

Vein Biometric Recognition Methods and Systems: A Review

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ABSTRACT

The Finger-vein recognition (FVR) method has received increasing attention in recent years. It is a new method of personal identification and biometric technology that identifies individuals using unique finger-vein patterns, which is the first reliable and suitable area to be recognized. It was discovered for the first time with a home imaging system; it is characterized by high accuracy and high processing speed. Also, the presence of patterns of veins inside one's body makes it almost difficult to repeat and difficult to steal. Based on the increased focus on protecting privacy, that also produces vein biometrics safer alternatives without forgery, damage, or alteration over time. Fingerprint recognition is beneficial because it includes the use of low-cost, small devices which are difficult to counterfeit. This paper discusses preceding finger-vein recognition approaches systems with the methodologies taken from other researchers' work about image acquisition, pretreatment, vein extraction, and matching. It is reviewing the latest algorithms; continues to critically review the strengths and weaknesses of these methods, and it states the modern results following a key comparative analysis of methods.

Keywords: biometric technology, finger vein recognition, pre-processing, feature extraction, matching.

INTRODUCTION

Personal identifying technology has the shape of security schemes and its importance has grown in recent years, especially authentication manners, where passwords and magnetic cards are no longer secure enough, they can be stolen easily or be forgotten by the owner. Therefore, to reach a highly secure interaction, biometric technologies have been invented to apply to wide systems categories like smart devices logins and house securing systems, and other control systems [1]. Therefore, the issue of human identity recognition has become an important issue. Securing financial accounts from identity theft and providing the integrity of the existing systems can be accomplished by the automation control authentication systems to identify criminal acts, independent selling, automated banking, and more [2]. Biometrics is a mechanism that works on providing automatic verification for users relying on unique behavioral manners. Physiological features are inherited traits from embryonic stages of human

development. As a newly emerging technology, vein-based biometrics technology was invented to recognize biometrics as an attractive technology when compared to traditional types like: (fingerprints, palm print, iris, and face). They can obtain the vein recognition method data sets at a low cost and in a simple manner as they are global dynamic processes [3]. This technology is immune against fraud or theft since the vein is in the body of man, is less prone to skin illness and diseases. This technology mainly uses manual vein, palm vein, and finger-vein [4]. It only takes a simple, cheap, and compact chip to recognize the actual user. What makes it attractive are the quick and cumulative results got from the identification process, unlike other methods such as fingerprints [3]. Whereas fingerprints have shown serious limitations with inaccurate results like degradation of finger skin, finger surface particles, etc. and Vein recognition systems view good and accurate results that can overcome the limitations of fingerprints, thanks to its unique characteristics such as (i) vein images are maintained unchangeable

although human aging, (ii) hand and finger-vein discovery systems are not harmful to the user’s general health, (iii) the state of the skin like (uneven tone and/or skin burns) does not change the outcomes of vein discovery, and (iv) The shapes of the vein are challenging to deceive and replace even with surgery [5, 6]. The performance of the detector is widely related to the quality of the extraction of the venous figure and it has an immediate influence on feature extraction and matching standards. The process is about acquiring the image of finger-vein by implementing near-infrared spectroscopy at a wavelength of 760 nm. When it is placed near this wave, the vein designs are caught. The greatest difficulty with the Biometric system optimizes the Reconnaissance process [7].

SECURITY BIOMETRIC

Security is enhanced by biometric systems. One of the most important advantages of biometric security devices is that they may help you improve your security. Cloning or stealing a fingerprint, for example, is significantly more difficult than cloning or stealing an access card. Biometrics can also be utilized for multifactor verification in instances where security is a concern, and the next Table 1 shows the fames technique used in security [8].

FINGER VEIN RECOGNITION CONCEPT

Finger vein biometrics is rapidly establishing itself as the most secure means of automated personal identification. The finger vein is a unique physiological biometric that allows for the identification of people based on the physical traits and properties of the vein patterns in the human finger. It is a relatively new technological advancement in the field of biometrics that is being used in a variety of industries including healthcare, finance,

law enforcement, and other applications that need a high level of confidentiality or privacy. This technique is amazing since it needs a compact, reasonably inexpensive single-chip design and has a very quick identification procedure that is contactless and more accurate than other biometric identification methods such as fingerprint, iris, or face. This increased accuracy is not unrelated to the fact that finger vein patterns are extremely hard to counterfeit. As a result, it has become one of the fastest developing new biometric technologies, rapidly moving from research laboratories to commercial development. Historically, Hitachi’s R&D department established that finger vein pattern recognition was a feasible biometric for personal identification technology in 1997–2000 and was the first to commercialize the technology in various product forms, such as ATMs, between 2000 and 2005 [9].

FINGER-VEIN RECOGNITION DEVICE

Veins locating techniques have been introduced by the medical center in Japan. Since then, these techniques have gained popularity and many countries have developed different vein recognition systems [2, 10]. These systems implement many features on different human body veins like palm, foot, manual, and Nigerian vein. The finger vein, on the other hand, is the most preferred one because it only requires small and simple tools than other veins [11]. The uniqueness of the vein extends to being different even for identical twins, also remains unchangeable during human life. More importantly, each vein of yoke does not change during life. The Fingerprint Vein Recognition Device idea is simple. It only requires the following: (i) Image capture unit, (ii) Digital Special Processing (DSP) board, and (iii) Human automated communication unit [12]. The image acquisition unit is used to extract vein pictures from the fingers, and the DSP board is equipped

Table 1. Various biometric traits [7, 8]

Technique	Security level	Cost	Sensor	Pros.	Cons.	Size of template	Long term stability	Accuracy (ACC)
Face	Normal	Low	Non-contact	Captured from a remote area	Lighting conditions	Large	Low	Medium
Voice	Normal	Low	Non-contact	Natural & convenient	Noisy	Small	Low	Low
Iris scan	Medium	High	Non-contact	High accuracy	Glasses	Small	Medium	High
Fingerprint	Good	Low	Contact	Greatly applied	Skin	Small size	Bottom	High
Finger vein	Higher	Middle	Non-contact	High-security level	Disease	Middle	High	High

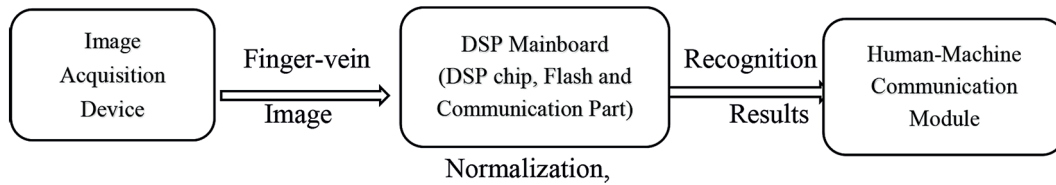


Fig. 1. Hardware systems diagram [13]

with (memory, a chip, and a communication port to compromise the implanted). Finally, a human automated communication unit is constructed to examine the extracted findings. This unit is composed of Light Emitting Diodes (LEDs) and/or a keyboard [13]. Figure 1 shows the structure diagram of the finger vein recognition system.

In general, finger-vein recognition algorithms have two main steps: (i) registration and verification Both start with a pre-finger-vein image that requires the following: (1) detection of the targeted which region is the Region of Interest (ROI), (2) align Illustration and segment it, and (3) optimization. The registration stage creates the database necessary for storing the extracted pictures, and the verification step pairs the input image with a comparable pattern after exporting its attributes [14]. The method depicted in Figure 2 is one in which near-infrared rays created by a sequence of LEDs enter the finger and are absorbed by the hemoglobin, with the finger contained within the Infrared Light Emitting Diodes (IR-LEDs) and the identification engine.

IMAGE DEVICE

Special hardware has been developed to gain a high-quality Near-Infra Red (NIR) image, to extract vein images without being affected by

ambient temperature. Three methods are implemented to create a finger-vein picture: (i) “light-transmission method” (ii) “a light-reflection method”, and (iii) “a method for multi-way radiation method” [13]. The Transmission method gives a sharp variation image, therefore it is the most implemented method; the main variation within transition and reflections methods is that the location of NIR and Charge Coupled Device (CCD) camera [15]. There are some challenges facing image extracting like noise and it is important to get high-quality results in this step, but it is impossible to implement enhancement methods during image acquisition. Therefore, pre-processing steps are invented to overcome the challenges [16].

STEPS OF FINGER-VEIN RECOGNITION

The recognition system contains three processes as the following: (i) pre-processing the image, (ii) extracting the features, and (iii) matching methods there are three types of recognition systems known as a conventional method, machine learning, and mixing machine learning with conventional methods. Some of these methods require preprocessing set steps to improve the picture quality [17]. Figure 3 views the diagram of the recognition system.

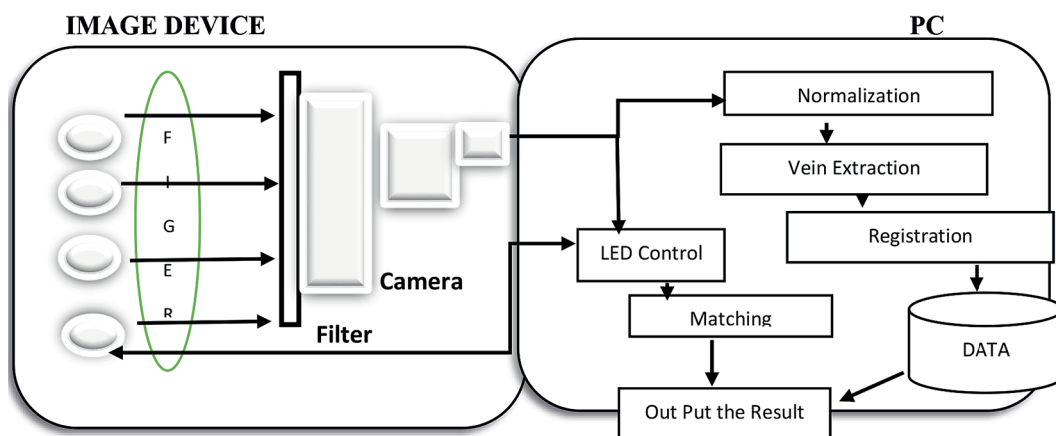


Fig. 2. Extraction function of finger-vein patterns [14]

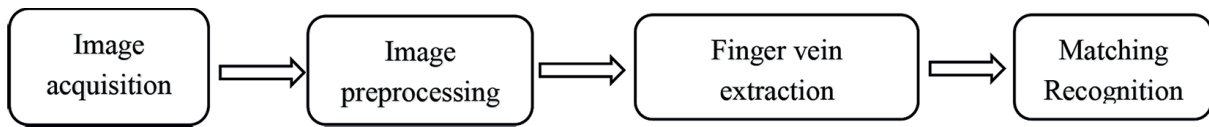


Fig. 3. Block diagram of digit-vein recognition system [17]

Image acquisition step

The acquisition includes NIR modeling of the finger's position, as well as the CCD utilized to capture the picture of the finger vein. While infrared light may pass through a finger, hemoglobin is more efficient at absorbing light than other substances such as muscles and bones [18].

Pre-processing step

As previously stated, pre-processing processes are critical for overcoming picture quality issues. Three phases comprise the recognition procedure [19]. (i) "Pre-processing", (ii) "Feature extraction," and (iii) "Classification". The challenges that are facing the extracted images, especially the smaller ones, are noise, low contrast, and ghosting. These challenges depend mainly on the quality of the device. Some works have implemented the pre-processing step as an optimization option for the gained image. After this step, the output image gets a higher quality as the performance of the system by improving the contrast and the brightness at the same time reducing the noise [20]. Un-matching light usually arises because of the specific variations in the size of the finger or lighting positions. should just select the vein features from the unstable image. The accuracy of the identification process depends heavily on the pre-processing step which contains a set of operations like ROI detection, image enhancement, segmentation, and filtering [21].

Feature-vein extraction step

The vein can be recognized in a variety of ways based on the criteria used to extract the features. In essence, all of these techniques fall into three categories: dimension reduction, local binomial, and vein-based. Several algorithms have been produced to contribute to enhancing this step. This step could be split into two categories: (i) threshold algorithm and (ii) hash algorithm based on image content [18]. There are many methods to extract vein features based on dimensions, style, and local two-way, which are predominant, in finger-vein extraction. The geometrical and topological structure of the extracted vein pattern is utilized to match between translation and rotation of pixels [17]. Figure 4 illustrated how to extract the final-vein-image.

Table 2 summarizes a study to compare the feature extraction methods of the three methods that implement vein recognition along with the results obtained.

Matching step

It is the final step where it is utilized to make a comparison of the input image and the saved image to ensure whether they are belonging to the same person where the results are shown after the matching process when measuring conformity between the images [31]. There are two matching types methods (i) distance-based (ii) matching classics [32]. Minor veins matching uses a distance-based method while machine learning algorithms like fuzzy logic, "Natural Language

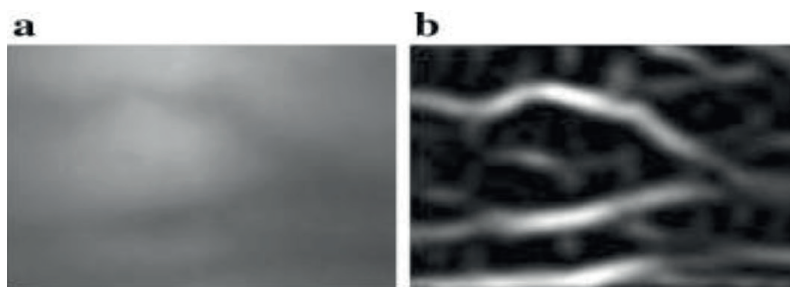


Fig. 4. Extraction of the vein pattern on the finger; a) Original image b) Map of vein patterns [23]

Table 2. Feature extraction methods

References	Approach	Category	Advantage	Disadvantage
2010 [24]	Manifold Learning	Dimensionality Reduction Based	This approach has the benefit of a high recognition rate due to the feature's small dimensions, a reduction that changes the picture from a higher to a smaller dimension.	Low recognition rate, insufficiency of robustness
2012 [25]	Principal Component Analysis (PCA)			Global features are highly dependent on parameters like location, occlusion, distortion, and lighting and are hence unsuitable for extraction as vein finger features.
2011 [26]	Local Line Binary Pattern (LLBP)	Local Binary-Based Method	Numerous characteristics; a minimal correlation between characteristics; high robustness	Numerous computations, time-consuming
2012 [27]	Location and Direction Coding (LDC)			
2019 [28]	Weber Local Descriptors (WLD)			The features of the line are of a slightly higher dimension.
2011 [29]	Mean Curvature (MC)	Vein Pattern Based	Insensitive to the unequal vein width, as well as the extraction of core venous sites.	Some pixels are not tuned correctly
2011 [30]	Gabor Filtering		Improve image quality; enhance recognition performance	Low robustness

Processing (NLP)”, “Artificial Neural Networks (ANNs)” use classic (traditional) methods and they are stronger against noisy data. In addition, these methods are systematically adaptive and have a parallel mathematical structure. Many researchers have implemented classification-based matching with vein recognition systems [33], and many finger-vein templates exist to reduce the changes during the matching process [34]. There are two major challenges facing the identification process and enhancing the verification: (i) extracting robust vein-features even within a noisy environment and (ii) optimizing system efficiency to achieve high-quality matching [35]. Additionally, the database might have an effect on the extraction process and the system’s performance [36]. The conventional finger-vein recognition method has become very popular in recent years. The researchers have developed a finger-vein verification approach with very high-performance rates [24], as well, it achieved a minimum error rate after the recognition with different datasets [37]. However, the computational cost remains high [38]. This method is less robust in a noisy environment than other methods [39]. As a result, it necessitates additional processes prior to the final findings, such as pre-processing procedures used before feature extraction and matching. Table 3 summarizes the finger vein recognition approaches. Machine learning has been used extensively in biometric feature extraction and phase matching. Using these types of techniques, feature extraction, matching, and FVR method

improvement have been proven to be useful in extracting features, matching, and enhancing the performance of machine learning that is based on learning representations of data. Machine learning techniques can be classified as supervised or unsupervised. Because supervised machine learning approaches train classification models using pictures with their ground truth labels, we apply k-nearest neighbor (k-NN), support vector machine (SVM), artificial neural network (ANN), and fuzzy algorithms. Segmentation is conducted using unsupervised algorithms such as gaussian mixture models (GMM), fuzzy c-means (FCM), and k-means clustering [15]. Deep learning technologies for finger-vein recognition are very powerful in the case of direct learning from raw pixels without any directions; this powerfulness increases the accuracy, which makes it very attractive. Multiple layers in deep learning algorithms help to learn representation/hierarchical features from datasets [33]. They were successfully applied to assess finger vein image quality and achieved high accuracy in determining quality while assessing current conventional image quality. Although there is a lack of providing a dataset for small-vein recognition, the accuracy is remarkable [40]. Deep Convolutional Neural Networks (DCNNs) were proposed with a challenging mining and validation method that performed with better results than commercial vein validation methods [41]. They have proposed to overcome the lack of storage space issues by reducing the template size, which eventually will reach a faster

Table 3. Shows approach to finger vein recognition methods with their respective scales

References	Method	Disadvantages	Matching
Vega A.P et al., 2014 [43]	Collaborative feature extraction and cross-correlation matching using Personalized Best Bit Maps (PBBM)	A reduction in the energy efficiency threshold value and a reduction in the value of the threshold value are both necessary	Conventional recognition
Vlachos M. and Dermatas E., 2015 [44]	Morphological expansion and filtering with thresholding of entropy for and matching of the template	Misalignment, finger vein darkening, and darkening of the finger veins all influence recognition performance	
Liu H. et al., 2017 [45]	Gray and size normalization with ROI extraction, Customized Local Line Binary Pattern (CLLBP) and matching score	Since it only deals with the acquisition system's image improvement direction, it needs to be central to this plan	
Park and Kang Ryoung, 2011 [46]	Local Binary Pattern (LBP) and SVM for matching	The information must be decreased to eliminate point characteristics such as bifurcation and the ends of finger vein lines, as well as to expand the data set to include more ages, genders, and vocations	Machine learning
Wu and Liu, 2011 [47]	PCA and Linear Discriminant Analysis (LDA), as well as matching through SVM and an Adaptive Neuro Fuzzy Inference System (ANFIS)	It only works in an environment with controlled background noise, some images are damaged due to poor lighting, observation angle, and other parameters	
Wang et al., 2012 [21]	A variance of local binary patterns (LBPV), Gaussian filter, and Global Matching SVM	To compute the SVM, each input data set requires its own technique of feature extraction and dimension reduction	
Khellat-kihel S. et al., 2014 [15]	Information capacity, a gradient in the spatial domain, entropy with Image contrast and Gabor feature and matching by Support Vector Regression (SVR)	Focus on integrating and creating an ROI in the venous system. A multimodal scheme as many biometric systems	
Veluchamy S. and L. Karlmarx R., 2016 [48]	Location on a grid, feature-level fusion by Fractional Firefly (FFF) and matching by K-Means Support Vector Regression (K-SVM)	Various objective functions are required to be developed to find the ideal weight score and to improve results	
Khanam R. et al., 2019 [49]	Discriminant Analysis (DA) and k-NN	Low robustness and not using all data set	
Ng Tze Han et al., 2021 [50]	Adaptive K-nearest Centroid Neighbor (Ak-NCN)	Not using data set for two sessions, but one session from data	
Qin H. et al., 2017 [51]	Fully Convolutional Network (FCN)	Much more remains to be done to improve verification accuracy	Deep learning
Huafeng Qin and Mounim, 2017 [52]	Extraction and patching of gabor features - Deep Neural Network (DNN)+ Probabilistic Support Vector Machines (P-SVM)	Not to use representative learning in other stages of biometrics of finger veins, i.e., background vein segmentation and verification	
Das R. et al., 2018 [53]	Five convolutional layers, three max-pooling layers, one SoftMax layer, and one ReLu layer with contrast-limited adaptive histogram equalization make up the Convolutional Neural Network (CNN) Model (CLAH)	Cannot be used on photos of non-trained classes' finger veins.	
Avc A. et al., 2019 [54]	4 CNN model	Data augmentation may be used to enhance training samples for four datasets using non-publicly available data to reduce over-customization of the CNN designs.	
Boukari S. et al., 2020 [55]	CNN and k-NN	Results need to be improved because grading takes a long time	
Zhao et al., 2020 [56]	Three convolutional layers, three max-pooling layers, and two fully linked layers comprise the CNN model (FCL)	The suggested system is not robust, and you should improve the performance accuracy. Second, the details of this model should be enhanced and supplemented with the loss function in trials to enable comparison of comparable performance and study of the benefits and drawbacks of each loss function	

matching process rather than traditional methods that rewire additional steps and more processing time and effort. Many researchers suggested a robust DCNNs model to overcome the problem of alignment and vignetting and to lessen the complexity of pre-processing and feature extraction steps [40]. Recommended a powerful and DCNNs model to conquer the issue of arrangement and vignetting. It likewise decreases the time and exertion required for pre-preparing and highlight extraction, which lessens the computational expense of highlight extraction [42]. A profound learning impact doesn't need confounded handling and image preparing. Besides, profound learning strategies are hearty in confronting issues of clamor and inconsistency [33].

DATASET

Datasets are an important component of any vein recognition system. It comprises images obtained from different individuals with the help of some scanners. Venous biometric data includes images of the finger-veins. However, the technology implemented in the production of vein capture devices has not been standardized because this field is new and has not been discussed in great detail. Each scanner has different specifications and results with different image quality. It can generate artificial venous patterns instead of getting them from people. These artificial vein images are used to train and test different biometrics systems [3]. Lack of dataset availability will lead to a lack of performance

measures; many universities provide free access to different datasets in the field of FVR for researchers. However, the provided datasets were not perfectly organized in most cases. For example, these databases may contain only finger vein images or simply finger texture photos, with no reference to the users' gender, blood type, skin color, or nationality. All of this information is crucial and can have a significant impact on the device's functionality. There are several publicly available knowledge bases on five-finger veins, which are included in Table 4. These databases were created uniquely through the use of diverse photographs, the number of fingers, the structure of the images, and so on [57].

THE MOST IMPOTENT STUDIES COMPARE

The following Table 5. Presents the most important recent studies to identify the finger vein and display the percentages of accuracy (ACC) and error (ERR) in it for different datasets from 2015 to 2021.

CONCLUSION

This review article summarizes several current studies on the recognition of the finger vein, in which researchers evaluated the merits and disadvantages of the various methodologies employed in biometric identification systems and detailed the methodology. In particular, the steps used to obtain images were reduced and how to evaluate

Table 4. Public finger-vein databases

Reference	No. image	No. of Sample	No. of finger per sample	No. of image per finger	Resolution (pixel)	Owner
PKU, 2010, [58]	50,700	5,208	10,140	5	512 × 384	Peking University
HKPU-FV, 2011, [30]	3744	156	2 (Left-hand index & middle finger)	12	513×256	Hong Kong Polytechnic University Campus
THU-FVFD, 2012, [59]	880	220	1	4	720×576	Tsinghua University
FV-USM, 2014, [60]	5904	123	12 (Left & right-hand index & middle finger)	4	640 × 480	Sains Malaysia
UTFV, 2013, [61]	1440	60	6 (Index, the ring area, and the middle area) for both hands	4	672×380	University of Twente by completing
MMCBNU_6000, 2013, [57]	6000	100		10	480×640	The Chonbuk University in South Korea
SDMULA-HMT, 2011 [62]	3816	106		6	320×240	The Shandong University of China
UTFVP, 2014, [63]	1440	60	4	6	672 × 380	University of Twente

Table 5. Comparing the most important studies with the results

Reference	Method	Dataset	Number of images from dataset	Final result	Advantage	Disadvantage
2015 Ardianto W. et.al., [64]	Local Hybrid Binary Gradient Contour (LHBGC)	SDUMLA FV-USM	3816 2952	EER =0.0359% =0.0038%	It handles noise introduced by imprecise capture equipment, signal distortion, and individual physical appearance fluctuations over time	I treated the noise problem and neglected other problems such as contrast and blue, and the second dataset (FV-USM) was not fully used, but I used one photo session
2016 Shirong Q. et.al., [65]	Dual-Sliding Window Localization	SDUMLA FV-USM THU		RR= 97.61 97.02 96.52	To eliminate superfluous data in finger images and to minimize disparities	1. Develop more robust and practical identification methods to mitigate the effect of certain factors on the recognition result in real-world applications, such as finger position variance, environmental capture, and endogenous age change (that is, an image of the same person's finger vein taken at a different age). Using a huge training dataset obtained through data aggregation, we are studying a more intelligent and economical method for improving vein determination performance. 2. The study and creation of a finger vein classifier to minimize the time required to determine the reaction time for a large-scale database using finger vein dilation. 3. The search for multi-biometric models (vein (finger vein/palm vein) + fingerprint (fingerprint/palm print)) incorporates human-based fusion recognition technology to enhance the identification system's performance
2017 Nordiana M. et.al., [66]	Interval Valued Fuzzy Sets K-nearest Neighbors (IVFKNN)	FV-USM	2,952	ACC= 78.1504	Allows for the definition of membership values using a lower bound and an upper bound, as well as the interval's length.	You need to use evolution-seeking approaches to the model as a means of self-improvement to produce the parameters necessary to enhance the accuracy rate
2018 Shazeeda S. et.al., [67]	Classification strategies based on the Closest Centroid Neighbor And Sparse Representation (kNCN-SRC)	FV-USM SDUMLA HKPU	5904 3816 6,264	94.13 66.56 69.52 96.88	To improve the discriminating rate, the method, distance, and spatial distribution are addressed.	Reconstruction error-based decision-making is not ideal. Additionally, this requires experimentation with k = 600 to attempt to enhance accuracy
2019 Shazeeda S. et.al., [68]	Sparse Representation Classification (SRC)	FV-USM SDUMLA HKPU	5904 3816 6,264	95.73 68.08 76.11	By categorizing the test in which the sample is determined not only by its sparse nearest neighbor but also by the training sample selection, the test treats the sample as its nearest neighbor (NN).	The extensive testing findings indicated that no one winner can attain the greatest performance across all data sets in terms of classification accuracy and computing efficiency. Thus, more efficient and effective methods should be developed for future study on cross-representation without sacrificing classification accuracy compared to other algorithms
2020 Dongdong z. et.al., [56]	Using Convolutional Neural Networks (CNNs) with a center loss function and dynamic regulation, we can define finger veins	MMCBNU_6000 FV-USM	6000 2952	99.05 97.95	Convolutional Neural Networks (CNNs) with a center loss function and dynamic regulation for the purpose of defining finger veins	More persuasive assessment criteria must be implemented since the parameters must be optimized because they are assigned to a random value
2021 Bakhtiar A. et.al., [50]	Analyses of the principal components and an Adaptive K-Nearest Centroid Neighbour Classifier	FV-USM	2,952	85.64	As an upgrade to the kNCN classifier, an Adaptive Centroid Closer Neighbor (akNCN) is presented.	In the two experiments at akNCN. .v1 and akNCN.v2 The accuracy was 85.64 and there was no improvement in accuracy but the time difference was up to 5,153 seconds for v2 while it was 6,321 for v1. The proposed classifier achieves little classification accuracy compared to the original kNCN being compared. On Asaha, on the other hand, a lot of information is neglected. This method reduces the size of the training data and removes templates

algorithms in the main recognition steps for image acquisition were studied, like pre-processing, image enhancement methods, feature extraction, and matching. Pretreatment is an important part of any system, as it largely depends on the state of the data. However, pretreatment and intensive filtering may not always be necessary. Indeed, excessive pre-treatment can lead to undesirable results as some valuable details may be lost in the process, especially when working to extract the features inscribed in the veins. Besides, the traditional feature extraction methods were combined because they provided the best pathological results. Moreover, most studies have focused on the use of local features because they have proven to be much better than holistic approaches. The conventional veins were identified for the matching step. Additionally, because FVR methods are based on machine learning algorithms, machine learning approaches are critical for finding ancient veins. This technology has a high probability of being the focus of future study in this sector. A comparison among different methods for identifying newly developed traditional veins was illustrated. However, deep learning models give a remarkable enhancement compared with the primary vein-recognition models despite the challenges to be solved. The introduction of deep learning approaches to FVR can enhance recognition performance in its broadest sense. Furthermore, some shortcomings of the offered system, the system is more reliable and safer compared to other biometrics methods. While obtaining the image, good image capture requires a system to enhance the qualities of the smaller venous image, wide datasets are required as well. This may help assess all types of FVR technologies.

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