https://doi.org/10.48047/AFJBS.6.12.2024.1601-1610

AFJBS African Journal of Biological Sciences
Journal homepage: http://www.afjbs.com
Research Paper Open Access

Verification of finger veins Recognition using deep and machine learning techniques: A Survey

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Article History
Volume 6 Issue 12, 2024
Received: 25 May 2024
Accepted : 30 June 2024
doi:
10.48047/AFJBS.6.12.2024.1601-1610

Abstract
Biometric recognition relies importantly on finger vein image recognition technology, which has been effectively implemented in many fields. Because veins are hidden beneath the surface of the skin, finger vein image recognition offers the unique advantage of resisting interference from external sources. This review paper is considered the most recent among its peers, as this paper is unique in discussing the details of research published between the years 2020 and 2023 in terms of the methods used in previous studies on the stages of pre-processing, feature extraction, and classification using machine learning methods and deep learning techniques. In addition, it explains the difficulties, advantages and disadvantages of this biometric technology.
Keywords: biometrics; finger vein recognition; machine learning; deep learning

Introduction

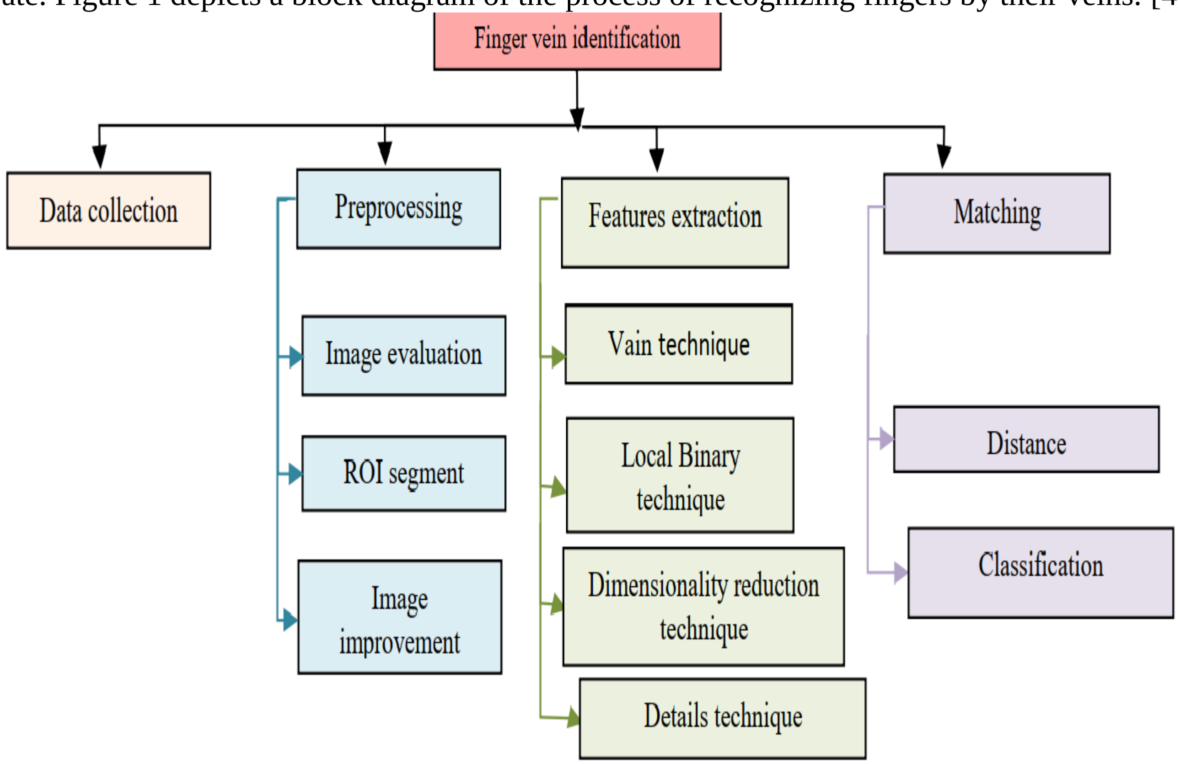
Biometrics is simply the estimation and measurement of the body concerning human characteristics. In computer science, biometric verification is used as a requirement for recognition or identification, as well as approach control. This method is also used to identify a single person in groups that are being watched. Biometric modifiers are specific, quantifiable characteristics used to describe each individual. Realistic identifiers are frequently classified as corporal characteristics related to body appearance. Genuine The utilization of biometric technology is specialized by its specific application. Biometrics that are determined will have a superior performance compared to other security systems. Biometrics is a field that is popular at the moment. Because it's still in the early stages of development compared to other biometric fields, the information that's already been conducted is limited. The benefits of using the veins of the fingers as biometrics are sufficient and constitute the primary impetus for applying this technology. Initially, it's a biometric trait that is difficult to imitate, the primary function is to emit infrared light into the finger and record the shape of the finger's veins via a camera. It's common knowledge that the shape of the human finger's veins is singular, which makes the finger's veins an exceptional means of identification. Other benefits of the unique attribute of the finger's veins is that it can be achieved through any finger's vent, the patterns are permanent, which means that they do not change over time and can be measured without causing any pain to the subject. The trait of having seven factors is partially fulfilled by the finger's vein. that describe the potential usefulness of a biometric trait to authenticate identity: first the Universality, second the Uniqueness, third the Permanence, fourth the Measurability, fifth the Performance, and seventh the Circumvention. As a result, the finger's vein has become biometrically significant due to the aforementioned advantages. This has led to the majority of researchers wanting to study the field.

Since the decade preceding this one, the biometric method of recognition based on vascular patterns has been of great interest to researchers and technologists. The most common pattern of vascularity is the finger-vein. A biometric system that uses a finger's patterns of veins is called a finger-vein system. This system is specifically designed to take pictures of the patterns of veins. Table [1] will discuss the benefits and drawbacks of each biological feature in different areas. [3].

Table1 . Properties of different biometric authentication types.[3]

Type	Characteristics	Weakness	Security	Sensor device	Cost
Voice	Natural/comfortable	Noise/ Diseases	Normal	No contact with the image device	Low
Face	Remote control/ comfortable	Light	Normal	with imaging device	Low
Fingerprint	Extensively used/ comfortable	Skin diseases	Good	Contact required	low
Iris	High accurate/comfortable	Eyeglasses	Excellent	No contact with the image device	High
Finger vein	High accurate/comfortable	Few	Excellent	with imaging device	Low

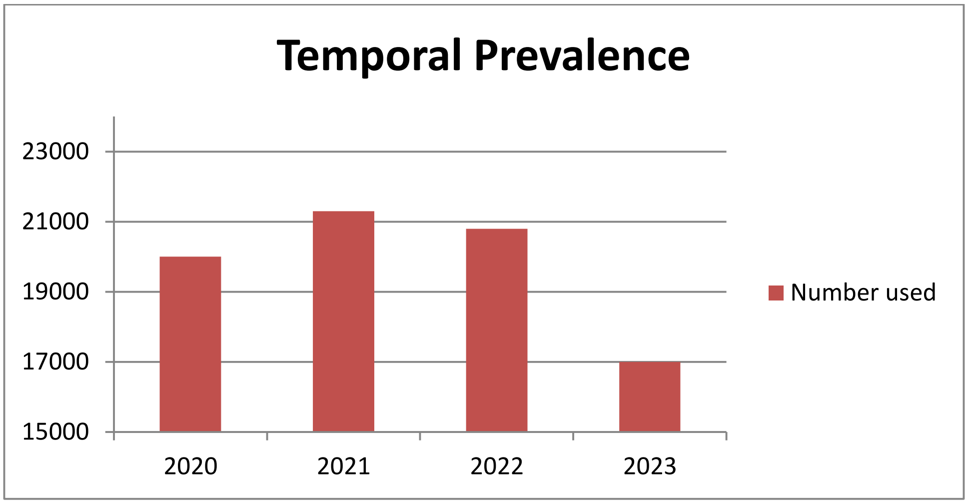
A system of identification by the finger's veins offers a dependable process that is safe, simple and highly accurate. Figure 1 depicts a block diagram of the process of recognizing fingers by their veins. [4].



Figure(1). Block diagram of finger vein recognition[4]

Temporal Prevalence of Finger Vein Technique

The technology of identifying people by detecting a finger vein has witnessed widespread and increasing use. It has been referred to and used in scientific research, especially for the period from 2020 to 2023, and this can be inferred by searching on the Google Scholar website. As shown in Figure (2).

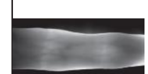
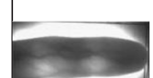
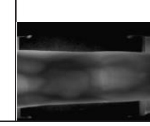


Figure(2). Temporal Prevalence

Finger Veins Dataset

As Table 2 illustrates, there are numerous publicly accessible finger vein databases. These databases aren't regarded as typical databases for finger vein applications, though. Except for the UTFV database, which only has samples for 60 subjects, these databases offer samples for over 100 subjects. A significant amount of noise exists in some of the low-quality samples that are provided. Furthermore, a few of the samples are severely misaligned or skewed. As a result, certain databases might be appropriate for a given application while others might not. A person's finger is often guided during the entire fingerprint capture procedure in any fingerprint capture device. Similarly to this, there is a designated area for placing a finger in the finger-vein-capturing device. As a result, the skewed or misaligned finger vein images provided by publicly accessible databases are meaningless, and there’s no significant reason to use them [5].

Table2. Finger Veins Datasets Details [5]

Database	**No ofimages**	**No ofSubject**	**er Number perSubject**	**nage Number perFinger**	**Imageresolution**	**Format**	**TypicalImage**	**Number of mentions and uses**
THU-FVFDT1	440	220	1	1	720x576pxl(raw)	.BMP		7
UTFV	1440	60	ndex,ring,middle,of bothhands)	4	672x380pxl	8-bitgray scale .PNG		74
MMCBNU_6000	6000	100	ndex,ring,middle,of bothhands)	10	480x640pxl	.BMP		132
HKPU-FV	6264	156	ıdex,ring,middleofl efthand)	12/6*	513x256pxl	.BMP		55
SDMULA-HMT	3816	106	ndex,ring,middle,of bothhands)	6	320x240pxl	.BMP		10

VERA	440	110	2 (left index and right index)	2	665×250 pxl	.Png		70
PLUSVein-FV3	1800	60		5	736×192 pxl	.Png		44

The Main Stages of Finger Vein Detection

During the acquisition of images, FV images are recorded using a device that acquires images. These images are influenced by multiple factors, including blood pressure, body temperature, and environmental effects. Pre-processing is employed to enhance the quality of images. Pre-processing involves the extraction of regions of interest (ROI) from images, the removal of the image's background and the enhancement of the images. Feature extraction is critical to the authentication process. In this phase, several properties, including edges and curves, are derived from FV images using descriptors, such as the maximum curvature method or local binary patterns (LBPs) [6]. The final component is user verification, which involves following the same procedure but with an extra step: matching. During this process, the pattern that was received from the enrollment location and the pattern that was stored in the system's database are compared to determine if the user is genuine or an imposter. The process of verifying users is demonstrated in Figure4.

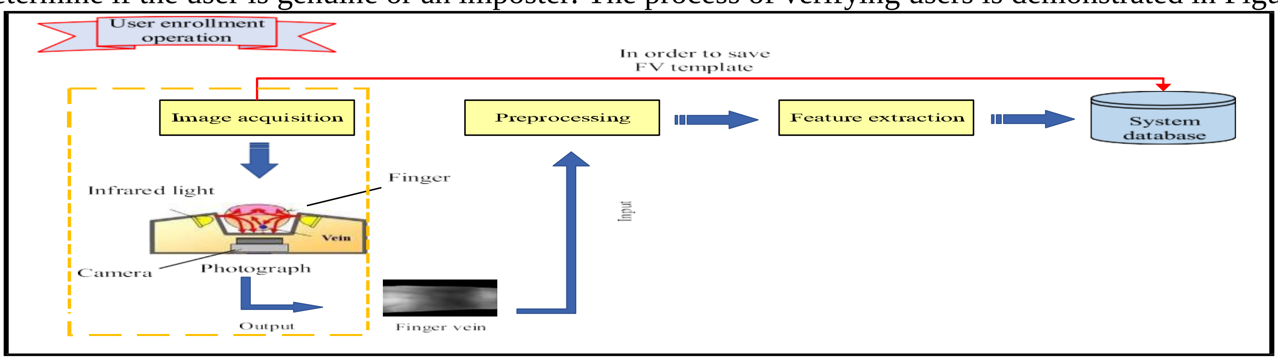


Figure 3. Userenrolmentoperation.[6]

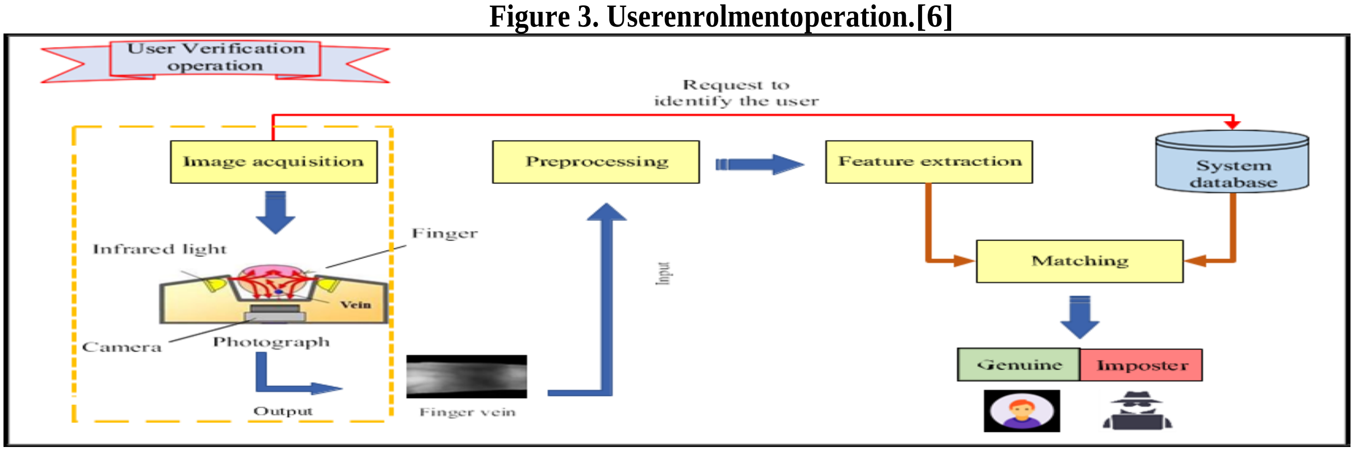


Figure 4.Userverificationoperation[6]

Literature Studies

In this section, literary studies that aimed to identify the finger vein will be discussed and will be divided into two parts, works that used machine learning methods and deep learning techniques.

A. Literary Papers using Machine Learning Methods

In 2021, they demonstrated an impostor detection system based on the Support Vector Machine (SVM) algorithm, they then discussed the preprocessing of the data, the extraction of features using Linear

Discriminant Analysis (LDA), and the evaluation of the system using k-fold validation. The (UTFV) dataset and (SDUMLA-HMT) Dataset are the two datasets that contain these measurements. Support Vector Machine (SVM) was the classifier that produced the results, with an accuracy of 93.17%.

In 2023, they utilized PCA (principal component analysis) to pattern the veins and SVM (support vector machine) to categorize. The process is entirely based on the different qualities of pattern that the vein exhibits. The most effective optimal design was employed in creating the efficient framework. They're utilizing the three publicly accessible datasets, THU-FVFDT2, SDUMLA-HMT, and FV-USM. The average outcome is 92.89[7].

In 2022, they released a fully automated, unsupervised learning strategy (K-mean) for creating training data. The procedure is intended to isolate and create a decent training dataset for the binary mask method SDUMLA-HMT was employed automatically. In this method, two optimization processes are designed and employed. The first step of optimization is to create an automated, unsupervised image classification system based on the finger's veins. In the second optimization, the lines of finger's veins that areretrieved are optimized. Ultimately, the proposed system has a pattern recognition accuracy of 99.6% [8].

In 2022, the proposed method will involve two steps of optimization that will lead to the automated extraction of finger patterns based on learned behavior. The initial level of optimization involves creating a completely automated, unsupervised finger vein image localization utilizing an efficient image clustering technique. The second optimization stage involves creating a Global Pattern optimization (GPO) based on the extraction, indication, and optimization of finger's veins, The database of finger's veins (SDUMLA-HMT) was employed. The proposed system attained a 99.6% success rate.

In 2021, they proposed a method of recognizing fingers based on the robust association of key points. A method that uses a scale-invariant feature transform (SIFT) as the base recognizer is employed. Next, a MIMO structure with multiple inputs and multiple outputs (MIMO) is designed based on the different physical properties of the finger's veins in order to increase the potential matches. After that, the integration of each pair of correspondence that is matched (e.g., the combination of two images) is clustered; the information regarding deformation is utilized to do so. This is accomplished by a novel technique of simulatingclustering. Ultimately, the matching score is calculated as the number of pairs of matching scores after clustering: this is the number of pairs that are considered. Large experiments on HKPU and FV-SDUMLA-HMT's open data base demonstrate the effectiveness of the proposed method, the average success rate is 98.72%. [10].

In 2020, they released PCANet as a means to extract features. Factors that affect PCANet are evaluated in order to recognize the shortcomings of PCANet. The classifier employed in FVRS is a k-nearest-neighbor with a Euclidean distance. The outcomes returned indicate that the performance of PCANet is not easily affected by the variability within classes and the limited training datasets. Meanwhile, the investigation observed the difficulty in recognizing the age as increasing. The performance of the evaluated dataset (FV) is 92.67% with the utilization of PCANet.

In 2022, they released two FVR proposals that used FV quality metrics and an enhancement algorithm. Initially, features like contrast, entropy and information capacity were derived from images of finger's veins. Next, the quality of the image is assessed by the KNN with the r-smote technique to differentiate between High Quality (HQ) and Low Quality (LQ) images. Second, a new method of enhancing images called guided filter and bilateral filter (GFBF) is employed to augment the low quality FV images. Afterward, they assess the effectiveness of the enhancement method by utilizing SSIM and PSNR. Review the proposed system's effectiveness in terms of accuracy, for both Classifier and Recognition performance, respectively, on a (complete dataset) of 1052 FV images. The experimental results completed demonstrated that the proposed method of image assessment and enhancement was superior to other schemes by having a recognition accuracy of 93%.

In 2021, they developed a practical framework for recognizing fingers via the hybrid Local Phase Quantization (LPQ) for obtaining effective features, and the Grey Wolf optimization-based SVM (GWO-SVM) to determine the optimal combination of SVM for maximized results in the classification of binary

data. First, the features derived from the finger's veins are extracted by combining the LPQ, which is insensitive to motion blur and deformation, with the Local Directional Pattern (LDP), which is resistant to random noise and illumination changes, both of these are combined to increase the recognition rate and reduce the computational time. Next, GWO-SVM is employed for classification in order to maximize the accuracy of their classification by determining the optimal parameters of SVM. The four tested finger vein datasets(HKPU), (SDUMLA), (FV-USM) and (THU-FVDT2). It had a recognition rate of 98% [13].
In 2022, they employed a deep forest (D.P) algorithm to process the finger-vein images. Initially, the data regarding the finger's veins in the database of images is preprocessed in order to prepare for the following feature extraction and comparison. Next, the deep forest algorithm is employed to locate the feature points, and the ORB algorithm is employed to associate the features with their respective angles, the information regarding the final identity is then gained via the sparse distribution of angles. The reliability of the (SDUMLA) dataset, based on the deep forest algorithm, was 98.40%. The following table will explain and summarize the most important aspects of the discussion in question using machine learning methods..

Table.3 Details of the papers used for the machine learning method

NO.	Ref. Year	Dataset	Technique	result
1	**[4], 2021**	**UTFV) dataset and (SDUMLA-HMT**	SVM	93.17%
2	**[7], 2023**	**THU-FVFDT2, SDUMLA-HMT, and FV-USM**	SVM	92.89%
3	**[8],2022**	**SDUMLA-HMT**	K-mean	99.6%
4	**[9] , 2022**	**SDUMLA -HMT**	GPO	99.6%
5	**[10] , 2021**	**HkPU and FV-SDUMLA-HMT**	MIMO	98.72%
6	**[11] ,2020**	**collected (FV)**	KNN	92.67%
7	**[12] ,2022**	**collected (FV)**	KNN	93%
8	**[13] , 2021**	**HKPU,SDUMLA,FV-USM and THU-FVDT2**	GWO-SVM	98%
9	**[14] ,2022**	**SDUMLA**	D.P	98.40

B. Literary Papers using Deep Learning Methods

In 2021, they developed a general model for recognizing fingers via the vein in a general way called the Deep Generalized Labeling Algorithm for Finger Vein Recognition (DGLFV), this had a high degree of success and practical value. Apply a complex algorithm for extracting masks that is based on the Mask-RCNN method to obtain accurate masks, both for classes that are already known and classes that are not. Next, a more complex method of bidirectional travel and centered diffusion is proposed to acquire a fingertip ROI. For classes that are not observed, this model employs a deep neural network to instruct them on how to utilize a large database of images and achieve active recognition. A recognition algorithm based on Softmax was developed to determine the boundaries of validation for each class. Through experiments on FV-SIPL and SDUMLA-HMT databases, the identification average accuracy of DGLFV reached 99.1% [15].
In 2022, they developed a method for The identification process that involves the extraction of ROI and the training of CNNs. This paper employs a ROI method to locate the area that is to be identified. The brightness of the image varies depending on the device and the environment, so the visualized image of the ROI is altered using parametric-based histogram equalization (POHE) and contrast-limited adaptive equalization (CLAHE) to enhance and maintain the character of the vein. The system employs DL to associate user's veins with images of their registered counterparts in the database, it then outputs the results of the identification. The proposed method of edge detection takes into account the detected fingers' rotational and translational behavior as well as the interference of external light and other factors. This research also determines the value of preprocessing methods towards the system's effectiveness. The

experimental results demonstrate that the proposed system has an average accuracy of 98.5% in various environments, using the FV-USM and SDUMLA-HMT datasets from 16. In 2021, they propose a system that employs CNNs and utilizes the triplet loss function along with a hard triplet criterion for the recognition of finger's veins. The CNNs are employed for three different purposes, the classical recognition purpose, which involves considering every finger of a subject as a separate class, the similarity of the left and right fingers of the same subject is evaluated, and the similarity of different fingers of the same subject is assessed. Four different datasets were employed (SDUMLA, The University of Twente's Finger Vascular Patterns Database (UTFVP), PLUS, and The Hong Kong Polytechnic University's Finger Image Database (HKPU). The outcomes demonstrate that the proposed nets have an average effectiveness of 79.125%.

In 2023, a multi-scale feature-based network (MSFBF-Net) was created. The network model first extracts the global characteristics and local specific details of the finger's veins, then it performs a linear combination to create a more informative second-order feature. Next, the convolutional layer that is depth-wise separated replaces the ordinary layer, this eliminates the computational complexity of the network model greatly. Ultimately, a multiple attention mechanism (MAM) was developed that is appropriate for the finger's veins, this mechanism can simultaneously acquire the channel, space, direction, and position information. The experimental results that were applied to two different data sets (SDUMLA and FV-USM) indicate that the average accuracy of the two public finger vein datasets is 99.86 [18].

In 2022, they proposed that the finger's veins be imaged in blocks to calculate the average value, the proposed method will calculate the matrix after Blocking and Averaging, then the Centro-symmetric coding will take place using the generated matrix. The obtained code words were combined as the individual feature words of the image. The similarity of vein codes is determined by the ratio of the minimum distance of Hamming to the length of the code. This method is referred to as (BACS-LBP). The experiments on two public finger database instances, HKPU and USM, demonstrate the proposed methodology. The average outcome was 98.6% [19].

In 2021, they proposed a new model of Deep Learning (DL) called the Re-enforced Deep Learning (RDL). This method offers a new way of personally verifying one's identity using the Finger Veins (FVs). The RDL is composed of multiple layers that have feedback. Two fingers are used per person; the first personal verification uses the index finger's FV, and the middle finger's FV is employed for additional verification. The employed database is derived from the Hong Kong Polytechnic University Finger Image (PolyUFI) database. The outcome demonstrates that the proposed RDL had a successful performance of 91.19% [20].

In 2023, they proposed a deep learning method that is intended to address the SSPP problem of recognizing fingers and veins, multiple feature maps were created from a input image of a finger and its associated veins, these maps were derived from different deep learning-based classifiers.A shared learning scheme is studied among classifiers in order to augment their ability to represent features in a captive manner. The speed of learning for weak classifiers is also altered to maximize performance. A complex learning model is built by combining all of these altered classifiers. The proposed approach is evaluated with two publicly accessible finger vein datasets (HKPU and FV-USM). The average outcome is 93.15% [21].

In 2023, their research will concentrate on a Near-Infra-Red (NIR)-based biometric system that utilizes both Finger Texture and Finger Vein. The individual results of the biometric traits are aggregated using a fuzzy system, and the final identification result is achieved. Experiments are conducted for three different data sources, which are the Near-Infra-Red Hand Images (NIRHI), the Hong Kong Polytechnic University (HKPU) and the University of Twente Finger Vein Pattern (UTFVP) data sources. Initially, the Finger Texture biometric employs a textured feature extraction algorithm that is efficient, for example, Linear Binary Pattern. Next, the classification is conducted using a Support Vector Machine, an algorithm that is already proven in the machine learning field. Second, the transfer of pre-trained convolutional neural networks (CNNs) is accomplished for the Finger Vein biometric, utilizing two different approaches. The three selected CNNs are AlexNet, VGG16 and VGG19. In Approach 1, the images are first fed through a preprocessor that processes the NIR images prior to the training of the CNN. In Approach 2, before the pre-processing step, image brightness optimization is also employed to make the image have a uniform brightness. NIRHI is superior to HKPU and UTFVP in both of the modalities of focus, it is also superior to unimodal setups as well as multimodal ones. The proposed biometric system had an accuracy of 99.62% [22].

In 2022, they employed deep learning and triplet loss functions in the verification of finger veins, the model is trained andvalidated on three different datasets including FV-USM, HKPU, and SDUMLA-HMT. This research's accuracy is said to have been 98% [23].

In 2020, they developed a new deep network that is more efficient, named Merge convolutional neural network (Merge CNN), this network employs several short-circuited CNNs. The scheme is based on the utilization of multiple identical CNNs with identical input image characteristics, and combining their outputs into a single layer. They created different networks and dedicated them to the FV-USM dataset. The most effective CNN design was employed to create our final combined CNN-affined A, which is a hybrid of the original image and an enhanced version with the Contrast Limited Adaptive Histogram (CLAH) method. Using six images to train, the FV-USM database achieved a recognition rate of 96.75% using six images as the input. The proposed methodology had a greater success, with the SDUMLA-HMT database having a recognition rate of 99.48%, when using five images for training. The proposed methodology had a recognition rate of 99.56% for the THU-FVFDT2 database. As a result, they attained an average accuracy of 98.56% [24].

The outcomes and methods mentioned in the literature will be considered and explained, and will appear in a Table. [4].

Table4. Literature SummaryDeep learning technique

No.	Ref. Year	Dataset	Technique	result
1`	**[15], 2021**	**FV-SIPL and SDUMLA-HMT**	RCNN	99.1%
2	**[16] , 2022**	**FV-USM and SDUMLA-HMT**	CNN	98.5%
3	**[17] ,2023**	**SDUMLA, (UTFVP), PLUS, and (HKPU)**	CNN	79.1%
4	**[18], 2023**	**SDUMLA and FV-USM**	MAM	99.86%
5	**[19], 2022**	**HKPU and (USM)**	BACS-LBP	98.6%
6	**[20], 2021**	**PolyUFI**	RDL	91.19%
7	**[21], 2023**	**HKPU and FV-USM**	CNN	93.15%
8	**[22], 2023**	**(HKPU) and (UTFVP)**	CNN	99.62%
9	**[23], 2022**	**FV-USM, HKPU, and SDUMLA-HMT**	CNN	98%
10	**[24], 2020**	**FV-USM, SDUMLA-HMT and THU-FVFDT2**	Merge CNN	98.56

Conclusions

In this brief study, we contrasted the properties of finger's veins, biometric attributes, and the evolution of finger's veins detection technology and its increasing popularity. we discuss the fundamental principles of deep and machine learning technology regarding the Finger's Vein. First, we discuss the fundamental information regarding the commonly utilized public datasets that are used by many machine learning algorithms and popular CNN structures. After that, we discuss 19 related studies on Finger Veins that are based on deep learning and machine learning from 2020-2023 and classify them according to the purpose of neural networks, which is to classify, extract features, enhance images, segment images, and encrypt them. Ultimately, we talk about the current troubles and intended future steps of Finger vein. From the review, it is apparent that the responsibilities of neural networks are diverse in Finger Vein, and this comparison to other biometric recognition systems demonstrates the unique benefits of Finger Vein. In the future, we will explore additional literature and methods ofDL in the Finger's Vein in order to propose a comprehensive analysis..

References

[1] Geraldin B. Dela Cruz, Rayner Alfred, "Importance of Data Biometric in the Organisational Culture",Technoarete Transactions on Intelligent Data Mining and Knowledge Discovery (TTIDMKD), Vol-2, Issue-2, May 2022.

[2]Sidiropoulos, George K., PolixeniKiratsa, PetrosChatzipetrou, and George A. Papakostas. "Feature extraction for finger-vein-based identity recognition." Journal of Imaging 7, no. 5 (2021): 89.

[3] A. Tahseen Ali, H. Abdullah and M. Fadhil, "Intelligent system for imposter detection: Asurvey", Materials Today: Proceedings, 2021. Available: 10.1016/j.matpr.2021.04.074.

[4] Ali, Ashraf Tahseen, Hasanen Abdullah, and Mohammed NatiqFadhil. "Impostor Detection Based Finger Veins Applying Machine Learning Methods." IRAQI JOURNAL OF COMPUTERS, COMMUNICATIONS, CONTROL AND SYSTEMS ENGINEERING 21, no. 3 (1970): 98-111.

[5] Zayed, Hossam L., Heba M. Abdel Hamid, Yasser M. Kamal, and Abdel Halim A. Zekry. "A Comprehensive Survey on Finger Vein Biometric." Journal of Advances in Information Technology 14, no. 2 (2023).

[6] Mohsin, Ali H., A. A. Zaidan, B. B. Zaidan, O. S. Albahri, ShamsulArrieya Bin Ariffin, Ahmed Alemran, OdaiEnaizan et al. "Finger vein biometrics: taxonomy analysis, open challenges, future directions, and recommended solution for decentralised network architectures." Ieee Access 8 (2020): 9821-9845.

[7] Shakil, Samiya, Deepak Arora, and TaskeenZaidi. "An optimal method for identification of finger vein using supervised learning." Measurement: Sensors 25 (2023): 100583.

[8] Hameed, Ali Salah, and Adil Al-Azzawi. "Fully automated human finger vein binary pattern extraction-based double optimization stages of unsupervised learning approach." International Journal of Nonlinear Analysis and Applications 13, no. 2 (2022): 2311-2323.

[9] Hameed, Ali Salah, and Adil Al-Azzawi. "Fully Automated Binary Pattern Extraction For Finger Vein Identification using Double Optimization Stages-Based Unsupervised Learning Approach." arXiv preprint arXiv:2205.03840 (2022).

[10] Zhang, Guang, and XianjingMeng. "High-security finger vein recognition based on robust keypoint correspondence clustering." IEEE Access 9 (2021): 154058-154070.

[11] Wen, QuekEe, NurulMaisarahKamaruddin, and BakhtiarAffendiRosdi. "Raspberry Pi-based Finger Vein Recognition System using PCANet." In Journal of Physics: Conference Series, vol. 1529, no. 2, p. 022068. IOP Publishing, 2020.

[12] Shaheed, Kashif, and Imran Qureshi. "A hybrid proposed image quality assessment and enhancement framework for finger vein recognition." Multimedia Tools and Applications (2022): 1-26.

[13] Kapoor, Kanika, Shalli Rani, Munish Kumar, Vinay Chopra, and Gubinder Singh Brar. "Hybrid local phase quantization and grey wolf optimization based SVM for finger vein recognition." Multimedia Tools and Applications 80 (2021): 15233-15271.

[14] Wan, Zhi Chong, Lan Chen, Tao Wang, and Guo Chun Wan. "An Optimization Algorithm to Improve the Accuracy of Finger Vein Recognition." IEEE Access 10 (2022): 127440-127449.

[15] Tao, Zhiyong, Haotong Wang, Yalei Hu, Yueming Han, Sen Lin, and Ying Liu. "DGLFV: Deep generalized label algorithm for finger-vein recognition." IEEE Access 9 (2021): 78594-78606.

[16] Hsia, Chih-Hsien, Zi-Han Yang, Hong-Jyun Wang, and Kuei-Kuei Lai. "A New Enhancement Edge Detection of Finger-Vein Identification for Carputer System." Applied Sciences 12, no. 19 (2022): 10127.

[17] Wimmer, Georg, Bernhard Prommegger, and Andreas Uhl. "Finger vein recognition and intra-subject similarity evaluation of finger veins using the cnn triplet loss." In 2020 25th International Conference on Pattern Recognition (ICPR), pp. 400-406. IEEE, 2021.

[18] Ma, Bin, Kaixuan Wang, and Yueli Hu. "Finger vein recognition based on bilinear fusion of multiscale features." Scientific Reports 13, no. 1 (2023): 249.

[19] Zhang, Zhongxia, and Mingwen Wang. "A simple and efficient method for finger vein recognition." Sensors 22, no. 6 (2022): 2234.

[20]Najeeb, ShaimaMiqdad Mohamed, Raid Rafi Omar Al-Nima, and MohandLokman Al-Dabag. "Reinforced Deep Learning for Verifying Finger Veins." International Journal of Online & Biomedical Engineering 17, no. 7 (2021).

[21] Liu, Chongwen, Huafeng Qin, Qun Song, Huyong Yan, and Fen Luo. "A deep ensemble learning method for single finger-vein identification." Frontiers in Neurorobotics 16 (2023): 1065099.

[22] Haider, Syed Aqeel, Shahzad Ashraf, Raja MasoodLarik, Nusrat Husain, Hafiz Abdul Muqeet, UsmanHumayun, Ashraf Yahya, Zeeshan Ahmad Arfeen, and Muhammad Farhan Khan. "An Improved Multimodal Biometric Identification System Employing Score-Level Fuzzification of Finger Texture and Finger Vein Biometrics." Sensors 23, no. 24 (2023): 9706.

[23] Li, Jun, Luokun Yang, Mingquan Ye, Yang Su, and Juntong Liu. "Finger Vein Verification on Different Datasets Based on Deep Learning with Triplet Loss." Computational and Mathematical Methods in Medicine 2022 (2022).

[24] Boucherit, Ismail, Mohamed OuldZmirli, HamzaHentabli, and BakhtiarAffendiRosdi. "Finger vein identification using deeply-fused Convolutional Neural Network." Journal of King Saud University-Computer and Information Sciences 34, no. 3 (2022): 646-656.