A Comprehensive Survey on Finger Vein Biometric

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***Abstract*—In the present society with quick outgrowth in electronic field info innovation , the security issue became important demand. Because of this truth, biometric verification has earned populist as it grants reliable and high-security methodology for personalized authentication. Finger vein biometry is a recognition strategy utilized to investigate finger vein models of people for proper verification. Finger vein biometry is one of the arising technics of different types owing to its aliveness baring, its qualities of low faking risk, and a part of stability throughout a significant time. A review of advances in biometrics of finger veins is presented in the paper. It concentrates on the following sides: the overall finger vein presentation, its stages comprising image acquisition, preprocessing, extraction of features, as well as matching, the current research work review, and the common datasets. At last, the applications, the challenges, and future directions are worked out. The paper is trying to collect all studies on finger vein biometry to be one comprehensive which helps the researcher to get easily started with their investigations in the finger vein biometry where it also demonstrates the advantages and disadvantages of different biometric traits to choose from them, it focuses on explaining each part in finger vein biometry, it highlights the current challenges, provides a proposed solution and shows different technologies to encourage the scientific researchers to complete working on it.**

***Keywords*—biometrics, vein recognition, enrollment and decision, vein databases**

I. Introduction

The significance of biometrics starts with the Greeks. Bio, which means life, and metric, which is important to measure, are half-Greeks [1].

Biometrics is a computerized recognition of people dependent on the uniqueness of their biological or behavioral characteristics. personal information can be protected in the shape of biometrics, so it is used as a security technique in the last period and becomes commonly applied in many verification scenarios [2]. Where the crime rate increases,conventional authentication frameworks like password or an identity card can be effectively got by an unauthorized individual [3]. Security is fundamental [4] so every one of these conventional authentication schemes is increasingly being replaced by biometric frameworks such as fingerprints [5], iris [6], DNA, palm print, voice [7], face [8], signature, and veins [9]. These biometric trait methodologies can be partitioned into two classifications: (i) extrinsic highlights like iris, face, fingerprint, and palm print and (ii) intrinsic highlights such hand, palm, and finger vein(FV)[10]. Extrinsic highlights are more noticeable and have more contrary factors when contrasted with intrinsic ones.The strong light intensity used to extract iris characteristics has an effect on the retinal surface [11]. The accuracy of face identification is also warped because of differences in brightness, facial expression, blood vein blockage, and posture [12]. The biometric verification framework is picked over the conventional authentication system as a result of its distinctiveness and highly secured nature. Biometrics are used in multiple systems where it needs high security as ATMs for transactions, online banking, and driver identification, and plays a leading role in crime investigation [13].

A few aspects [14] such as measurability, uniqueness, permanence, universality, performance, and acceptability are weighted in biometrics for use in a particular application. Universality; is the idea that every individual utilizing a framework should have the characteristic. Uniqueness implies that characteristics should be enough different for people that they can be distinguished from one another. Permanence; indicates how a characteristic shifts after some time. Measurability; assigns to the simplicity of the gain or gauge of the characteristic. Performance; refers to the accuracy, speed, and strength of the technique utilized. Acceptability mentions how well peoples in the related populace acknowledge the tech such that they will have their biometric attributes captured and evaluated. A performance comparison of various biometric frameworks is depicted in Table I and Table II [15], where G=Good, N = Normal, and I = Insufficient.

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One of the arising strategies is biometric by FV since it has the following benefits [18, 19]:

(a) A model of a FV is differentiated and unmatched even for identical twins [20].

(b) A person's finger veins differ from finger to finger.

(c) A vein is not visible externally and is hidden in the body, so it is very finical to forge or steal, and it is usually observed by the Near-Infrared (NIR) light [21] instead of visible light.

TABLE I: COMPARISON OF MAJOR BIOMETRIC [15 WHERE I=INSUFFICIENT, N=NORMAL, G=GOOD.]

Biometric	Anti-forgery	Accuracy	Speed	Enrolment rate	Resistance	Cost
Fingerprint	I	N	N	I	I	G
Iris	N	G	N	N	I	I
Face	N	I	N	N	G	I
Voice	N	I	N	N	G	N
Vein	G	G	G	N	N	N

TABLE II: COMPARISON OF EXISTING BIOMETRIC TRAITS

Biometric trait	Main Advantage	Disadvantage
Face	1-Remote capture [11]. 2-This accomplishes widespread identification that is typically impossible for other biometric systems to accomplish [16]. 3-The-systems do not need direct-contact with an individual to verify his/her identity [16]. 4-It does not require the test subject's cooperation to perform any work [16].	1-Lighting conditions [11]. 2-Ineffective for photographs with poor resolution[16]. 3-A significant issue is that if facial expressions change, many systems tend to be less effective.Even a huge grin or chuckle can reduce the system's effectiveness [16]. 4-Compared to some other strategies, it is more expensive and difficult when used for security purposes [16].
Voice	1-Natural and Convenient [11] 2- Those who have trouble utilising their hands can benefit from this method [16]. 3-It requires no training for users [16].	1-When there is noise or confusion in the environment, even the most effective voice recognition frameworks frequently make mistakes [11]. 2- Largely expensive [16]. 3- May be hacked with prerecorded voice messages [16].
Fingerprint	1-Widely applied [11]. 2-These systems are often easy to instal and utilise [16]. 3-It necessitates cheap machinery with a typically limited power intake [[16].	1-Fingerprint scanners may be inaccurate because they only scan a portion of people's fingers [16]. 2-Many scanning systems can be tricked by using prosthetic fingers or possibly by displaying another person's finger [16]. 3-People who work in the chemical industry frequently have their fingerprints altered [16].
Iris	1-High precision [11]. 2- Iris possesses a unique structure [16]. 3-Iris is always stable for life [16].	1- Iris scanners are typically more expensive than other biometrics [16]. 2- The scanning devices can be difficult to adapt and may irritate a number of people of different heights [16]. 3-Iris recognition is difficult to do well at a distance greater than a few metres because the iris is a small organ that must be scanned from a great distance [16].
Finger-Vein	1-High-security Level [11]. 2- Even even identical twins, finger vein patterns tend to be unique to each individual [14]. 3- Live body identification. 4-Resistant to criminal tampering [14] 5-It remains constant throughout life [14]. 6- When a finger is wet, dirty, or dry, the vein is not responsive to the surroundings or to the finger circumstances [14].	1- If a user loses a finger due to an accident, it could be difficult to complete the verification process [16]. 2- Light control: Lights can interfere with the system, although covers for external usage exist to address this issue [17]. 3- Bigger Size: The system is larger due to the inclusion of a CC camera. [16].

(d) The veins of the finger do not leave any follow during the check process and along these lines, it cannot be copied.

(e) The patterns of finger veins must be taken by the alive individual and have high protection against criminal attacks.

(f) A finger pattern is permanent over time [20] and thus re-enrollment of the vein model is not needed once signed up.

Finger Vein Recognition (FVR) techniques are used in many applications [22, 23] that required high security, such as:

(1) Login authentication
(2) Door security controls.
(3) Personal Computer Security.
(4) Physical access management.
(5) Health care.
(6) financial security systems
(7) controlled border crossing and attendance systems
(8) Driver identification.
(9) area entry/exit control
(10) Bank ATM (Automatic Teller Machine).

Fig. 1(a), (b), and (c) shows pictures of commercial fingure vein authentication units with different authentication applications.

This paper is organized as follows: Section II explains related work. The general framework of vein recognition is discussed in Section III. Section IV shows the recognition of FV stages in detail. Public databases are given in Section V, whereas the implementation of FVR is found in Section VI. Section VII concludes by talking about the difficulties and upcoming efforts.

(a)

(b)

(c)

Figure 1. Finger vein authentication unit for (a) area entry/exit control [24], (b) ATMs [24], and (c) driver identification [25].

II. General Framework of Vein Recognition

Vein recognition technology can be used to verify and identify certain individuals. As shown in the following Fig. 2, an overall architecture including these two applications is incorporated. This architecture comprises four sections, enrollment, identification, authentication, and decision.

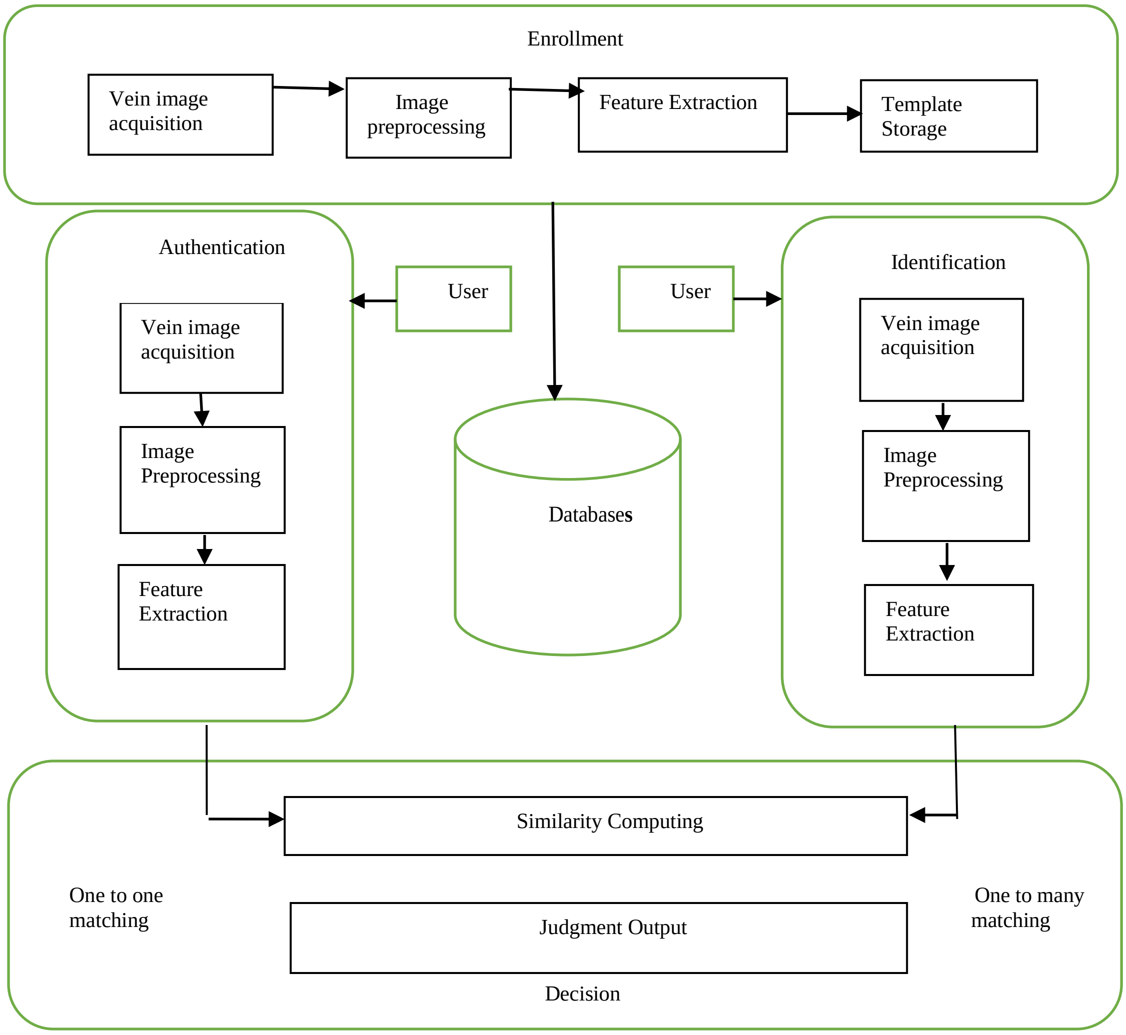

Figure 2. A general framework of vein recognition.

Enrollment: It is also known as registration and consists of image acquisition, preprocessing, and feature extraction. Finally, a dataset containing the produced templates is saved.

Verification is the term used for authentication.It is matching one to one.The venous image should be collected for a specific user, followed by preprocessing, feature extraction, and transformation into a vector of features in accordance with an organization method predetermined in advance.

Identification: The identification stage is a one-to-many matching process in contrast to authentication.

The steps are identical to those taken during the authentication phase.

Decision: Feature matching is the primary method used in this step.Calculate the similarity between the query feature template and its one-by-one database counterparts. After that, a judgement can be made using the computed similarity.

III. Finger Vein Recognition

This section will discuss the portion of authentication and decision in the general framework of vein recognition where FVR composes of four modules: Image-acquisition, Pre-processing-module, feature-extraction, and finally-matching.

A. Image Acquistion

There are two methods of image acquisition: offline and online.Online images are those that are captured in real-time, whereas offline images are those that are retrieved from a pre-existing database.

A charged coupled device (CCD) pre-processor camera and a Near Infrared (NIR) finger position component are included in the venous image capture device [26]. An infrared LED light is sent through the finger to capture the vein images.Because light absorbs haemoglobin into the blood, the blood vessels look darker than the bones andmuscles [27]. Fig. 3 depicts an FVscanner.

Figure 3. A finger vein scanner [28].

Light transmission, light reflection, and side lighting approach have all been used to capture a picture of a vein pattern [29–31]. However, since light transmission produces an image with a high contrast, it is the method used by the majority of image acquisition devices. The LED and image sensor are placed on the same finger side in the light reflection method demonstrated in Fig. 4. It is claimed that the finger's exterior reflections of light are captured by the image sensor. The image of the vein pattern is shaped by minute variations in the force of the commutated light. This technique produces a picture that demonstrates a vein that emits slim light and a blood vessel that emits shine light.

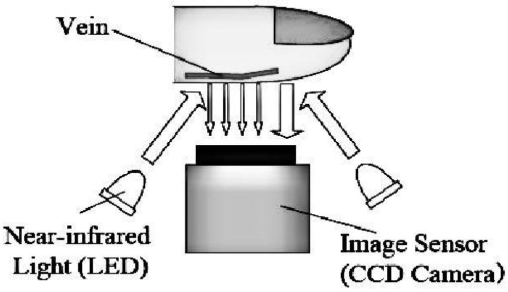

Figure 4. Light Reflection method [32].

In order to demonstrate the process of light transmission, position your finger between the sensor and LED source as demonstrated in Fig. 5. As the Near IR light from the LED source passes through the finger, the image sensor on the other side of the finger captures the shadow of the vein pattern.

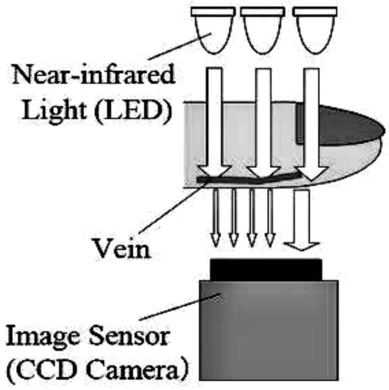

Figure 5. Light transmission method [32].

A comparison between the two types of image acquisition is demonstrated in Table III.

TABLE III: Comparison of Light Reflection and Light Transmission Method [33]

Light Reflection	Light Transmission
The finger is put along at the sides.	Between the LED and the image sensor, a finger is positioned
This technology removes all barriers between the user and the device by combining a light source and a sensor in one package.	The lack of compactness of the item is considered to make it uncomfortable for the user
Due to limited sidelight penetration, the image contrast is low and the vein pattern is caught during the reflection process.	This technique provides a vein pattern in high contrast.

Fig. 6 illustrates the side lighting technique by placing an LED source on each side of the finger. The image sensor detects the vein pattern image as the near-infrared light travels through the finger, scatters inside the finger, and then travels through the opposite side of the finger. A high-contract image is provided by this novel technique.However, in the pictures, the finger's sides are overexposed.

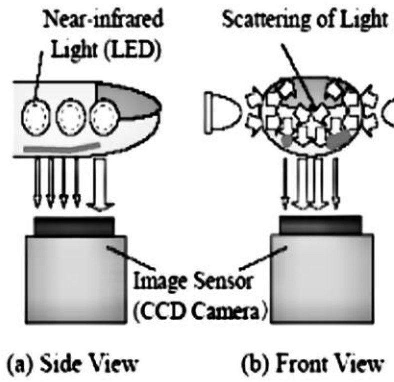

Figure 6. Side view and Front view [32].

B. Preprocessing

Before changing the image quality, pre-processing chores are necessary since a greater image quality will increase the biometric system's accuracy [34]. Low contrast, brightness, edge information, noise reduction, and image sharpening are a few of these jobs. This is due to changes in the finger's translation and rotation, variations in the light, and the functionality of the capturing device. To minimise these problems, preprocessing is used. Image quality assessment, region of interest (ROI) extraction, and enhancement and normalization are the three fundamental preprocessing steps.

1) Image quality assessment

The first step in the preprocessing process is image assessment. The quality of the captured image samples is analyzed at this stage to determine their appropriateness for additional processing. A number of quality assessment techniques have been suggested to progress FV identification performance. Such as Image Brightness, Image contrast, and Edge Blue Degree [35–38].

2) ROI extraction

The extraction of ROI is the following most significant stage. In images of the vein, there are unrequired regions (background of the image) and desirable areas (finger area) . The desirable area is known as ROI, where ROI is the preparation to restrict and separate the finger region from the acquired picture and eliminate the background of the image [39, 40]. various methodologies are utilized to portion the finger area from the captured picture, for example, thresholding, region-based technique, edge-based strategy, and template method [41].

3) Normalization and enhancement

Normalization is an operation that standardizes the scope of values of pixel-intensity in a picture. After separating ROI, the picture of the FV is-normalized-to suit geometric variations and to produce a fixed picture size [42]. Moreover, normalization in the stage of preprocessing removes the various variance issues of the picture [43].

The preprocessing stage also includes an important step called image enhancement. The main goal of enhancement is to make data in images easier for human viewers to understand or to obtain a standard better image from an ambiguously acquired image [35]. To increase matching performance in FVR, a picture must be enhanced.Contrast enhancement and noise removal are the main focuses of image enhancement.

C. Feature Extraction

The use of feature extraction to identify people makes it a fundamental advancement in FVR.It is an exclusive kind of dimension reduction. In this stage, input data is transformed into a set of features to create a biometric trait known as the FV template [44]. The effectiveness of the feature extraction method enhances recognition precision. For finger veins, a variety of feature extraction techniques were used, however deep learning-based methods are more accurate than most conventional methods [4] including local binary-based [45, 46], dimensionality-based [47, 48], and minutiae-based methods [49, 50].

D. Matching

The final step in recognition determines if an input image is genuine or a forgery by calculating how similar the input picture and the enrolled template are. There are two different kinds of matching methods used: classifier-based matching and distance-based matching. Classifier-based matching can be utilized in machine learning techniques, whereas distance-based matching is utilized in the conventional FV identification strategy [51, 52].

IV. LITERATURE REVIEW

The four main processes of FV biometric systems are image acquisition, preprocessing, feature extraction, and matching. Finger veins have been used extensively in the biometrics sector for a number of applications on many platforms, including authentication.This section examines some earlier research on FV and discusses biometric security methods. c security systems are surveyed.

A. Literature Review on Image Acquisition

During the time spent picture checking, vein pictures are found using an infrared scanner. Gotten pictures affect beat condition conditions ought precision. Picture-affirming sort for instance segregated and online [53, 54].

David Mulyonoet *et al.* in [18] Propose an ideology for the FV figures for an offline and online acquisition. The images captured in real-time are referred to as online images. Images that are acquired from already existing sources such as databases and historical information are called Offline images.

There are three methods to capture an image of a vein pattern, namely light-reflection, light-transmission, and side-lighting-method [30, 31, 55]. These methods were discussed exhaustively in the previous section.

B. Literature Review on Image Preprocessing

In the preprocessing stage of an image, numerous operations are carried out to improve the image's quality, including noise removal, resizing, sharpening, locating the region of interest, image enhancement, blurring, and deblurring.

Histogram equalization [31, 56] is an image enhancement technique. In this technique, the image gray-level distribution changes in such a form as to get an even(plane) developing histogram.Histogram equalisation has been employed by Kumar and Zhou [57], Prasanna *et al.* [58], Khan and Ramsoful [59] in their method to improve the contrast of the vein picture.

Adaptive-Histogram-Equalization-and-Contrast-Limited -Adaptive-Histogram-Equalization (CLAHE) [60] are some such techniques. This is different from regular histogram equalization in that it can compute many histograms such that each histogram corresponds to a discrete sector of the image and utilize it to reassign the smallest amounts of lightness in the image. Adaptive histogram-equalisation was later utilised by Liu [61], however this method has a tendency to exaggerate a little quantity of image noise. CLAHE was employed by Prabhakar, Rossan and Khan [62], Thomas [63], and Lu *et al*. [64] to mask the shortcomings-of-adaptive histogram-equalisation.

The Gaussian filter and median filter are frequently used to remove noise from venous pictures. The noisy vein picture was enhanced and smoothed utilizing the Gaussian filter. The median filter can decrease undesirable defects and remove burrs. Depending on how much noise there is in the vein picture, this noise is eliminated. Both the median filter and the Gaussian filter have been employed alone or in combination by Yu *et al.* [65], Gu [66], Park and Kim [67], Uriarte-Antonio *et al.* [68] in their methodology.

In order to reduce noise and detect edges, Wang and Chen developed a custom created filter employing the Laplacian of Gaussian (LoG) [69]. The noise from the LoG was then removed using a median filter.

There are typically two types of threshold segmentation techniques: global and local. The global threshold served as a benchmark for thresholding in the global threshold technique. Because of this, the overall threshold result is insufficient. Better segmentation is achieved by the local thresholding technique, which determines the threshold at each individual pixel. The local dynamic threshold segmentation method was utilised by Liu [70], Wu *et al.* [71], Hongxing *et al.* [72], and Yun-Peng *et al.* [73]. It is straightforward and efficient.Zhao *et al.* [74] found that using this strategy will cause a loss of connectivity in the vein pattern in photos with non-uniform distribution. They improved the local dynamic threshold segment algorithm by improving the algorithm's standard deviation computation algorithm.

C. Literature Review on Feature Extraction

In the stage of feature extraction, the discriminant features are inferred to be utilized in the matching phase. It is a special form of dimensionality decrease that modifies the input data into the features' course of action.

A median filter and a Gabor filter are utilized for extraction of features to remove the features of the veins without noise and distortion. Ajay-Kumar *et al.* [75], Yang *et al.* [76], and Babu *et al.* [77] used the Gabor filter to extract features. Khalil-Hani [30] has applied a Median filter for extraction

The amount of times the tracking lines pass through the points determines repeated line tracking. The technique starts at different points and follows a line tracking. Naoto Miura *et al*. [78], Mulyono D *et al.* [79], Nivas *et al.* [80], and Mohammed *et al.* [81] used repeated line tracking. In order to identify people using the patterns of their FVs, Iram Malik *et al.* [82] use repeated line tracking and Gabor filtering techniques. Despite the fact that these two factors are used to infer the features, they integrated these two methods to improve their efficacy and dependability.

Dimensions are reduced using Principal Component Analysis (PCA), and features are extracted using Linear Discriminant Analysis (LDA). Wu *et al.* combine these two approaches, which results in superior classification performance by reducing the quantity of redundant and unnecessary data in the data [83].

The feature vector can be shrunk to any desired length using a number of PCA techniques, which are typically used in dimensionality lowering methodologies. As a result, this kind of feature extraction can produce positive outcomes, and the majority of tests had high accuracy rates. The local texture characteristics are extracted using a Multiscale Uniform Local Binary Pattern block [76], and the local data of the FV pictures is then preserved using a block-based (2D) 2 PCA approach.

The extraction-of-feature-biometrics has made utilize of a few machine learning approaches, including as SVM (Support Vector Machine), neural-networks, and fuzzy-logic [4]. These-sorts-of strategies-have-additionally ended up being proficient for-feature-extraction-and-improving the- FVR-performance.

Multiple layers of learning algorithms make up the machine learning technique known as "Deep Learning" (DL). The automation, optimization and strong ability with feature personification of DL are some of the factors contributing to its rise. DL technique, has grown quickly in-recent-years Compared to traditional methods, it begins to be the mainstream technique in-many chores of computer-vision [85], like autonomous driving [86], biomedical-image-analysis [87], and biometric recognition [88] where it achieves a crushing performance in these tasks. For instance, Convolutional Neural Networks (CNN), the most often used DL patterns for-computer-vision-applications, comprise numerous feature-extraction levels prior to the ultimate decision layers. The feature extraction layers figure out how to separate convolutional kernels, which are optimal feature representations, from the training pictures. In this context, the most common way of utilizing earlier information to separate the important features from a picture has been changed into a feature-learning-task dependent on a huge amount of training photos.

A DL approach for the FV domain called CNN [89] placed more attention on preprocessing and building a CNN model. Segmentation is possible by utilising local dynamic thresholding, which lowers computation complexity. The CNN architecture is made up of layers that combine convolutional and subsampling techniques.

Radzi *et al.* [89]'s initial attempt to implement DL models in FV biometrics involved preprocessing the FV picture in order to obtain a ROI. The custom-mode four-layer CNN design was then given the image. This method's application on an internal FVdataset proved quite promising. Itqan *et al.* used a similar approach when creating a used authentication application in the MATLAB IDE [90].

A deep CNN prototype [91] is utilized to address shading and misalignment problems. Additionally It detracts from the effort and time needed for preprocessing and extracting feature. A deep CNN with Hard mining [92], accelerates the training process and has also achieved a better verification rendition, and a CNN with supervised discrete hashing for identifying FV [93] is used to overshadow the issue of several storage space expected for huge templates to minimize the size's template, subsequently speeding up. The design of a CNN that involved five convolution layers [94] was tried across four public datasets. They accomplished high scores, particularly in cases when four images were utilized for training. [95] invests a deep Convolutional Auto-Encoder (CAE) structure and a bio-hashing algorithm to cryptography the feature templates of FV.

Generative Adversarial Networks (GAN) in veins of finger representation field are introduced in [96], where they demonstrated improved robustness to outliers and vessel breakage. It utilizes fully convolutional networks instead of CNN's fully connected layers, which minimizes computational costs to extract a feature. Hou and Yan utilizes GAN to produce data in the FVR operation to hide overfitting [97].

D. Literature Review on Matching Stage

The extracted feature is then compared to the template that has been saved to authenticate.

SVM is frequently utilized for matching and classification tasks [96]. This technique can perform both linear and non-linear classification. It has been effectively utilized as a part of various applications since it can handle nonlinearly separable data, runs quickly, and is a reliable classifier.

The SVM is broadly utilized for image classification [83, 98]. The SVM classifier includes finding a hyperplane classifier.

A normalized-distance-between-two-feature-vectors is defined in [15, 99] to measure similarity.Two-feature-vectors-are said to be more similar if their normalised distances are less.

In comparison of biometric templates, the-Hamming-distance (HD) is typically utilized. It is utilized to determine how closely the extracted binary codes and the enrolled code resemble each other [100].

Phase-only correlation (POC) at the matching phase is utilized [101], this strategy utilizes the phase component of a two-dimensional-discrete-Fourier-transform (2D-DFT) of a picture. The normalised score is equal to one if two photos match. In any case, the score is debased if two distinct images of a similar finger match.When calculating the cross-phase spectrum, a high-frequency-component is discarded in order to remove it.This technique, known as Band Limited POC (BLPOC) [60], removes the high-frequency-component by setting a band limit by computation of the cross-phase spectrum. The-BLPOC-function-is calculated for each set of photos in the registered and input images' shaded regions.The final matching score is picked as the set with the highest score. The matching technology offers exceptional precision.

V. PUBLIC DATABASES

There are many open FV data sets, for example, SDUMLA-HMT [102], HKPU-FV [103], UTFV [104], MMCBNU_6000 [105], THU-FV [106], FV-USM [107] University developed their FV dataset called (HKPU-FV) [91], which contains low texture images and vein of finger and it was published by Hong Kong Polytechnic University. In 2010, the University of Shandong delivered one multimodal attribute dataset SDUMLA-FV [102]. The third dataset UTFV [104] is introduced by Twente University. In the new past, two databases of a FV, MMCBU_6000 [105] and THU-FVFD [107], were distributed by Chunbuk and Tsinghua Nation University consecutively. This load of public datasets gives more than 100 subjects, except for the UTFV dataset which gives 60 persons. FV-USM was created by the University of Sains Malaysia in 2013 which was the infrared FV picture dataset [109]. In 2014, the VERA database [110] was created by the Idiap Research Institute in Martigny and Haute Ecole Specialisee de Suisse Occidentale in Sion, Switzerland [111]. In PLUSVein-FV3 [112], The Wavelab Group at the University of Salzburg, Salzburg, AUSTRIA (henceforth, PLUS) possesses the copyright to this dataset and is answerable for the dispersion of the database. The portion of the previously mentioned data sets might be appropriate for one specific application and may not suit other applications. Table IV shows the datasets of the FV.

TABLE IV: THE COMPARISON BETWEEN TYPICAL PUBLIC FINGER VEIN DATABASES

Database	Acquision Method	No. of Subjects	No.of Images	No. of Fingers for Each Subject	No. of Images for Each Subject	Image Format	Size of Images
SDUMLA-FV [102]	Light transmission	106	3816	6 (both hands middle, index, ring)	6	Bitmap	320×240 pxl
THU-FVFD [106]	Light transmission	220	440	1	1	Bitmap	200×100 pxl
UTFV [104]	Light transmission	60	1440	6 (both hands middle, ring, index)	4	PNG, 8 Bit Grayscale	672×380 pxl

HKPU-FV [103]	Light transmission	156	6264	3 (left-hand middle, ring, index)	12/6*	Bitmap	513×256 pxl
MMCBNU_6000 [105]	Light transmission	100	6000	6 (both hands middle, ring, index)	10	Bitmap	640×480 pxl
FV-USM [107]	Light transmission	123	5904	4 (both index fingers, both middle fingers)	6	Bitmap	640×480 pxl
VERA [110]	Light transmission	110	440	2 (left index and right index)	2	PNG	665×250 pxl
PLUSVein-FV3 [112]	Light transmission	60	1800	6	5	PNG	736×192 pxl

*Only 105 subjects turned up for the imaging during the second session, so each of the fingers from these subjects has 6 images, but the other fingers each have 12 images.

VI. Evaluation Criteria

The suggested approach performance is evaluated for the following metrics and their definition as follows:

- Recognition Rate (RR)

It is identified as the total number of correctly classified images of finger veins divided by the total number of pictures in the database.

- Equal Error Rate (EER)

It is commonly utilized as a system evaluation metric for computing recognition errors. It is computed between the FAR and FRR. The higher error rates indicate the framework has obtained poor performance.

- Processing Time (PT)

It refers to how much time is taken for processing the FVR. It is computed based on how many processes were used to recognize the FV images.

- False Acceptance Rate (FAR)

It serves as a unit metric that is utilized to quantify the FVR system by determining the rate at which genuine images are verified.

- False Rejection Rate (FRR)

It is a metric that will incorrectly reject the genuine finger vein picture and misclassified genuine as an impostor.

- Receiver Operating Characteristic (ROC) Curve

The curve of ROC is utilized for showing the relationship between FAR and FRR. It is a visual description of the compromise between the FAR and the FRR, in which the FAR and FRR are represented by the horizontal and vertical axes or vice versa, respectively.

A. *Spoofing Attack (Presentation Attack) in FVR*

Biometric frameworks are susceptible to a variety of attacks, which can be roughly divided into two categories [113]: (1) Direct attack (presentation attack): In this attack, Biometric materials are directly introduced to the device (sensor); (2) Indirect attack: A virus or other malware is used to attack a section of a biometric framework. Because of the security analysis, the direct attack or presentation attack is of great interest in biometric frameworks. When compared to other biometric modalities, FVR formerly had a good spoofing resistance, however recent research has revealed that FVR devices are susceptible to spoofing attacks [113, 114].

The presenting attack in a picture of a FV is recommended to be distinguished using a variety of conventional hand-crafted, machine learning techniques [113, 115, 116]. Usually, the presentation attack detection (PAD) framework comprises a binary classifier and a feature extractor [117]. As far as we are aware, Matsumoto uses a synthetic artifact to deceive a framework, making it appear like a FV is being depicted [115]. Fourier Spectral Energy Ratio and Discrete Wavelet Transform (FSER-DWT)-based traditional PAD approach was proposed [118]. In any event, even on a tiny dataset of 33 persons, the result was unacceptable. Five conventional PAD techniques, including Monogenic scale space (MSS), binarized statistical image features (BSIF), residual local binary pattern (RLBP), Fourier spectral bandwidth energy (FSBE), and Weber local descriptor, have recently been introduced at the International Conference on Biometrics (ICB) 2015 [114]. (LPQ-WLD). Anyway, on both cropped and full-picture datasets, none of them managed to achieve 100% recognition precision. A CNN with SVM and PCA was presented by Nguyen *et al.* [116] to overcome any feature extraction limitations in presentation attack methodologies. The suggested method accomplished 100% recognition precision on two huge datasets Istituto Dalle Molle di Intelligenza Artificiale Percettiva (IDIAP) [114] and ISPR [118] which included both cropped and whole copies of pictures. As far as we could know, it was the main tried to identify a spoofing attack utilizing a deep learning architecture.

We involve the main definitions for biometric PAD [119]:

(1) Bona fide presentation: "interaction between the biometric catch subject and the biometric information capture subsystem in the fashion planned by the biometric framework's policy". That is a typical or genuine presentation.

(2) Attack presentation/presentation attack: "presentation to the biometric information capture subsystem to interfere with the process of the biometric framework". That is an attempt to trick the capture system into hiding your identity or mistaking you for someone else.

(3) Presentation Attack Instrument (PAI): "biometric trademark or object utilized in a presentation attack". For example, a silicone 3D mask or an eco-flex fingerprint overlay.

(4) PAI species: "class of presentation attack instruments made utilizing a common manufacturing strategy and dependent on various biometric parameters ".

The following measures need to be used to gauge how PA-prone biometric frameworks are:

- Impostor Attack Presentation Match Rate (IAPMR) is defined as the percentage of impostor attack presentations utilizing related PAI species

in which the objective reference is evenly matched
- Attack Presentation Classification Error Rate (APCER): the percentage of attack presentations using related PAI species that were incorrectly categorized as bona fide presentations in a certain scenario
- Bona Fide Presentation Classification Error Rate (BPCER): "proportion of bona fide presentations mistakenly labeled as presentation attacks in a given scenario".

We introduce the liveness of the FV [120] properties as they are presented to the sensor. The core idea is to amplify the blood moving through a finger vein to gauge its liveness. To this degree, we utilize the Eulerian Video Magnification (EVM) way to enhance the blood's motion in the recorded finger vein video. We then perform additional processing on the enlarged video using an optical stream to separate the FV artifacts and eliminate the movement-based characteristics.

VII. Challenges and Future Research Directions

Even though some remarkable research advancements have been done in the field of FVR through the previous decade, numerous shortfalls ought to be tended to [42].

(1) The ROI extraction strategy used for image preprocessing is where this problem is found, as most ROI extraction methods have a problem with vein information loss. Therefore, a reliable ROI extraction technique is needed to combat information loss and improve the accuracy of FVR.

(2) Fat, tissue, muscle, water, and other components of finger tissue have received minimal consideration, resulting in a low-quality FVR. As a result, the fundamental issue with FV detection systems continues to be poor performance. A satisfactory level of performance in terms of recognition is still a work in progress at this point.

(3) The size of the present FV data set identifies this problem. Most conventional recognition techniques function admirably on small databases, but big datasets are required to evaluate the effectiveness of the recognition techniques.

(4) Further research should be done on bimodal fingerprint and FV biometrics, which offer the chance to combine their advantages.

(5) The image acquisition equipment and how the pixel quality changes with sensor ageing should receive further attention [121]. The performance of the FVR system will be impacted by the picture quality if the is device's sensor utilized for a prolonged period of time, hence efforts should be made to miniaturize the imaging device and lower the cost of the FVR system.

VIII. Conclusions

This study presented the survey on FVR for individual identification since it is among the most crucial fields of security lately where it provided the benefits, of the related work of FVR and explained the different stages of FVR viz picture acquisition, preprocessing stage, features extraction stage, and matching. The light transmission technique was thought to be the most effective for acquiring rising quality images. Techniques for picture enhancement and ROI extraction were investigated in the context of image preprocessing. Likewise, the traditional feature extraction strategies were arranged into four groups (i.e., dimensionality, vein, minutiae, local binary-based method) and presented the two different types of matching techniques, i.e., distance-based matching and classifier-based matching.

The paper provided the public databases which are utilized in FVR and the challenges that must be overcome. A good image acquisition device is necessary for particular for image acquisition to enhance the quality of the picture. Large-scale datasets are required to evaluate the effectiveness of recognition techniques. The finger tissue components — fat, water, tissue, muscle, etc. — that influence the image's quality must be our main concern. the quality of the image. They consequently have an impact on recognition performance. To address the issue of information loss and improve the effectiveness of FVR, a reliable ROI extraction technique is required.

As The literature that is now accessible indicates that the FV biometric ensures great performance, spoofing resistance, and fraud-proof authentication. Additionally, its hardware implementation can be used for various applications, increasing reliability, high accuracy, and security.The FVR technology is therefore more trustworthy and safe than other traditional modalities.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

Under the supervision of Prof. Abdel Halim A. Zekry, Prof. Yasser M. Kamal, and Dr. Hossam L. Zayed, Heba M. Abdel Hamid collected and wrote the paper; all authors had approved the final version.

References

[1] A. Ross, K. Nandakumar, and A. K. Jain, *Handbook of Multibiometrics*, 1 st ed: Springer, 2006, ch. XXII, p. 198.

[2] N. Kaur, *et al.*, "A study of biometric identification and verification system," in *Proc. 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, 2021, vol. 64, p. 60.

[3] A. K. Jain, S. Pankanti, S. Prabhakar, H. Lin, and A. Ross, "Biometric: a grand challenge," in *Proc. 17th International Conference on Pattern Recognition (ICPR)*, 2004, vol. 2, pp. 935–942.

[4] K. Shaheed, H. Liu, G. Yang, I. Qureshi, J. Gou, *et al.*, "A systematic review of finger vein recognition techniques," *Information*, MDPI, Basel, Switzerland, vol. 9, 2018.

[5] R. A. Mohamed, M. F. Mahmoud, and H. L. A. F. Zayed, "Identification of persons by fingerprint recognition and verification using minutiae extraction technique with compression technique," *International Journal of Advanced Engineering and Nano Technology (IJAENT)*, vol. 2, issue 9, August 2015.

[6] S. Lei, B. Dong, A. Shan, Y. Li, W. Zhang, *et al*., "Attention meta-transfer learning approach for few-shot iris recognition," *Computers and Electrical Engineering*, vol. 99, 107848, 2022.

[7] V. Antonova, K. Balakin, N. Grechishkina, and N. Kuznetsov, "Development of an authentication system using voice verification," *Journal of Communications Technology and Electronics*, vol. 65, issue 12, pp. 1460–1468, 2020.

[8] W. Ali, W. Tian, S. U. Din, D. Iradukunda, and A. A. Khan, "Classical and modern face recognition approaches a complete review," *Multimedia Tools and Applications*, vol. 80, issue 3, pp. 4825–4880, 2021.

[9] K. N. Mishra, K. N. Mishra, and A. Agrawal, "Veins based personal identification systems: A review," *Int. J. Intell. Syst. Appl*, vol. 8, pp. 68–85, 2016.

[10] H. Qin, X. He, X. Yao, and H. Li," Finger-vein verification based on the curvature in radon space," *Expert Syst. Appl.*, vol. 82, pp. 151–161, 2017.

[11] K. Syazana-Itqan, A. R. Syafeeza, M. N. Saad, N. A. Hamid, and W. H. M. Saad, "A review of finger-vein biometrics identification approaches," *Indian J. Sci. Technol*., vol. 9, 2016.

[12] Y. Lu, S. Wu, Z. Fang, N. Xiong, S. Yoon, and D. S. Park, "Exploring finger vein-based personal authentication for secure IoT," *Future Gener. Comput. Syst*, vol. 77, pp. 149–160, 2017.

[13] E. A. lrahawe, V. T. Humbe, and G. Shinde, "A biometric technology-based framework for tackling and preventing crimes, " *Intelligent Data Analytics for Terror Threat Prediction: Architectures, Methodologies, Techniques and Applications*, pp. 133–160, 2021.

[14] L. Yang, G. Yang, Y. Yin, and R. Xiao, "Sliding window-based region of interest extraction for finger vein images," *Sensors(Basel)*, vol. 13, pp. 3799–3815, 2013.

[15] A. Ushapriya and M.Subramani, "Highly secure and reliable user identification based on finger vein patterns," *Double Blind Peer Reviewed International Research Journal*, vol. 11, 2011.

[16] D. Mulyono, "A study of finger vein biometric for personal identification," in *Proc. the International Symposium Biometrics and Security Technologies*, 2008, pp. 134–141.

[17] A. Kumar and Y. B. Zhou, "Human identification using finger images," *IEEE Transactions on Image Process*, vol. 21, pp. 2228–2244, 2012.

[18] R. Saini and N. Rana, "Comparison of various biometric methods," *International Journal of Advances in Science and Technology (IJAST)*, vol. 2, pp. 24–30, March 2014.

[19] F. Yousefi, "Analysis of methods for finger vein recognition," M.S. thesis, Dept. Medical Informatics., Middle East Technical University, Ankara, Turkey, November 2013.

[20] R. S. Al-Khafaji and M. S. Al-Tamimi, "Vein biometric recognition methods and systems: A review," *Advances in Science and Technology Research Journal*, vol. 16, issue 1, 2022.

[21] C. Kauba, M. Drahansky, M. Novakova, A. Uhl, and S. Rydlo, "Three-dimensional finger vein recognition: A novel mirror-based imaging device," *Journal of Imaging*, vol. 8, issue 5, p. 148, 2022.

[22] Z. Liu, Y. Yin, H. Wang, S. Song, and Q. Li, "Finger vein recognition with manifold learning," *Journal of Network and Computer Applications*, vol. 33, pp. 275–282, 2010.

[23] A. H. Mohsin, A. A. Zaidan, B. B. Zaidan, *et al.*, "Finger vein biometrics: taxonomy analysis, open challenges, future directions, and the recommended solution for decentralized network architectures," *IEEE Access*, vol. 8, pp. 9821–9845, January 2020.

[24] Practical application of finger vein authentication technology. [Online]. Available: https://dbnst.nii.ac.jp/english/detail/1916

[25] Hitachi, *Hitachi Develops Finger Vein Authentication Technology for Steering Wheels*, October 25, 2007.

[26] N. Tiwari, "An overview and analysis based on biometric framework technique and fingerprint biometric technology," *International Journal of Scientific Research in Computer Science and Engineering*, vol. 5, issue 6, pp. 69–74, 2017.

[27] X. J . Meng, G. P. Yang, Y. L. Yin, and R. Y. Xiao, "Finger vein recognition based on local directional code," *Sensors*, vol. 12, no. 11, pp. 14937–14952, 2012.

[28] Retail systems. [Online]. Available: http://www.retailsystemspl.com.au

[29] S. Xie, L. Fang, Z. Wang, Z. Ma, and J. Li, "Review of personal identification based on near-infrared vein imaging of finger," in *Proc. the 2017 2nd International Conference on Image, Vision, and Computing (ICIVC)*, Chengdu, China, pp. 206–213, 2017.

[30] M. Khalil-Hani and P. C. Eng, "FPGA-based embedded system implementation of finger vein biometrics," presented at IEEE Symposium on Industrial Electronics and Applications (ISIEA), 2010.

[31] Z. Liu and S. Song, "An embedded real-time finger-vein recognition system for mobile devices," *IEEE Transactions on Consumer Electronics*, vol. 58, issue 2, pp. 522–527, 2012.

[32] Hitachi LTD, "Finger vein authentication," White Paper, pp. 1–4, 2006.

[33] J. Yang and Y. Shi, "Finger–vein ROI localization and vein ridge enhancement," *Pattern Recognition Letters*, vol. 33, pp. 1569–1579, 2012.

[34] K. Wang, A. S. Khisa, X. Q. Wu, and Q. S. Zhao, "Finger vein recognition using LBP variance with global matching," in *Proc. the Wavelet Analysis and Pattern Recognition (ICWAPR), 2012 International Conference*, Guangdong, China, pp. 196–201, 2012.

[35] H. Qin, S. Li, A. C. Kot, and L. Qin, " Quality assessment of the finger-vein image," in *Proc. the 2012 Asia Pacific Signal & Information Processing Association Annual Summit and Conference (APSIPA ASC)*, Hollywood, CA, USA, pp. 1–4, 2012.

[36] S. J. Xie, B. Zhou, J. Yang, Y. Lu, and Y. Pan, "Novel hierarchical structure-based finger vein image quality assessment," *Biometric Recognition,* Cham, Switzerland: Springer, 2013, pp. 266–273.

[37] H. Qin and M. A. El-Yacoubi, "Finger-vein quality assessment by representation learning from binary images," in *Proc. the International Conference on Neural Information Processing*, Istanbul, Turkey, 2015, Springer, pp. 421–431.

[38] Z. Huang, W. Kang, Q.Wu, J. Zhao, and W. A. Jia, "Finger vein identification system based on image quality assessment, " in *Proc. the Chinese Conference on Biometric Recognition*, Chengdu, China, 2016, Springer:, pp. 244–254.

[39] S. Brindha, "Finger vein recognition," *Int. J. Renew. Energy Technol*., vol. 4, pp. 1298–1300, 2017.

[40] V. Ramya and P. V. Kumar, "A novel design of finger vein recognition for personal authentication and vehicle security," *Journal of Theoretical and Applied Information Technology*, vol. 65, 2014.

[41] A. N. Hoshyar and R. Sulaiman, "Review on finger vein authentication system by applying neural network," in *Proc. the 2010 International Symposium on Information Technology (ITSim)*, 2010, pp. 1020–1023.

[42] D. Ezhilmaran and P. R B. Joseph, "A study of feature extraction techniques and image enhancement algorithms for finger vein recognition," *International Journal of PharmTech Research CODEN (USA): IJPRIF*, vol. 8, no. 8, pp. 222–229, 2015.

[43] S. J. Xie, Y. Lu, S. Yoon, J. Yang, and D. S. Park, "Intensity variation normalization for finger vein recognition using a guided filter-based single scale retinex," *Sensors*, vol. 15, pp. 17089–17105, 2015.

[44] V. K. Jain and N. Tripathi, "Speech features analysis and biometric person identification in a multilingual environment," *International Journal of Scientific Research in Network Security and Communication*, vol. 6, issue 1, pp. 7–11, 2018.

[45] X. Xi, L. Yang, and Y. Yin, "Learning discriminative binary codes for finger vein recognition," *Pattern Recognition*, vol. 66, pp. 26–33, 2017.

[46] H. C. Lee, B. J. Kang, E. C. Lee, and K. R. Park, "Finger vein recognition using weighted local binary pattern code based on a support vector machine," *J. Zhejiang Univ. Sci. C*, vol. 11, pp. 514–524, 2010.

[47] G. Yang, X. Xi, and Y. Yin, "Finger vein recognition based on (2D) 2 PCA and metric learning," *J. Biomed. Biotechnol*, vol. 2012, 324249, 2012.

[48] A. Hajian and S. Damavandinejadmonfared, "Optimal feature extraction dimension in finger vein recognition using kernel principal component analysis," *Int. J. Comput. Inf. Syst. Control Eng*., vol. 8, no. 9, pp. 1637–1640, 2014.

[49] N. Mantrao and K. Sukhpreet, "An efficient minutiae matching method for finger vein recognition," *Int. J. Adv. Res. Comput. Sci. Softw. Eng*., vol. 5, pp. 657–660, 2015.

[50] W. N. Aziz, I. Abdullah, K. Seman, and N. N. S. Sayuti, "Finger vein minutiae points extraction based on maximum curvature points in image profile and fingerprint application methods," *Aust. J. Basic Appl. Sci*., vol. 7, pp. 751–756, 2013.

[51] V. Davis and S. Devane, "Diagnosis of brain hemorrhage using artificial neural network," *International Journal of Scientific Research in Network Security and Communication*, vol. 5, issue 1, pp. 20–23, 2017.
[52] C. Kauba, J. Reissig, and A. Uhl, "Pre-processing cascades and fusion in finger vein recognition," in *Proc. the 2014 International Conference of the Biometrics Special Interest Group (BIOSIG)*, 2014, pp. 1-6.
[53] S. Kharabe and C. Nalini, "Survey on finger-vein segmentation and authentication," *International Journal of Engineering & Technology*, vol. 7, no. 12, pp. 9–14, 2018.
[54] S. Kharabe and C. Nalini, "Robust ROI localization-based finger vein authentication using adaptive thresholding extraction with deep learning technique," *Jour of Adv Research in Dynamical & Control Systems*, vol. 10, 2018.
[55] S. Xie, L. Fang, Z. Wang, Z. Ma, and J. Li, "Review of personal identification based on near-infrared vein imaging of finger," in *Proc. the 2017 2nd International Conference on Image, Vision, Computing (ICIVC)*, 2017, pp. 206–213.
[56] M. Jadhav and PM. Nerkar, "FPGA-Based finger vein recognition system for personal verification," *International Journal of Engineering Research and General Science*, vol. 3, issue 4, pp. 382–388, 2015.
[57] Y. Zhou and A. Kumar, "Human identification using palm-vein images," *IEEE Trans. Inf. Forensics Secure*., vol. 6, no. 4, pp. 1259–1274, Dec. 2011.
[58] R. D. Prasanna, P. Neelamegam, S. Sriram, and N. Raju, "Enhancement of vein patterns in hand image for biometric and biomedical application using various image enhancement techniques," *Procedia Eng.*, vol. 8, pp. 1174–1185, Jan. 2012.
[59] P. Ramsoful and M. H.-M. Khan, "Feature extraction techniques for dorsal hand vein pattern," in *Proc. Third Int. Conf. Innov. Comput. Technol. (INTECH 2013)*, Aug. 2013, pp. 49–53.
[60] N. Mahri, S. A. S. Suandi, and B. A. Rosdi, "Finger vein recognition algorithm using phase-only correlation," in *Proc. 2010 International Workshop on Emerging Techniques and Challenges for Hand-Based Biometrics (ETCHB)*, IEEE, 2010.
[61] I. Rossan and M. H.-M. Khan, "Impact of changing parameters when preprocessing dorsal hand vein pattern," *Procedia Comput. Sci*., vol. 32, pp. 513–520, 2014.
[62] P. Prabhakar and T. Thomas, "Finger vein identification based on minutiae feature extraction with spurious minutiae removal," in *Proc. 2013 Third Int. Conf. Adv. Comput. Commun.*, pp. 196–199, Aug. 2013.
[63] Y. Lu, S. J. Xie, S. Yoon, and D. S. Park, "Finger vein identification using poly directional local line binary pattern," in *Proc. 2013 Int. Conf. ICT Converg*., pp. 61–65, Oct. 2013.
[64] Y. Ding, D. Zhuang, and K. Wang, "A study of hand vein recognition method," in *Proc. IEEE International Conference Mechatronics and Automation*, 2005, vol. 4, pp. 2106–2110, 2005.
[65] C.-B. Yu, H. Qin, L. Zhang, and Y.-Z. Cui, "Finger-vein image recognition combining modified Hausdorff distance with minutiae feature matching," *J. Biomed. Sci. Eng.*, vol. 02, no. 04, pp. 261–272, 2009.
[66] X. Gu, "A method for hand vein recognition based on Curvelet Transform phase feature," in *Proc. 2011 Int. Conf. Transp. Mech. Electr. Eng.*, Dec. 2011, pp. 1693–1696.
[67] G.-T. Park and S.-W. Kim, "Embedded processor optimized for vascular pattern recognition," *IET Circuits, Devices Syst*., vol. 7, no. 2, pp. 81–92, Mar. 2013.
[68] J. Uriarte-Antonio, D. Hartung, J. E. S. Pascual, and R. Sanchez-Reillo, "Vascular biometrics based on a minutiae extraction approach," in *Proc. 2011 Carnahan Conference on Security Technology*, pp. 1–7, 2011.
[69] J.-W. Wang and T.-H. Chen, "Building palm vein capturing system for extraction," in *Proc. 2011 21st Int. Conf. Syst. Eng.*, pp. 311–314, Aug. 2011.
[70] C. Liu, "A new finger vein feature extraction algorithm," in *Proc. 2013 6th Int. Conf. Image Signal Process*., *(Cisp)*, pp. 395–399, Dec. 2013.
[71] Z. Wu, Y. Zhou, X. Hu, M. Zhou, X. Dai, X. Li, and D. Wang, "A vein image enhancement algorithm for the multi-spectral illumination," in *Proc. 2013 IEEE Int. Conf. Imaging Syst. Tech*., pp. 332–336, Oct. 2013.
[72] S. Hongxing, L. Wang, and W. Jiayi, "Hand vein recognition technology based on region code," in *Proc. 2013 Int. Conf. Mechatron. Sci. Electr. Eng. Comput.*, pp. 1212–1215, Dec. 2013.
[73] Y.-P. Hu, Z.-Y. Wang, X.P. Yang, and Y.-M. Xue, "Hand vein recognition based on the connection lines of reference point and feature point," *Infrared Phys. Technol*., vol. 62, pp. 110–114, Jan. 2014.
[74] L. You, X. Li, L. Sun, and F. Li, "Finger vein recognition method based on gaussian low-pass filter and direction detection," in *Proc. 2014 Int. Conf. Inf. Commun. Technol. (ICT 2014)*, 2014.
[75] A. Kumar and Y. Zhou, "Human identification using finger images," *IEEE Transactions on Image Processing*, 2012, vol. 21, pp. 2228–2244.
[76] J. Yang, Y. Shi, and R. Wu, "Finger-vein recognition based on Gabor features," *Biom. Syst. Des. Appl*., pp. 17–32, 2011.
[77] G. S. Babu, N. D. Bobby, M. A. Bennet, B. Shalini, and K. Srilakshmi, "Multistage feature extraction of finger vein patterns using Gabor filters, " *Iioab J.*, vol. 8, pp. 84–91, 2017.
[78] N. Miura, A. Nagasaka, and T. Miyatake, "Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification," *Machine Vision and Applications*, vol. 15, pp. 194–203, 2004.
[79] D. Mulyono and H. S. Jinn, "A study of finger vein biometric for personal identification," in *Proc. 2008 2008 International Symposium on Biometrics and Security Technologies, IEEE,* 2008.
[80] S. Nivas and P. Prakash, "Real-time finger-vein recognition system, " *Int. J. Eng. Res. Gen. Sci*, vol. 2, pp. 580–591, 2014.
[81] F. E. Mohammed, E. M. Aldaidamony, and A. M. Raid, "Multi modal-biometric identification system: Finger vein and iris," *Int. J. Soft Comput. Eng*, vol. 4, pp. 50–55, 2014.
[82] I. Malik, R. Sharma, and M. J. Mir, "Finger vein pattern matching for human identification," *International Journal of Engineering Research &Technology (IJERT)*, vol. 3, issue 2, February 2014.
[83] J. D. Wu and C. T. Liu, "Finger-vein pattern identification using SVM and neural network Technique," *Expert Syst. Appl.*, vol. 38, pp. 14284–14289, 2011.
[84] N. Hu, H. Ma, and T. Zhan, "Finger vein biometric verification using block multi-scale uniform local binary pattern features and block two-directional two-dimension principal component analysis," *Computer Science, Optik*, vol. 208, 163664, 2020.
[85] J. Zhang, C. Li, Y. Yin, J. Zhang, and M. Grzegorzek, "Applications of artificial neural networks in microorganism image analysis: A comprehensive review from conventional multilayer perceptron to popular convolutional neural network and potential visual transformer," *Artificial Intelligence Review*, pp. 1–58, 2022.
[86] R Qian, X Lai, and X Li, "3D object detection for autonomous driving: A survey," *Pattern Recognition*, vol. 130, 108796, 2022.
[87] J. Zhang, C. Li, S. Kosov, M. Grzegorzek, K. Shirahama, *et al*., "Lcu-net: A novel low-cost u-net for environmental microorganism image segmentation," *Pattern Recognition*, vol. 115, 107885, 2021.
[88] U. B. Ghosh, R. Sharma, and A. Kesharwani, "Symptoms-based bio-metric pattern detection and recognition," *Augmented Intelligence in Healthcare: A Pragmatic and Integrated Analysis*, Springer, 2022.
[89] S. A. Radzi, M. Khalil-Hani, and R. Bakhtiari, "Finger vein biometric identification using convolutional neural network," *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 24, pp. 1863–1878, 2016.
[90] K. S. Itqan, A. R. Syafeeza, M. M. Ibrahim, *et al*., "User identification system based on finger-vein patterns using convolutional neural network," *ARPN J. Eng. Appl. Sci*, vol. 11, pp. 3316–3319, 2016.
[91] H. G. Hong, M. B. Lee, and K. R. Park, "Convolutional neural network-based finger-vein recognition using NIR image sensors," *Sensors*, vol. 17, p. 1297, 2017.
[92] H. Huang, S. Liu, H. Zheng, L. Ni, L, Y. Zhang, and W. Li, "Deep vein: novel finger vein verification methods based on deep convolutional neural networks," in *Proc. the 2017 IEEE International Conference on Identity, Security and Behavior Analysis (ISBA)*, 2017, pp. 1–8.
[93] C. Xie and A. Kumar, "Finger vein identification using convolutional neural network and supervised discrete hashing," *Deep Learning for Biometrics*, Switzerland: Springer, pp. 109–132, 2017.

[94] R. Das, E. Piciucc, E. Maiorana, and P. Campisi, "Convolutional neural network for finger-vein-based biometric identification," *IEEE Trans. Inf. Forensics Secure*, vol. 14, pp. 360–373, 2019.
[95] M. Madhusudhan, V. U. Rani, and C. Hegde, "Finger vein recognition model for biometric authentication using intelligent deep learning," *International Journal of Image and Graphics*, 2240004, 2021.
[96] W. Yang, C. Hui, Z. Chen, J. Xue, and Q. Liao, "FV-GAN: Finger vein representation using generative adversarial networks," *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 9, pp. 2512–2524, Sept. 2019.
[97] B. Hou and R. Yan, "Triplet-classier gan for finger-vein verification," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–12, 2022.
[98] P. Gowtham, C. C. Sekar, *et al*., "Identification of finger images using score-level fusion," *International Journal of Engineering Science Invention*, vol. 2, issue. 2, pp. 12–23, February 2013.
[99] D. Wang, J. Li, and G. Memik, "User identification based on finger vein patterns for consumer electronics devices," *IEEE Transactions on Consumer Electronics*, vol. 56, no. 2, pp. 799–804, 2010.
[100]E. C. Lee, H. Jung, and D. Kim, "New finger biometric method using near-infrared imaging," *Sensors* 2011, vol. 11, pp. 2319–2333, 2011.
[101]J. Yang and Y. Shi, "Towards finger-vein image restoration and enhancement for finger-vein recognition," *Inf. Sci*, vol. 268, pp. 33–52, 2014.
[102]Y. Yin, L. Liu, and X. Sun, "SDUMLA-HMT: A multimodal biometric database," in *Proc. the Chinese Conference on Biometric Recognition*, December 2011, pp. 260–268.
[103]X. Qiu, W. Kang, S. Tian, W. Jia, and Z. Huang, "Finger vein presentation attack detection using total variation decomposition," *IEEE Trans. Inf. Forensics Secure*, vol. 13, pp. 465–477, 2018.
[104]B. T. Ton and R. N. J. Veldhuis, "A high-quality finger vascular pattern dataset was collected using a custom-designed capturing device," in *Proc. the 2013 International Conference on Biometrics*, vol. 2013, pp. 1–5, 2013.
[105]Y. Lu, S. J. Xie, S. Yoon, Z. Wang, and D. S. Park, "An available database for the research of finger vein recognition," in *Proc. the 2013 6th International Conference on Image and Signal Processing (CISP)*, 2013, pp. 410–415.
[106]Tsinghua University Finger Vein and Finger Dorsal Texture Database (THU-FVFDT). [Online]. Available: https://www.sigs.tsinghua.edu.cn/labs/vipl/thu-fvfdt.html
[107]FV-USM finger vein image database. [Online]. Available: http://drfendi.com/fv_usm_database
[108]W. Yang, X. Huang, F. Zhou, and Q. Liao, "Comparative competitive coding for personal identification by using finger vein and finger dorsal texture fusion," *Inf. Sci*, vol. 268, pp. 20–32, 2014.
[109]K. A. Akintoye, M. R. M. Shafry, and H. Abdullah, "A novel approach for finger vein pattern enhancement using gabor and canny edge detector," *Int. J. Comput. Appl*, vol. 157, pp. 16–20, 2017.
[110]VERA Finger Vein Data Base. [Online]. Available: https://www.idiap.ch/dataset/vera-fingervein
[111]M. Vanoni, P. Tome, L. E. Shafey, and S. Marcel, "Cross-database evaluation using an open finger vein sensor," in *Proc. the 2014 IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS)*, 2014, pp. 30–35.
[112]Salzburg University, "PLUS Vein-FV3 LED-laser dorsal-palmar finger vein database," Salzburg, Austria, 2018.
[113]R. Raghavendra and C. Busch, "Presentation attack detection algorithms for finger vein biometrics: A comprehensive study," in *Proc. the 2015 11th International Conference on Signal-Image Technology& Internet-Based Systems (SITIS)*, 2015, pp. 628–632.
[114]P. Tome, R. Raghavendra, *et al.*, "The 1st competition on countermeasures to finger vein spoofing attacks," in *Proc. of the 2015 International Conference on Biometrics (ICB)*, 2015, pp. 513–518.
[115]H. Ding, "Anti-Spoofing a finger vascular recognition device with pulse detection," *Computer Science*, 2016
[116]D. T. Nguyen, H. S. Yoon *et al.*, "Spoof detection for finger-vein recognition system using NIR camera," *Sensors*, 2017, vol. 17, p. 2261.
[117]S. Marcel, M. S. Nixon, J. Fierrez, and N. Evans, *Handbook of Biometric Anti-Spoofing: Presentation Attack Detection*, 2nd ed. 2019.
[118]D. T. Nguyen, Y. H. Park, *et al.*, "Fake finger-vein image detection based on Fourier and wavelet transforms," *Digit. Signal Process*, vol. 23, pp. 1401–1413, 2013.
[119]A. Uhl, C. Busch, S. Marcel, and R. Veldhuis, *Handbook of Vascular Biometrics*, 1st ed. 2020.
[120]R. Raghavendra, M. Avinash, S. Marcel, and C. Busch, "Finger vein liveness detection using motion magnification," in *Proc. 2015 IEEE 7th International Conference on Biometric Theory, Applications and Systems (BTAS)*, Sep 2015, pp. 1–7.
[121]Y. Lu, S. Yoon, S. J. Xie, S. J. Yang, Z. Wang, and D. S. Park, "Finger vein recognition using generalized local line binary pattern," *KSII Trans. Internet Inf. Syst.*, vol. 8, pp. 1766–1784, 2014.

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