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A systematic review of palm and dorsal hand vein recognition techniques

Una revisión sistemática de las técnicas de reconocimiento de las venas de la palma y la vena dorsal de la mano

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Abstract

Introduction: Use of vein patterns for biometric recognition is being seen as an efficient identification method because of hygiene and security reasons.
Methods: Several methods and techniques based on traditional computer vision and deep learning for palm and dorsal hand vein recognition have been developed in last 10 years, however, still, the commercialization of vein recognition is very limited.
Results: The deep learning methods have shown significantly better performance over traditional vein apperception techniques predicated on computer vision.
Conclusion: This paper presents a comparative study of methods and techniques used along with their merits and demerits in last 10 years for palm and dorsal hand vein.

Keywords: Vein biometrics, vein patterns, pattern recognition, computer vision, deep learning, CNN, NIR.

Resumen

Antecedentes: El uso de patrones venosos para el reconocimiento biométrico se considera un método de identificación eficaz por razones de higiene y seguridad.
Material y métodos: En los últimos 10 años se han desarrollado varios métodos y técnicas basados en la visión tradicional por computadora y el aprendizaje profundo para el reconocimiento de las venas de la palma de la mano y dorsal, sin embargo, aún así, la comercialización del reconocimiento de las venas es muy limitada.
Conclusiones: Este artículo presenta un estudio comparativo de los métodos y técnicas utilizados junto con sus méritos y deméritos en los últimos 10 años para la palma y la vena dorsal de la mano.

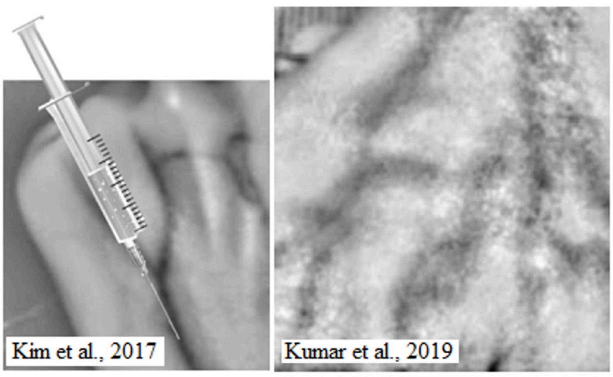
Palabras clave: biometría de venas, patrones de venas, reconocimiento de patrones, visión por computadora, aprendizaje profundo, CNN, NIR.

Introduction

The effectiveness of a vein recognition method depends upon theoretical analysis, security, reliability, etc. the vein recognition in contrast to other physiological traits like a fingerprint, palm-print, face recognition, etc. is much secure as the vein patterns are underneath the skin and it is very difficult to capture them without apprising a person especially a finger and palm veins. However, the dorsal hand vein and face veins can be captured from a distance using a far-infrared sensor as the face and lower part of the hand are open most of the time at public places.

The notion of vein recognition has initiated from medical imaging. Many times, the medical practitioners need Venepuncture as an important diagnosis process for vein locating in infants and obese persons. Also, for coloured skin patients, it is still a difficult task even for skilled practitioners. To deal with such cases, different infrared vein finders have been used and commercially available for vein pattern acquisition for research purposes. Different vein finders have been used in medical institutes and hospitals to detect the veins to inject the drugs[23]. **Figure 1** shows the use of a vein finder in the medical field and a vein images of dorsal hand.

Figure 1: : (a) Venipuncture using Vein Finder (b) Dorsal hand Vein image.



(a) (b)

As the time passed, the medical scientist observed that the vein patterns are unique for every person. Later, it was observed that vein patterns are also different even in twins[62]. Several researchers were then encouraged to study vein patterns as biometric recognition. Several methods and techniques based on traditional computer vision[3,13,14,20,21,28,29,34,57] were developed and enhanced over the years.

General Framework for Vein Recognition

This review of palm and dorsal hand vein recognition techniques and methods includes traditional computer vision (conventional system) and deep learning both. The need and size of the dataset decides the method and technology adapted. If it is a vein based attendance system in an office, then a template based matching system is sufficient as it is easy and simple to implement up to few hundreds or thousands persons to monitor. But, if it is a huge system contains lakhs or million persons like AADHAR or a banking system for user authentication using template based vein pattern matching is much inconvenient and the best solution is deep learning.

Conventional or Computer Vision based Vein Recognition

Image classification began with a non-training based system, also known as traditional computer vision or conventional methods that use the traditional way of feature extraction in conjunction with digital image processing to classify objects. Traditional computer vision uses feature descriptors such as minutiae-based matching, scale-invariant feature transform (SIFT)[37], speed up robust features (SURF)[36], binary robust independent elementary features (BRIEF)[21], local binary patterns (LBP)[32], etc. Unlike traditional computer vision, deep learning uses deep neural networks for object detection and classification.

Conventional palm and dorsal hand vein recognition methods are less robust to noise and misalignment-problem than the deep learning approaches. The image pre-processing methods are conventionally applied to make fast the feature extraction process and matching to surmount the verbalized quandaries. However, various traditional vein recognition methods are developed achieving noteworthy development.

The methods for vein recognition, based on traditional computer vision use the concepts of digital image processing for feature extraction and matching. The very common and effective methods under traditional computer vision are SIFT, SURF, LBP, BRIEF, etc. The major drawback of these methods is that it is very difficult for them to handle a large amount of data because the features are extracted manually and one-to-one matching is performed. Therefore, it is a manual and very time consuming manual process. The solution to overcome this problem is to adapt the training based system popularly known as deep learning.

Deep Learning based Vein Recognition

Some deep learning techniques like SVM and CNN, etc. are applied for extracting the feature from vein images and match the biometric features for human identification. These techniques are already verified to be efficient for extraction of features, matching those features, and improving the performance of a vein recognition method. Most of the vein recognition methods, deep learning classifiers are applied as matching step[27]. However, traditional vein recognition approaches apply Euclidian distance calculation for matching purposes[37].

The training based systems use light[58] and deep convolution neural networks (CNNs) to build models that can predict the classes more accurately[63]. The deep CNNs use filters (also known as kernels) to extract the features from images constituting a class. Once the model is trained with good validation accuracy and minimum losses, it predicts the classes very fast and efficiently. The major drawbacks of deep learning models include (i) too much time-consuming training process (ii) dataset with a sufficient number of vein images in each class[25].

The deep learning models take too much time while trained with central processing unit (CPU) rather than graphics processing unit (GPU) and the programmer often needs to repeat the training process again and again until the desired training accuracy is achieved. Deep learning should not be used just because it is trending. The programmer's experience states that one should go for deep learning training, only when it is highly required (in case a large amount of data to be handled) otherwise a few lines code based on traditional computer vision (template based matching) may work well[25].

The main components and parameters in the design of a CNN model are input layer, activation function[24], filters, pooling layer, stride and padding, dropout probability[49], batch normalization[17], dense or fully connected layer, classifier, and output layer.

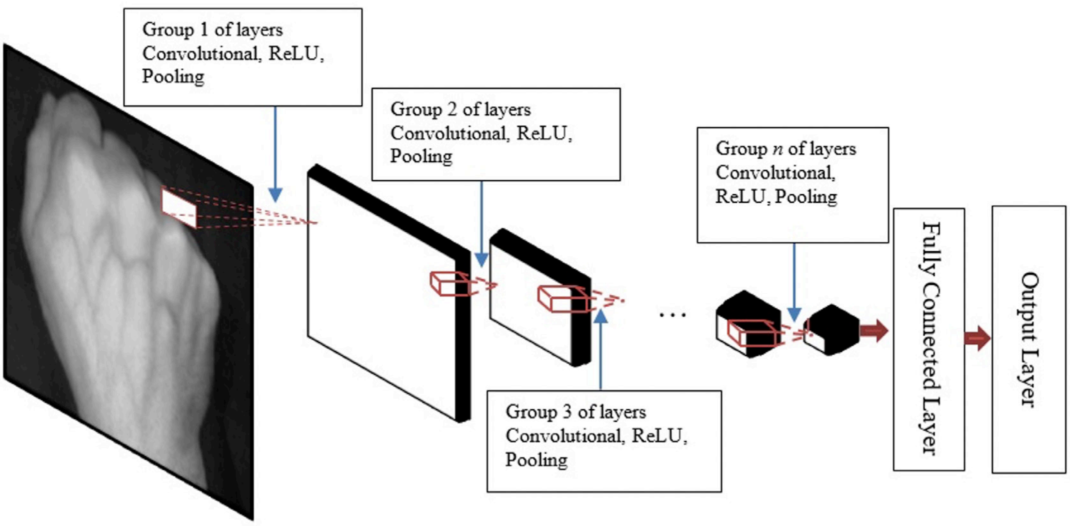
The most common activation functions are *tanh, sigmoid*, and *ReLU*. In recent years, *ReLU* has gained much popularity in object detection and classification models. The activation functions create non-linearity in the image. To reduce the training time and occupancy of high memory, a technique called pooling[10] is used in CNN hidden layer. The pooling layer shortens the size of the feature map so that the computational cost is reduced. The common pooling techniques are max-pooling and average-pooling. The most used classifier at the output layer is softmax for image classification. The specific collection of layers between the input and output layer lies in hidden layers. The counting of hidden layers depends upon how minute feature details need to be extracted from images and also it is problem-centric. The vein recognition for human identification is a multiclass classification problem that requires models with 4-5 convolutional layers to VGG Net-16[46] and above. With the development of residual networks, the very deep CNN are very much in practice to produce high performance. Kumar et al. presented a very deep learning model based on residual blocks having 35 convolutional layers for dorsal hand vein recognition using children and adults' datasets[27].

The deep learning models learn from examples therefore, deep models for image classification need many images in the dataset by using those the model trained. The insufficient number and low-quality images produce overfitting during the training and cause to termination of the training process in middle by the programmer. The problem of overfitting may be reduced by adding dropout layer(s) in the CNN.

The CNN Architecture

Figure 2 presents the basic components of a CNN architecture. It consists of an input and output layer along with one or more hidden layers. The hidden layers contain a specific combination of convolutional, ReLU, pooling, dropout layers followed by one or more fully connected layers.

Figure 2: The architecture of CNN.



The NIR Sensors

The infrastructure support required for a vein recognition system includes an NIR sensor equipped with a web camera for the acquisition of vein images. **Figure 3** presents some popular vein finders and NIR sensors for vein image acquisition. The wavelength of near-infrared sensor applicable for this purpose lies between 800 nm and 1000 nm.

Figure 3: Different NIR sensors for vain pattern acquisition[56].

The NIR modules by researchers

The majority of vein acquisition prototypes built by the researcher are contactless. These prototypes consist of NIR LEDs for infrared illumination, a camera to acquire vain images during illuminance, and a power source inside a cabinet. The researchers set up their vein acquisition systems by placing the components as per their plan and requirement.

Kauba et al. 2019, presented a touchless hand vein capturing device (**Figure 4**) comprising an NIR enhanced camera, an NIR pass-through filter, two NIR illuminators, a laser module and an illumination control board inside a wooden cabinet.

A palm vein acquisition prototype developed HES-SO and the [Idiap] comprised of a camera, ICX618 sensor, and infrared LEDs of wavelength 940 nm as shown in **figure 5**.

Figure 5: A prototype for palm vein acquisition[51].

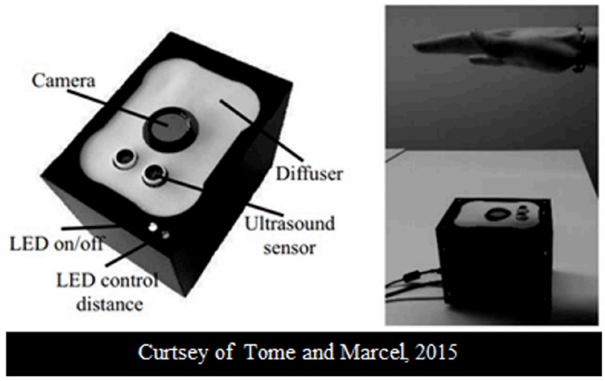


Figure 6 shows the dorsal hand vein and fingerprint acquisition system28. The vein finder VF620 and a fingerprint scanner were connected to laptop through USB port for data acquisition. This acquisition system created SRD dataset of 8000 dorsal hand vein images from 400 volunteers (both hands and 10 images per hand in different environmental conditions).

Figure 6: Dorsal hand vein acquisition using NIR camera VF620[26]

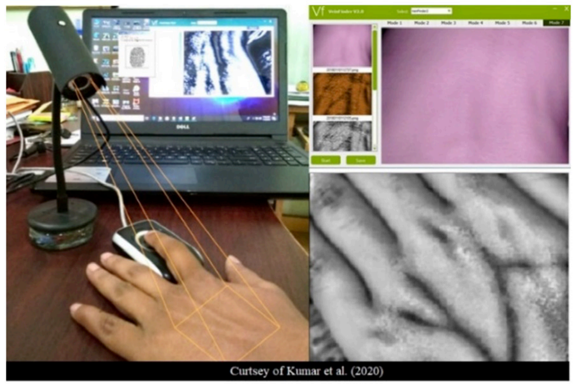
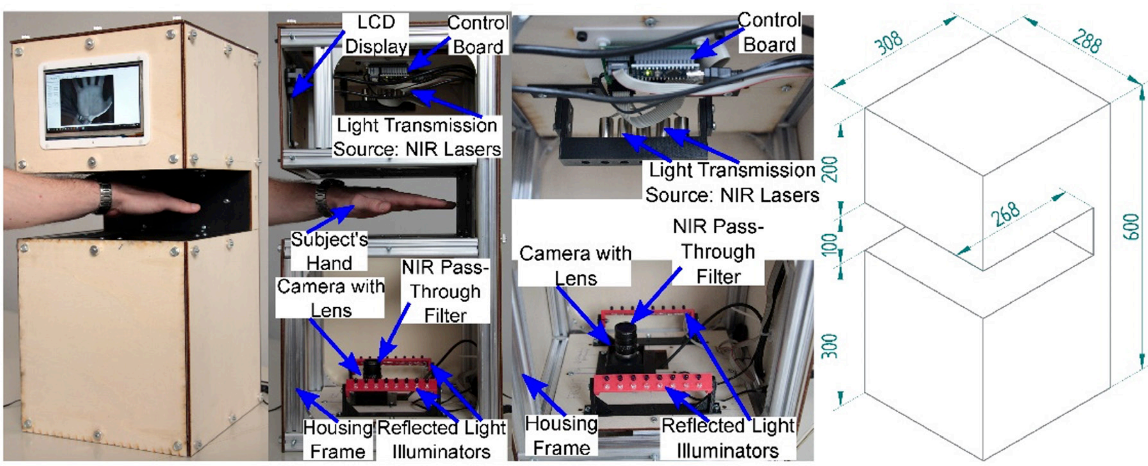


Figure 4: Touchless hand vein capturing device[22].



Different researchers developed low-cost prototypes using NIR sensors. A low-cost system[18] is developed for dorsal hand vein image acquisition. It consists of a modified infrared filter, an image pickup sensor for the camera to pass the light, and a high pass filter to block the visible light to the human eyes and allowing only infrared radiation. **Figure 7** shows this setup. (a) presents the modified camera (b) presents the CMOS sensor. (c) shows inside the housing of the camera lens where the infrared filter is installed and (d) shows the filter that allows the passage of the visible light. Janes and Junior acquired a total of 1240 images from 248 volunteers in self-constructed dataset. The accuracy of recognition they observed is 3.15% in terms of EER using the receiver optical characteristic (ROC) curve[18].

The Vein Datasets

The datasets have a key role in traditional computer vision and machine learning methods for image classification. The datasets are either self-constructed by the researchers or the downloaded datasets which are available for research purpose. As much the images are provided to the deep-learning model for training, the model learns faster and improves the accuracy. Also, the matching and classification accuracy depends upon the quality of input images.

Some Popular Existing Vein Datasets

The deep models are trained over the image datasets. The dataset is split into two parts training set and test set as per the defined split ratio. The popular datasets available for palm and dorsal hand vein recognition research are presented in **table I**, along with details like the number of images in the dataset, number of samples per volunteer, and image format.

Before the launch of commercial products for palm vein recognition, the most complete research followed by patents is conducted by Fujitsu in Japan[55]. The research comprised of a dataset of 150000 palm vein images acquired from 75000 volunteers of different age groups. This dataset was not available for non-Fujitsu researches and therefore no further details are accessible.

Image Augmentation

Artificially generating many images from a given input image using image transformation methods is known as image augmentation. It is highly desirable in deep model training for better accuracy. The Keras function Image data generator is mostly used to generate augmented images. Keras data generator alters images with varying slight rotation, shear, zoom, width and height shift, brightness, etc. This increases the size of training and test datasets. Önsen Toygar et al. increased the training dataset size[35] of Dr. Badawi dataset from 50 to 5000 and

Figure 7: A modified NIR sensor.

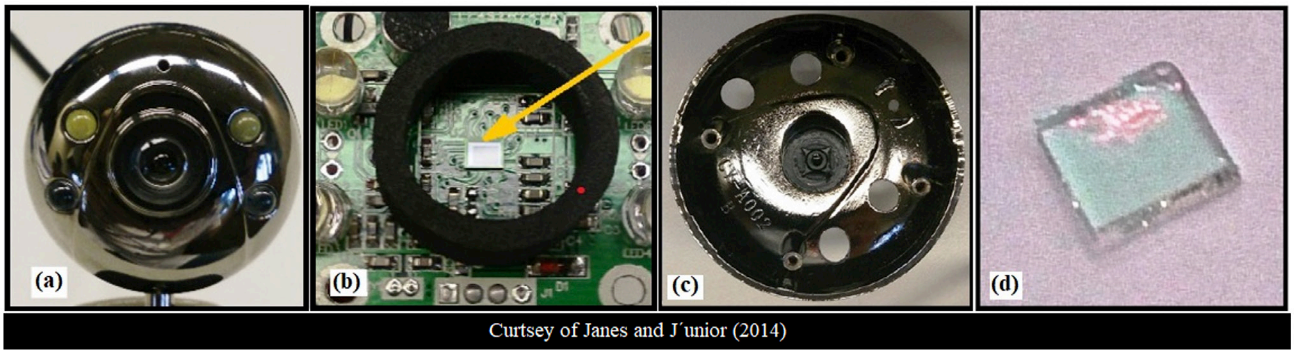


Table I: Major Datasets of palm and dorsal hand vein images.

Dataset Type	Name of Dataset	Number of images	Sampling	Image size and format
Palm Vein	Institute of Automation, Chinese Academy of Sciences (CASIA)[6]	7200	100 volunteers	200×266 (jpeg)
	Idiap Research Institute VERA Palmvein Database [Idiap][16]	2200	110 volunteers (40 women and 70 men)	480×680 (png)
	FYO-PV[35]	1920	160 volunteers (111 males and 49 females)	800×600 (png)
Dorsal Hand Vein	SRD Lab2[6]	8000	400 volunteers (200 males, 150 females, and 50 children 10 images of left hand 10 images of the right hand	640×480 (png)
	BOSPHORUS[5]	1575	100 volunteers with 3 images per hand in 5 conditions and another 75 images in normal condition.	300×240 (bmp)
	Dr. Badawi[45]	500	50 volunteers with 5 image of the left hand and 5 images of the right hand	320×240 (bmp)
	Sakarya University of Applied Sciences (SUAS)[50]	919	155 adults (80 male, 75 female)	256×192 (jpeg)
	FYODV35	640	160 volunteers and 2 images per hand	800×600 (png)

test dataset from 5 to 500; Bosphorus training dataset from 54 to 5400 and test dataset from 6 to 600; VERA Training dataset from 45 to 4950 and test dataset from 5 to 550; and FYO training dataset from 18 to 5760 and test dataset from 2 to 640. To avoid the model from overfitting, the technique used is dropout. Also, the cross-validation is performed by swapping the test set with a section of the training set and repeating the model training for better understanding of accuracy. This repetition may be done many times without repeating the test set.

Palm-Vein Recognition

The palm-vein recognition offers big space for feature extraction to produce better recognition than finger vein. Most of the palm-vein scanners use touch of the palm with scanner. Therefore, it is little bit unhygienic, however it is more secure than dorsal hand vein recognition as the palm-vein patterns are very difficult to capture by cyber criminals without the consent of a person. **Table II** presents some major contributions in palm-vein recognition research.

Table II: Some major palm-vein recognition contributions.

Contribution	Technique	Dataset(s) used	Major contribution	Recognition Accuracy
Palm vein recognition performance based on the geometrical structure				
Lee (2012)[30]	2D Gabor filter, Hamming distance	Self-constructed	Directional coding technique to encode the palm vein features	99.18%
Han and Lee (2012)[13]	Different types of Gabor filters, Hamming distance	Self-constructed	Encoding palm vein features in bit-string representation	Single Gabor 99.30% Multi Gabor 99.45% Adaptive Gabor 99.35%
Palm vein recognition performance based on Statistics data				
Ojala et al. (2002)[34]	Local Binary pattern, Score level fusion	PolyU	Generalized grayscale and rotational invariant operator presentation	99.87%
Mirmohamadsadeghi and Drygajlo (2011)[32]	Local derivative pattern, histogram intersection	CASIA	Local texture patterns	98.30%
Kang and Wu (2014)[19]	Local Binary pattern, Support Vector Machine	CASIA	Improved mutual foreground LBP	100%
Lu et al. (2016)[31]	Multi-scale Local Binary pattern, Local derivative pattern, similarity measure	CASIA	Discretional information derived from LBP	99.99%
Rivera et al. (2015)[43]	Local tetra pattern Local directional texture patterns	PUT	Facial expression and scene recognition	100%
Akbar et al. (2016)[1]	Local directional texture patterns, Chi-square dissimilarity test	CASIA	Local derivative patterns for feature extraction and histogram intersection	95%
Palm Vein recognition performance based on invariant features				
Ladoux et al. (2009)[29]	SURF, Score level fusion, Sum of absolute difference distance measure	PUT and PolyU	Prototype for image acquisition	98.81%
	SIFT, Euclidean distance	Self-constructed		99.86%
Hassan et al. (2012)[14]	SIFT Morphological features	Self-constructed using Fujitsu's PalmSecure™ scanner	Linear Vector Quantization classifier is used with changed parameters	Genuine Accept Rate at learning rate 0.05: 98.06% (SIFT) 95.99% (Morphological features)
Verma and Dubey (2014)[52]	Gaussian and low pass filters for edge detection	Not reported	Review of palm vein in last 10 years	Not applicable
Kang et al. (2014)[20]	SIFT, RootSIFT, Hellinger Kernel	CASIA, Self-constructed	Combining difference of Gaussian and histogram equalization	CASIA 99.006% Self-constructed 96.888%
Sayed (2015)[44]	Coset decomposition to identify encoded palm vein features	Dataset of 50 volunteers (5 images per volunteer with a 1-week interval per image)	Matching algorithm for extracting code word	99.80%
Yan et al. (2015)[61]	Score ORB and SIFT, bidirectional matching	Self-constructed	Score level fusion	99.86%
Palm Vein recognition performance based on the sub-space method				
Zhou and Kumar (2011)[64]	Neighborhood matching Radon Transform, Hessian Phase	CASIA	Orientation preserving features and novel region-based matching	NMRT 99.49% Hessian 98.56%
Perwira (2014)[38]	Principle component analysis, Probabilistic neural network	PolyU CASIA	Competitive hand valley detection	NMRT 99.996% Hessian 99.57% 84%
Zhou et al. (2014)[65]	Gaussian radon transform, principle oriented features	PolyU, CASIA	Algorithm to extract directions to compose for classification of subspace	PolyU 99.91% CASIA 99.33%
Elnasir and Shamsuddin (2015)[12]	Linear Discriminative analysis, Cosine distance	PolyU	Comparison with PCA and Gabor filter method	99.74%
Xu (2015a)[59]	2D Fisher Linear Discriminant, Euclidean distance	Self-constructed	The highly secure and high degree of user acceptance	99.29%
Xu (2015b)[60]	Partial least square, Euclidean distance	Automation research institute of Chinese academy of sciences	image coordinate in subspace for classification and recognition	98.70%
Cho & Kar-Ann (2018)[9]	Gabor filter, Hamming distance	PolyU	RGB palm-vein images	99.13%
Hernández-García et al. (2019)[15]	CLAHE	CASIA Multi-Spectral Palmprint Images	combining DAISY descriptor and the Coarse-to-fine PatchMatch	99.28%
Pititheeraphab et al. (2020)[39]	Geometric affine invariants	Self- constructed	geometry-modality	99.76%

Dorsal Hand Vein Recognition

Dorsal hand veins are much encouraged as the scanners used are contactless totally. Also, in the dorsal hand vein, big space is available so that sufficient features may be obtained resulting in better accuracy than finger vein recognition. **Table III** shows some major contributions in dorsal hand vein recognition using traditional computer vision and deep learning.

Traditional computer vision has its limitation like the features are extracted manually, therefore, such a system cannot handle a large amount of data. To overcome this problem the training-based methods are used generally known as deep learning. The datasets namely used are Bosphorus, SRD, Dr. Badawi, IITK and some those self-constructed.

Performance of Vein Biometric Systems

The reliability and applicability of a biometric system are based on its performance ability. Evaluating the performance is a complex process since many variables affect the system's performance. El-abed et al. stated that the performance of these systems is evaluated based on three broad categories: 1) Quality, 2) Usability, and 3) Security[11].

The performance evaluation of a vein recognition method is a paramount way to judge whether used algorithms are good or lamentable. ROC instinctively presents the steadiness between FAR and FRR. To make a judgment on the matching algorithms, a threshold is applied to fix EER optimally. If the threshold is decremented, the FAR is incremented, and FRR or FNMR is decremented. Similarly, when the threshold is incremented, the FRR is incremented, and FAR is decremented. The EER value can simply be obtained from ROC curve when FAR and FRR are equal. The lower the EER, the better is the system performance. Ideally, the EER should be 0%. Half Total Error Rate (HTER) is another way to measure the performance of a biometric system. It is calculated as an average of FAR and FRR. Genuine Accept Rate (GAR) is defined as the ratio of the number of input samples correctly classified out of the total number of positive input samples.

Additional way to observe the performance of a biometric system is the confusion matrix. The confusion matrix represents the true and false predictions for input samples. Four parameters are used to categorize the predicted results: true-positive (*TP*), true-negative (*TN*), false-positive (*FP*), and false-negative (*FN*).

Table III: Some major contributions in dorsal hand vein recognition.

Contribution	Technique	Dataset(s) used	Major contribution	Recognition Accuracy
Traditional computer vision-based contributions				
Wang (2008a)[53]	Minutiae features extraction	Self-constructed	Novel technique to analyse vein patterns	EER 0%
Wang (2008b)[54]	Wavelet algorithm	TJU dataset	Multi-resolution wavelet algorithm	EER 1.96%
Naidile and Shrividya (2015)[33]	Correlation method	Self-constructed	Applied maximum curvature against temporal fluctuation in vein brightness and width	Accuracy 75%
Raghavendra et al. (2015)[41]	Log-Gabor and Sparse representation classification	Self-constructed	New dorsal hand vein sensor for good quality vein acquisition	EER 0.7%
Belean et al. (2017)[4]	Geometry and pixel intensity distribution	Bosphorus dataset	Image processing pipeline for vein characterization	EER 0.83%
Kumar et al. (2019)[28]	SIFT, SURF, Euclidean distance	Self-constructed dataset	Children dataset Model for patient identification	EER 0.035%
Deep Learning based contributions				
Chin et al. (2020)[7]	Features extraction based on statistical and Gray Level Co-occurrence Matrix, ANN.	Bosphorus. dataset	ROI segmentation on Gray Level Co-occurrence Matrix	99.32%
Chin et al. (2021)[8]	ROI, mean filtering, CLAHE, histogram equalization, LBP, ROI, ANN	Bosphorus dataset	The ANN was then utilized in the MATLAB GUI program for testing 100 images	99.86%
Kumar et al. (2020)[25]	CNN	Self-Constructed and SRD dataset of good, medium, and low-quality images	Fine-tuning VGG Net-16 Difference image	99.60% (Good quality) 98.46% (Medium quality) 97.99% (low quality)
Al-Johania and Elrefai (2019)[2]	CNN	Dr. Badawi and BOSPHORUS	Error-correcting output codes with KNN and SVM	99.25%
Sree et al. (2014)[48]	Linear Hugh transform	Self-constructed	Morphological operations with KNN classifier	96.25%
Premvathi et al. (2018)[40]	Local binary pattern, Local ternary pattern, KNN	North China University of Technology (NCUT) dataset	New minimum distance classification	95.10%
Rajalakshmi et al. (2018)[42]	CNN, random forest, logistic regression	Self-constructed	Ensemble method to improve accuracy	96.77%
Soni et al. (2010)[47]	Traditional computer vision, morphological operations	IITK dataset	New absorption-based approach for data acquisition; Modified connected compound labelling algorithm	Not reported

Discussion

Excellent developments are seen around vein recognition and other related research for image classification using deep learning methods. In recent research, several improvements are observed in terms of activation function for better convolution, normalization for model stability, etc. The use of a graphics processing unit (GPU) has made computation much faster. Deep learning training using GPU involving feature extraction has speeded up many times than a CPU.

This paper presents a review of all the processing steps of vein recognition: image acquisition process, image pre-processing, feature extraction, and matching. We withal discuss different sensors, datasets and the performance of traditional computer vision and deep learning algorithms developed and utilized for vein apperception.

Some of the major palm vein researches are enlisted in **table II**. More than 98% contributions in last 10 years observed recognition accuracies between 98% to 100% using methods like LBP, SIFT, SURF, etc., with Gaussian filtering, low pass filtering, Coset decomposition, CLAHE, histogram intersection, local tetra patterns, etc. The contribution by Perwira[38] applying competitive hand valley detection with PCA and probabilistic neural network observed minimum accuracy of classification as 84% among all enlisted research. The **figure 8** presents accuracy graph of various palm vein recognition work done from 2011 to 2020.

Figure 8: Palm Vein Recognition Accuracy Graph of selected research between 2011-2020.

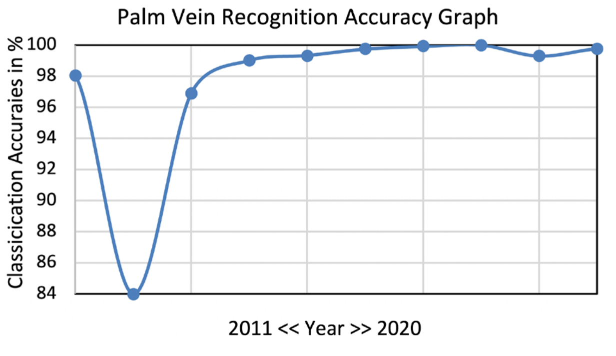
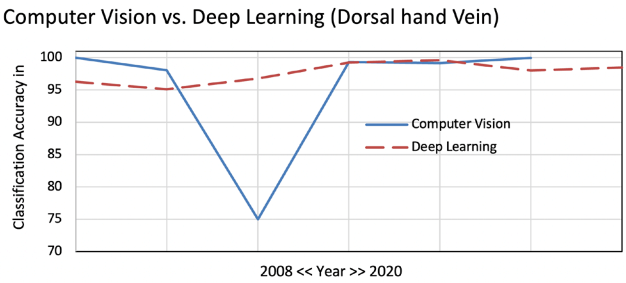


Table III presented some major contributions on dorsal hand vein using traditional computer vision and deep learning. The **figure 9** represent recognition accuracy graph for some researches. Naidile and Shrividya observed recognition accuracy as 75% using correlation method on self-constructed dataset[33]. Except this, other computer vision based researches observed recognition accuracy more than 98%. In deep learning based contributions, all observed recognition accuracy more than 95%, however, Soni et al. did not report recognition accuracy[47]. The **figure 9** presents accuracy graph of various dorsal hand vein recognition work done from 2008 to 2020.

Figure 9: Recognition accuracy graph for computer vision and deep learning methods on dorsal hand vein



Conclusions

This study provides an ample review of traditional computer vision and deep learning-predicated vein recognition approaches. The methods and techniques presented based on major work done are assessed in the key recognition steps of image acquisition, pre-processing, feature extraction, and features matching using various methods and techniques. Additionally, the feature extraction methods are regulated into two groups namely traditional computer vision and deep learning are discussed and compared. The deep learning methods have shown significantly better performance over traditional vein apperception techniques predicated on computer vision.

The study presented in this work, discussed the last 10 years' contributions in area of palm and dorsal hand vein recognition for human identification. Also, it has many challenges that need to be resolved. To get better performance of vein apperception, a good image acquisition system is required to get a good quality of vein images. A sizably voluminous dataset is needed as the deep models to learn from examples. A high apperception spoof detection in vein recognition methods is highly desirable to identify spoof attacks. Furthermore, deep learning approaches play a consequential role in vein recognition. With the prelude of deep learning approaches in vein apperception, the apperception performance is potentially enhanced in a broad sense. In conclusion, this review of vein recognition can be utilized as a platform for emerging approaches, and a commonplace for a wide range of benefits and challenges in biometrics.

Interests conflict

The authors declare no conflict of interest.

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