasks. A key methodological contribution is the joint use of center loss and softmax loss within a dynamic regularization framework, which aims to minimize intra-class variance while maximizing inter-class separation, enhancing feature discriminability and convergence speed.

In 2021, [80] proposed an end-to-end deep convolutional neural network on the SDUMLA and MMCBNU datasets. The proposed approach consists of two modules for the extraction of intrinsic and extrinsic features. The intrinsic feature learning module uses an autoencoder network, and the extrinsic feature learning module utilizes a Siamese network. The intrinsic module estimates intra-class expectations to capture stable patterns, while the extrinsic module focuses on learning inter-class discriminative features. With these modules, the proposed network achieves 0.47% and 0.1% Equal Error Rates for the SDUMLA and MMCBNU datasets. The evaluation was conducted under a closed-set verification protocol, and EER was used as the primary metric, which is appropriate for biometric verification tasks. A notable strength of the model is its robustness to intra-class variations and inter-class similarities, demonstrated by an ablation study confirming the contribution of the intrinsic feature learning module.

In 2021, [81] proposed a novel method using the triplet loss function to examine similarities between images of different fingers of the same subject using four publicly available datasets. They utilized SqNet, LCNN, and ResNet network architectures, and they used 2-fold cross-validation for experimental evaluation. They compared the recognition performance of the proposed method with conventional methods using the SDUMLA, HKPU, and UTFVP datasets. They also compared different training configurations of the proposed methods to achieve better verification performance. They achieved up to 2.7%, 3.7%, and 2.5% EER for these datasets using SqNet, respectively. The evaluation followed an open-set protocol with subject-disjoint 2-fold cross-validation, and EER was used as the primary metric, which is appropriate for score-based biometric systems. A key methodological contribution is the integration of hard triplet online selection with triplet loss to improve learning, along with the exploration of various CNN architectures. Strengths of the approach include its strong verification performance and its ability to uncover novel intra-subject similarities not reported in earlier studies.

In 2021, [82] used a fusion loss function and data augmentation for deep learning-based finger-vein recognition. Despite insufficient training images, they achieved feature generalization by combining classification loss and metric learning loss on the FVUSM, MMCBNU, and HKPU datasets. They used different network architectures like ResNet-18 and ResNet-34 for feature extraction, and they compared the obtained verification performance using different numbers of training and testing samples. They utilized data augmentation, and they compared the performances of these datasets using different augmentation schemes. With intensive experiments taking into account loss function design, data augmentation, and network selection, they achieved 0.48%, 0.21%, and 1.90% EER, respectively. Their evaluation followed an open-set verification protocol, using a metric such as EER, which is appropriate for biometric verification. A major strength of the approach is its strong generalization capability, even in cross-database scenarios, as well as the practical feasibility demonstrated by a real-time system prototype. However, the model remains sensitive to large intra-class variations such as pose or lighting, and to high inter-class similarity, which can lead to false rejections and acceptances.

In 2021, [83] proposed a novel architecture for authentication to address problems related to low image contrast. On the MMCBNU, SDUMLA, and FVUSM datasets, they used a joint attention mechanism with generalized mean pooling to improve feature representation while reducing the dimensionality of feature maps. They achieved superior performance compared to existing state-of-the-art methods. They achieved 0.08%, 0.35%, and 0.34% EER, respectively. The method was evaluated under a subject-independent open-set verification protocol, using appropriate metrics such as EER, FAR, and FRR. The key innovation of the proposed JAFVNet architecture lies in its Joint Attention (JA) module, which integrates spatial and channel attention mechanisms with positional encoding using factorized 1D pooling. A strength of the approach is the ability of the JA module to extract fine-grained features, as confirmed through visualizations, and the overall strong performance across datasets. However, limitations include the trade-off between recognition performance and resource demands, as well as the need for more efficient search strategies for large-scale user databases and improved generalization via cross-validation.

In 2022, [84] addressed the challenges of extracting features from vein images. They proposed a new loss function to extract discriminative features from these images to increase performance. They compared the performance of the proposed loss function, which is dynamic margin softmax loss, with existing loss functions. They confirmed that the proposed loss maximizes inter-class distances and minimizes intra-class distances. Using five different finger-vein datasets—SDUMLA, HKPU, MMCBNU, THU-FVFDT3, and FVUSM—they achieved 0.31%, 1.59%, 1.43%, 0.39%, and 0.81% EER, respectively. The evaluation was conducted under an open-set verification protocol, using standard metrics including EER, FAR, and FRR, which are appropriate for biometric verification tasks. A notable strength is the consistent performance improvement over conventional fixed-margin losses, demonstrating enhanced feature discrimination across multiple datasets.

In 2023, [85] proposed an authentication method based on a Siamese network with a self-attention mechanism. They used a Siamese network with self-attention to extract features from the SDUMLA, FVUSM, and MMCBNU datasets. They improved the obtained performance using the self-attention mechanism despite the low image quality, along with the lightweight structure of the Siamese network. Furthermore, they achieved high performance compared to other network architectures such as VGG16 and ResNet. The achieved EER values for these datasets are 0.0059%, 0.0019%, and 0.0012%, respectively. The method was evaluated under an open-set verification protocol using pairwise image comparisons, and performance was assessed with a standard metric including EER, which is appropriate for this task. The core methodological novelty lies in integrating a Global Context Network for capturing global features and employing a multi-scale fusion strategy to enhance feature diversity, particularly from low-quality inputs. This is further complemented by a Self-Attention Convolution module that refines the learned features.

In 2022, [86] proposed a framework to increase generalization while training a model with limited image data. Using a vein extraction network via a U-Net architecture with a local descriptor model, they avoided suffering from data dependency. They aimed to map a raw image onto a target domain. By reducing differences between data distributions, they aimed to increase generalization. The achieved EER values for the used datasets—SDUMLA, MMCBNU, FVUSM, HKPU, and UTFVP—are 3.37%, 0.05%, 0.89%, 0.70%, and 0.14%, respectively. The proposed system was evaluated using an open-set verification protocol and standard metrics such as ROC curves and EER, which are appropriate for the verification task. A major strength of this approach is its universality and retraining-free design, allowing for effective cross-dataset deployment without additional tuning or retraining. However, the method shows some limitations such as degraded performance on certain datasets and in cross-session evaluations.

In 2022, [87] focused on the issues related to blurred finger-vein images and tried to restore scattering, motion, and optical blurred images to decrease the EER value. They used an encoder, decoder, residual blocks, and feature concatenation without using a pooling mechanism to avoid feature loss. Their primary contribution is the design of RMOBF-Net, a restoration network specifically developed for motion and optical blur correction in the finger-vein domain. Using the SDUMLA and HKPU datasets, they implemented the proposed method and conducted an ablation analysis. They achieved 4.290–5.779% and 2.465–6.663% EER values for these datasets, respectively. The evaluation followed a twofold cross-validation scheme under an open-set verification protocol, with EER used as the primary performance metric, which is suitable for the task. However, the study notes that recognition accuracy on restored images remains lower than with original unblurred images, especially under severe blur conditions, due to difficulty in distinguishing genuine and imposter matches.

In 2022, [88] explored the effect of the usage of the Vision Transformer for finger-vein verification. They proposed a novel model FVT using conditional position embedding, a weight-shared expanded multilayer perceptron, a local-information-enhanced feedforward network, and an expansion-less mechanism. These custom modules were integrated into the ViT architecture to better capture finger-vein-specific features such as dynamic position codes, local texture information, and multiscale vein patterns. The model was evaluated under a subject-independent closed-set verification protocol on 9 different publicly available datasets, and they conducted authentication experiments and demonstrated the effect of each mechanism through ablation analysis. A standard metric such as EER was used for performance evaluation. They achieved a weighted average EER of 1.77%, and obtained state-of-the-art performance with a 1.50% EER on the SDUMLA dataset.

In 2022, [89] proposed a model to decrease memory consumption and address channel expansion of feature maps. They introduced a sparsified densely connected network (SC-SDCN) architecture with a novel connection cropping strategy to facilitate smaller model volumes and enable efficient feature aggregation with reduced memory overhead. Thus, they presented a model with faster convergence using FVUSM and MMCBNU datasets within an open-set evaluation protocol since connected blocks have a symmetrical structure. They also replaced standard convolutions with depth-wise separable convolutions to maintain a lightweight design, and incorporated an additive angular margin penalty (AAMP) loss function to enhance feature discrimination. They explored different experiments using different network architectures, training strategies, loss functions, and datasets. A key strength of their approach is the superior performance achieved even with limited training samples. However, the model size increases exponentially with the number of sparsified dense blocks, and deeper networks beyond two such blocks did not yield further performance gains, indicating limitations in scalability. They achieved 0.01% and 0.45% EER using MMCBNU and FVUSM datasets, respectively.

In 2023, [90] proposed a lightweight Siamese Gabor Residual Network (SGRN) for finger-vein verification. Built upon a Siamese framework with twin, parameter-sharing branches, the model incorporates ResNet blocks to maintain high verification accuracy while significantly reducing model parameter size and computational cost. A core innovation of the SGRN lies in the integration of Gabor orientation filters into the convolutional layers, allowing the model to better capture directional and scale-invariant vein features. Compared to existing networks like DenseNet-161 and ResNet18, the proposed network demonstrated better performance with fewer model parameters. They achieved 0.52% and 0.50% EER scores using MMCBNU and FVUSM, respectively. However, the study notes challenges in selecting optimal scale parameters for the Gabor filters and potential bias arising from equally spaced directional orientations.

In 2023, [91] proposed a model for finger-vein feature extraction that leverages both spatial and frequency domains. These modules collaboratively extract and integrate vein features using channel and spatial attention mechanisms, improving discriminability while maintaining a lightweight model structure. The network is evaluated under a subject-independent verification protocol, where training and test sets include images from distinct fingers, ensuring generalization. They conducted extensive experiments on nine publicly available datasets, achieving 0.18%, 1.18%, and 0.20% EER scores on MMCBNU, SDUMLA, and FVUSM, respectively. Compared to baseline models, FVFSNet achieves competitive accuracy with fewer parameters and reduced computational complexity.

In 2024, [92] introduced a finger-vein recognition model using DenseNet with a channel attention mechanism and hybrid pooling mechanism. Using preprocessing operations like ROI extraction and adaptive filtering, they tried to increase the obtained performance on FVUSM, HKPU, UTFVP, and MMCBNU datasets. A robust preprocessing pipeline was implemented to enhance vein patterns from degraded images before feature extraction. Using ablation analysis, they compared the performance of the proposed network with the existing structures. They demonstrated the superiority of their network in terms of EER for some datasets. Evaluation was performed under the verification setting using standard metrics such as Recognition Accuracy, EER, and ROC curves, which are suitable for balancing security and usability. They achieved remarkably lower EER for these datasets as 0.03%, 1.81%, 0.43%, and 1.80%, respectively, demonstrating strong generalization and robustness of SE-DenseNet-HP across different datasets.

In 2025, [97] introduced GLA-FD, a Global-Local Attention model based on Feature Decoupling, specifically designed for finger-vein recognition in security-critical applications such as online payment systems. The model's primary innovation lies in the integration of two core modules. The Feature Decoupling and Reconstruction Module (FDRM) separates background and texture information to generate enhanced vein maps. In parallel, the Global-Local Attention Module (GLAM) captures both global and local features to mitigate the effects of image translation artifacts. The proposed system was evaluated on six publicly available datasets under a closed-set protocol, where both training and testing samples were drawn from the same subjects. Performance was assessed using CIR and EER, which are standard metrics for identification and verification tasks. The GLA-FD model achieved an EER of 0.04% on the FVUSM dataset and demonstrated similarly strong results across the remaining datasets.

Table 3. The best results obtained in studies conducted in the field of verification on publicly available finger-vein datasets

Paper	Dataset	Performance (EER)	Year
[93]	FVUSM	0.091%	2021
[75]	HKPU	0.05%	2020
[93]	MMCBNU	0.09%	2021
[94]	SDUMLA	0.025%	2020
[36]	THU-FVFDT2	1.12%	2019
[95]	UTFVP	0.06%	2019

5. SUGGESTIONS AGAINST FLAWS IN PERFORMANCE EVALUATION

The performance of finger-vein recognition systems is evaluated by commonly used recognition metrics, and the performance results are compared against the ones reported in the literature on the same datasets. However, it is easy to observe common evaluation flaws in some of the publications related to finger-vein recognition, as seen for other authentication systems [96]. In this study, we list some suggestions against biases and errors in performance evaluation:

1) Common experimental protocols should be used and the details regarding employed protocols must be provided to enable comparison of the new results against the ones in the literature.

2) Rather than using a single metric, many other metrics should be used and provided to avoid incomplete performance reporting, since direct comparisons based on a single parameter or a metric do not show the whole performance better than the other.

3) Whole steps and details of experiments should be provided for reproducible works. Any augmentation, any preprocessing, or details of any other operations should not be missed.

4) Due to the black box structure of deep learning systems, it is easy to make misleading comparisons and to have different interpretations of performance results. Thus, ablation analyses should be provided for new network proposals. Also, performance results should be reported with model hyperparameters.

5) Not all publications use the same datasets and report the same performance metrics. Thus, performance results should not be compared to be consistent if they do not utilize the same datasets and metrics.

6) Essentially, authors should provide all publication materials available, including datasets and source code, using GitHub for reproducible works.

6. CHALLENGES AND OPPORTUNITIES

The existing challenges and opportunities in finger-vein biometrics can be listed as follows to help researchers: First, a dataset with a huge number of samples could be released either by designing an imaging system or by generating it via software artificially to increase generalizability for supervised learning. Since the limitation of obtained performance arises from a lack of a huge dataset, this study would help to train deep neural networks by datasets with a sufficient number of subjects and samples. Moreover, rather than using slight differences in convolutional neural network architectures for finger-vein recognition, natural language processing-oriented architectures should be utilized such as attention structure and transformers because slight changes in architectural design or ensemble models do not have a considerable effect on generalizability. Second, most of the studies in the literature did not evaluate the proposed methodology using a common protocol, and they even did not explain their experimental protocol clearly. Also, they select generally one to four of the publicly available datasets for their study, since the remaining datasets did not have good performance results. Therefore, writing manuscripts with evaluations of whole available datasets on previously proposed methods could be more inclusive and comprehensive. Third, due to the misconception that arises from the nuance about the titles of the studies in the literature, the content of some of the released studies does not match the title. Paradoxically, although the difference between recognition and identification and also between recognition and verification may seem a nuance, it matters greatly. So, studies on identification and verification should not be confused. The title of upcoming publications on finger-vein biometrics should be more precise. Lastly, explainable artificial intelligence (XAI) concepts should be integrated into finger-vein publications to provide interpretability and explainability. XAI interpretations using libraries such as SHAP and LIME should be included as an additional section in all studies. The glass box structure for deep learning-oriented recognition algorithms should be promoted. Thus, the enlarged gap between interpretability and what is intended by deep learning models can be closed.

7. CONCLUSION

In this study, distinguished 68 articles on deep learning-based finger-vein biometrics have been reviewed. The main purpose of writing this review is to create a readable synthesis of the novel deep learning-based resources available in the literature for finger-vein recognition. Recent studies in finger-vein recognition using deep learning techniques on publicly available datasets have been analyzed systematically. The examined articles were clustered into 2 categories, namely identification and verification. Rather than just presenting performance analysis, this paper analyzed the selected manuscripts for each category. Moreover, performance metrics for these categories were given in detail. According to biometric literature, the term 'biometric recognition' is clarified in this paper as an umbrella concept that includes both biometric identification and biometric verification. Several challenges have been identified from the finger-vein literature, including feature processing and model interpretability. Regarding faced problems and challenges in the literature, this study highlighted the need for test protocol and comparability without extending the scope of the study by adding insignificant details about finger-vein. The importance of providing employed experimental protocol and details were stated for reproducible and comparable results on the same datasets. To achieve a comparable study, the publicly available implementation of applied processes like image enhancement and data augmentation should be explained succinctly. Furthermore, the outputs of these operations should be downloadable for the sake of reproducible and interpretable research. This study argues that future studies should have applied a common and clearly defined experimental protocol by eliminating the uncertainty caused by the lack of protocol in this area. Thus, the evaluation of the findings will be facilitated, and erroneous evaluations and comparisons will be prevented. In short, this study can be used as a starting point to update the accumulated knowledge and generate a guideline on deep learning-based finger-vein biometrics.

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