International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-9 Issue-1, May 2020

Finger Vein Verification Techniques using Convolutional Neural Networks

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Abstract: ***Finger vein beneath our skin is one of the unique features for identifying an individual. Because of its uniqueness and security the finger vein recognition is considered as a powerful biometric identifier for user authentication. Several techniques have been evolved for finger vein recognition from its early stage of development, but majority approaches were based on hand crafted features which had limitations on quality of the image, positioning of the finger etc. The emergence of neural networks led to the development of various Convolutional Neural Networks (CNN) based approaches for identity verification. This paper surveys various finger vein verification techniques using CNN and determines the factors that will affect the final result. Publicly available finger vein datasets as well as user designed ones, which are of different qualities, are used for the experimental analysis of these techniques. Though CNN is used in all the cases each one differs in the number of layers used, weight updating methods, results obtained etc. It is found that higher recognition accuracy and lower equal error rate (EER) makes the finger vein verification system an effective one. This field has emerged wide popularity recently and is used in different applications where security is of prime importance.***

Keywords: ***Biometric identifier, Convolutional neural networks, Finger vein verification.***

I. INTRODUCTION

Accurate and reliable identity authentication is of great importance now days. Securities using passwords and magnetic cards are now far beyond the scope of the needs of the society. The thought of measures that cannot be stolen or forged led to the development of user authentication with the help of biometrics. Because of its uniqueness and stability several biometric measures such as finger print ,iris, face pattern, finger veins, palm veins etc came into existence. Since finger veins are beneath the skin it is difficult to steal or be worn, this makes the finger vein verification more popular among other biometric identifiers. Moreover the unique feature of live body detection ensures the security of finger vein authentication. Once enrolled vein images are not affected by any changes during the course of time, so the system is a reliable one with no variations in result as time progresses. All these factors enhance the scope of this area and attract the researchers all the time for further development.

The general scenario of finger vein verification comprises of image acquisition, image preprocessing, feature extraction and finally the pattern matching. Of these the feature extraction is of great importance because the performance of the system heavily depends on the discriminant features of the image. Several approaches have been developed for feature extraction and is still continuing. Broadly these methods can be categorized as (i) finger vein pattern based methods by extracting the vein patterns using line tracking, finding centerlines etc (ii) finger vein texture based methods which depends on the texture of the veins extracted using local binary pattern, local derivative pattern, personalized best bit maps etc. (iii) minutiae based methods which extracts minutiae using scale invariant finite transform features or other such methods

Several other techniques were also introduced such as principal com-ponent analysis based methods, manifold learning etc. All these algo-rithms were based on handcrafted features, sensitive to the quality of the image and position of finger. Shadings and misalignments cause major issues in the performance of the system. As a solution to this concern alternative ideas are investigated but majority results in fewer improvements with increased complexity. The emergence of big data and rapidly growing computing power led to deep learning which has made many breakthroughs in various fields and gained mass popularity. The neural network that mimics the operation of human brain and learns the underlying relationships in a set of data has its influence in the area of finger vein verification too. It started with a simple back propagation neural network now has several designs using convolutional neural networks. CNNs are mainly used in the analysis of visual imagery and they use convolutions, which is the sliding of filter over the input, in at least one of their layers. They generally consist of input, output and multiple hidden layers and the convolutions reduce the number of parameters which makes them efficient. Automatic detection of the features without any human support is the major advantage of using a CNN.

The following section shows the major techniques evolved in the finger vein verification system which made use of convolutional neural networks

Manuscript received on April 02, 2020.
Revised Manuscript received on April 15, 2020.
Manuscript published on May 30, 2020.
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II. CNN BASED FINGER VEIN VERIFICATION METHODS

The development of convolutional neural networks started to influence the field of finger vein verification from the year 2016 onwards and is still progressing with latest modifications. CNN alone can be used for feature extraction and verification in certain systems whereas it can be used along with other techniques also.

Depending on the purpose of CNN the number of layers are designed. Proper CNN design has its effect in the total complexity of the system which in turn determines the final performance.

A. Finger Vein Verification Using CNN Only

The significant advantage of CNN over other methods to simulta-neously extract features and reduce data dimensionality is used by Razdi.et.al [1] in their work of finger vein biometric identification using CNN.The method requires minimal image preprocessing and also classification in one network structure. A four layered CNN was developed with fused convolutional –sub sampling architecture and a modified stochastic diagonal algorithm Levenberg-Marquardt was applied for network training. The original images were cropped, resized and binarized in the preprocessing phase. Local dynamic thresholding was implemented here for the process of segmentation. The CNN architecture used here was known as 5-13-50 model de-pending on the number of feature maps in the convolution layers. Then the cross validation technique was applied for the best configuration model. The database of VCCAD Laboratory of Universiti Technologi Malaysia was used for the experimentation purpose which consists of 50 subjects with 10 samples taken from 6 different fingers. An identification rate of 100% was achieved with 99.38% accuracy. Since the testing was not conducted on any public datasets the results were not verifiable.

A MATLAB based finger vein recognition using CNN with the user input through graphical user interface was focused by Sya-feeza.et.al [2] during their research on user identification. This is also another four layered architecture where two layers were used to retrain the network for new incoming subjects. Here the image preprocessing and CNN design were carried out in different platforms and their linking was important in determining the performance of the system. Here the original image captured was cropped and set according to the centre pixel which was then resized to reduce the information content. The proposed system was based on LeNet5 architecture and was of smaller size. In this approach the convolution and sub sampling layers were fused and the fully connected single nodes will function as the classifier. The dataset consists of 600 samples, 10 each from 60 subjects. An accuracy of 96% was obtained with the identification of up to 10 new subjects in less than 10 seconds.

In 2017 Hong.et.al [3] developed a CNN based finger vein recog-nition using NIR image sensors which was robust to various data types and environmental changes. This new approach reduced the complexity of CNN structure by difference image as input Two masks were formed from the images obtained from the capturing device to detect the upper and lower boundaries of the finger and using these the region of interest was extracted. It was then resized into an image of 224x224 pixels without any filtering or quality enhancement. The difference image between input and the enrolled ROI was fed into the pretrained CNN and the recognition was on the basis of the CNN output.VGG Net 16 was the CNN model used here. A feature map of the image was obtained after passing through 13 convolutional layers,13 ReLU layers,5 pooling layers and 3 fully connected layers. Three databases were used in this work which was of good quality, mid quality and low quality.Higher recognition accuracy was obtained.

Finger vein recognition by Meng.et.al [4] developed a CNN model where input samples were directly fed into the model, feature vectors were extracted and authentication was performed by comparing the Euclidian distance between the vectors. In this approach first the feature vector of the image extracted using CNN was registered. Later during authentication the feature vector of that particular image was extracted and the Euclidian distance between that vector and other registered vectors were compared. If the distance was below the threshold it was considered as a genuine pair. The CNN model consists of 5 convolutional layers and 3 fully connected layers. Here the softmax loss was used as the cost function to maximize the inter class distance and to minimize the intraclass distance. Database used was obtained from DataTang which consist of 64 subjects with 15 samples for each person. Deep learning framework Caffe was adopted for the verification of this method and there was a rise in the speed and accuracy.99.4% accuracy was obtained with an EER of 0.21%

A deep learning model to extract and recover features using limited knowledge by Qin.et.al [6] was based on the identification of a clear and ambiguous region which depends on separability between vein pattern and background. Here the clear regions were labeled while the others got discarded. A dataset was constructed using labeled patches and was trained using a CNN to learn the finger vein pattern. Missing patterns were also considered using fully convolutional network. The main contributions of the work were labeling pixels in vein regions and background automatically with limited human knowledge and another one was proposing a CNN based scheme to learn features from raw pixels automatically. Here the patch of each pixel was given as input to CNN and the output indicates the probability whether the pixel belongs to the vein pattern. The CNN architecture had convolutional layers, pooling layer, local response normalization, drop out layer and an output layer of softmax classifier. Stochastic gradient descent was used for the parameter update during the training. In this method verification error rate was improved significantly and a promising performance was noticed. But here the CNN was not used to extract features directly, which makes process complex and time consuming. The databases used were one from Hong Kong polytechnic university image database containing 3132 images from 156 subjects and the other was the USM database captured from 123 subjects. The approach had an EER of 3.02 with the first database and 1.69 with the other one.

The year 2018 witnessed a lightweight two channel framework developed by Fang.et.al [7] with only three convolutional layers for verification. In this approach every two images in the database were combined to form one training sample. And it was given as input to the similarity measure network. Here the network chosen was a two channel network which was easy and very effective.

Two patches of input image pair was directly given to the first convolutional layer .For faster processing rate feature extraction network was designed consisting of 3 convolutional layers, batch normalization layer and a pooling layer. The difference between images was shown by the convolutional layers only. The two stream network was used to fuse the miniROI and the original image. The output of the two streams was concatenated using concat layer and the output was the feature which was further given to the SVM classifier for the final decision. The datasets used here were MMCBNU and SDUMLA and obtained an error rate of 0.10 and 0.47 respectively. Integration of mini-ROIs with the original image had helped to achieve superior results. Even though performance was comparably good, the usage of this method for practical application was impossible as feature was not extracted from a single vein image.

Even though good performances were offered by existing tech-niques, the quality of the analyzed vein images always makes its impact on the result. This paved the way for many new approaches in the year 2019.Das.et.al [10] proposed a CNN which was stable and highly accurate with different types of image qualities. This approach is of use when dealing with more realistic input image size with less kernel size and the results obtained had shown reduction in the training and testing time and also a very low learning rate for training. Preprocessing followed by template generation and CNN training were the steps involved in this type of user authentication. The proposed CNN consists of 5 convolutional layers,3 max pooling layers ,one ReLU activation layer and a softmax layer which was used to compute the softmax loss for back propagation. The preprocessing performed enhanced the image quality and the ROI was extracted. After that the images were transposed and resized into 65x153 pixels to reduce the complexity of CNN. Then the best possible combination of templates were found out for using in the recognition phase and these were the inputs of the CNN. The datasets used for the experimentation were HKPU with 210 classes taken from 105 subjects, FV-USM database with 492 classes ,4 fingers each of 123 subjects, SDUMLA database with 6 fingers each of 106 subjects and UTFVP database containing 6 fingers each of 60 subjects. An accuracy of more than 95%was obtained in all the cases during testing.

The use of pretrained based CNN model to identify finger vein was the proposal put forward by Fairuz.et.al [11] Transfer learning of pretrained Alex Net was used here.The verification of pattern was performed by the correct as well as incorrect test images. Based on deep CNN, a model named AlexNet was used which consists of five convolutional layers, three fully connected layers and a softmax output layer. First the images were preprocessed and were given to the CNN, developed by transfer learning the AlexNet. Each convolutional layer consists of convolutions, ReLU and pooling. The fully connected layer was used to connect neurons of one layer to the other. Finally the classification results were generated using the softmax loss function. This model was expected to give almost precise results. This can be extended in future for the development of a real time finger vein verification system

Manjith Singh.et.al [12]had investigated a deep learning based approach to achieve a stable response with accurate performance irrespective of image quality. The CNN consists of five convolutional layers with ELU activation, a fully connected layer, three max pooling layers and a softmax function. Generated templates were given as inputs to the CNN to extract low level feature set .High level features were obtained gradually in the subsequent layers. Appropriate kernel size was give higher priority to be used as a parameter in this approach. The identification was performed based on the threshold based matching. FVUSM dataset was used here which contains 6 samples each of two fingers from 123 subjects. The CNN design effectively fitted various training size of vein images and tested on one publicly available database with varieties of images with different qualities.99.52% identification accuracy was obtained by the proposed model .Effective training and testing strategies can yield more accuracy to the system.

Improved CNN segmentation based finger vein recognition using automatically generated and fused training labels by Uhl.et.al [15] researched on the label fusion between automatically generated and manually generated labels. The work flow consists of extraction of the vein patterns using three different segmentation CNN architectures then the generation of different training labels followed by the fusion technique. Three different FCN architectures were used for the extraction of vein patterns. The first one was a U-Net consisting of an encoder part and a decoder part. The encoding part was made up of two convolutional layers followed by a rectification layer and a pooling layer. The decoding consists of convolutional layers, a concatenation operator and again two convolutional layers followed by ReLU. The second architecture was RefineNet which was a multipath refinement network with four cascaded architectures containing four RefineNet units. Each unit had two residual convolutional units and a residual pooling block. This had enabled high resolution predictions depending on long range residual connections. The third network was the basic fully connected encoder decoder namely SegNet. The network encoder was divided into four stocks each containing a set of blocks. Each block was made up of convolution layer, a batch normalization layer, a ReLU layer and a pooling layer. The decoder had also similar organization except an up sampling layer in each block. Finally there was a softmax layer where the final segmentation map was generated. UTFVP database containing 1440 images from 60 volunteers was used here. The automatically generated labels had improved the network's performance in terms of achieved recognition accuracy Finger vein verification using Siamese CNN was the work of Tang.et.al [16] which had developed a pretrained weights based CNN first and using that a Siamese CNN was constructed and modified contrastive loss function was applied for improving the performance of the network. Finally the knowledge is transferred to a lightweight framework making it feasible for deploying on an embedded device.

The knowledge of ResNet50 was transferred in the proposed CNN up to 11 layers which forms the base network and the extended network was comprised of custom designed layers which include four convolutional layers with SELU activation function and batch normalization, two max pooling layers L2 normalization layer and two fully connected layers. Dropout method was used to reduce over fitting. Using this pretrained CNN, a Siamese network was constructed with modified contrastive loss function. Now the complexity was reduced by the knowledge distillation this Siamese network to a light weight framework FitNets, whose learning archi-tecture was composed of two models. The light weight CNN was the student model and the pretrained CNN was the teacher model. The output from the second max pooling layer in the teacher model forms the hint and the guiding layer was from the last layer in DSConv blocks3.The hint loss, knowledge distillation loss and the softmax loss were calculated together for the optimization of the network The da-tasets used were MMCBNU-6000, FVUSM and SDUMLA-HMT and achieved an EER of 0.08, 0.11 and 0.75 respectively. The result obtained was a small size network with incredible performance. The approach had produced lower EER which varies according to the database used.

B. Finger Vein Verification Using CNN And Combination Of Other Techniques

Chen.et.al [5] introduced a finger vein recognition algorithm based on deep learning using a feature block fusion and deep belief network and CNN. Here the vein image was processed first for the better performance of the network. The preprocessing phase involves ROI extraction, Image segmentation and image thinning. After that the algorithm named Feature Block Fusion and Deep Belief Net-work(FBF-DBN)was executed which contains feature extraction, feature block fusion and the judgment by DBN.The dataset used contains vein images of 64 individuals with 15 samples for each person. Using deep network the time in learning and detection were reduced effectively meeting the practical needs of biometric recognition system. This approach guaranteed better recognition performance and faster speed. An identification accuracy of 96.9% was obtained with an error rate of 1.5%

Li.et.al [8] created a finger vein verification based on local graph structural coding and CNN (LC-CNN) A weighted symmetric local graph structure (LGS) was proposed first which was used to locally indicate the gradient relationship among surrounding pixels. This was followed by the reconstruction of traditional local coding methods using a set of fixed sparse predefined binary convolution filters. Here the problem of over fitting of the network was eliminated by altering the standard convolution in pretrained CNN with the local coding convolution. The final part was the image classification using support vector machine which takes the input in the form of the extracted feature vectors. The experimental analysis indicates the proposed system had better performance compared to the other traditional coding methods for finger vein authentication.

Finger vein identification using CNN and supervised discrete hashing was the theory of Xie.et.al [9].They made comparisons on the performance of various CNN architectures and concluded that the most accurate performance was achieved by including the supervised discrete hashing from a CNN trained using triplet based loss function. Hashing had reduced the template size though separate training and testing were required. The light CNN architecture employed consists of 9 convolutional layers,4 pooling layers 2 fully connected layers and some assistant layers. The input set had n random samples,n positives and n negatives. These pairs were split into three parts and fed as input for computing the triplet loss function in a Siamese neural network. This was done for updating the neuron weights during training.VGGNet-16 was modified and used as CNN to recover matching scores. The framework used had an effective supervised hashing scheme to generate binary codes which were used for linear classification. The dataset used was the publicly available two session database of 6264 images from 156 different individuals. Here the matching accuracy had indicated an outperformed result.

A patch based approach using CNN was explored by Tugce Arican [13] which had increased the number of labeled data irrespective of brightness variations. Determination of patch properties, combining the patches and registration of the images were the new steps involved in this method, which can cause certain concerns too. Here the patch pairs were extracted based on their relative locations. So image registration had its effect in the overall network performance. Physical properties such as edges, reference points, landmarks etc were used for the registration .An iterative method was used for image registration depending on the matching score based approach for better accuracy. Geometric translations which minimize the matching score were used as the registration parameters. The steps involved in the proposed system were image registration, patch extraction, scoring, fusion and the final decision. Registration was done based on Iterative Closest Point algorithm. Then 31 pixels square patch pairs extracted from the finger region was fed into a CNN which outputs a matching score for each. These are then fused to an image score and the final decision was based on the comparison of this fused score against a threshold. The databases used were UTFVP consisting of1440 images from 60 subjects, SDUMLA-HMT comprising of 3816 images from 106 person..This approach had obtained an equal error rate (EER) of 0.3 on first database and an EER of 6.6 on the second one. The results achieved by the proposed optimizations were less satisfactory compared to the other state-of-the-art methods but can be enhanced further for better results.

A new end to end deep learning network for biometric verification was proposed by Manish Agnihotri.et.al [14] .The method consists of an auto encoder for learning domain specific features. These were then trained in a Siamese network via triplet loss for matching. The proposed system had used modified ROI extraction algorithm for finding the ROI. Then domain specific transformation learning was carried out using autoencoders. The autoencoder was based on U-Net model which was used for segmentation purposes.

The model had been modified for learning image transformations. The architecture consists of 15 convolutional layers with ReLU activation and batch normalization and max pooling layers for dimensionality reduction. The network was free from the gradient problem. For training autoencoders ground truth were extracted first using transformation operation known as TCM on 2400 finger vein samples and then another transformation known as IRT was performed for training image features. The method had used mean squared error as the loss function and the optimization was carried out using RMSPROP algorithm. Later on to match multi channel features a Siamese network was trained with triplet loss function. After training the Siamese net-work was combined with the autoencoder to perform end to end training of the whole network. Multispectral CASIA palm print database was used here which consists of palm vein and finger vein traits of 200 individuals. The experimental analysis had shown con-sistent high performance compared to several other approaches.

III. RESULT AND DISCUSSION

Performance evaluation is the method for recognizing whether the underlying algorithm is good or not..Even though different CNNs were made for finger vein verification, it is the final performance that matters to determine whether it is an effective biometric authentication system. The conventional methods of finger vein recognition were less robust to noise and misalignments. Also they use handcrafted features which were sensitive to image quality and finger position. These drawbacks led to the development of deep learning techniques in this field. The usage of convolutional neural networks is an effective approach in areas handling images where the features are automatically extracted without human supervision. As a result several CNN based finger vein verification techniques evolved. Designing a suitable architecture for the CNN is a very challenging task as it needs lot of attention in various stages. The time consumed by the network and the complexity are the major issues to be tackled while designing. It is found that the above factors cause delay in performance which cannot be accepted. Some of the techniques were not tested on open datasets which will be a problem in real cases making the method unsuitable for practical use. Lack of training data is another problem that we have seen in majority of the techniques. For a CNN large training data gives accurate results. As the number of data decreases it will heavily affect the precision of the system. All these factors should be considered while developing a CNN based technique. The findings can be consolidated as :

- Automatic feature extraction using CNN is far better than the traditional methods.
- CNN based finger vein recognition system can assure higher accuracy.
- Though preprocessing is not needed the extraction of ROI and image enhancement can increase the performance of the system.
- Training using more data gives better result. So data augmentation of the CNN input is a must.
- Transfer learning from other pretrained neural networks can assure better CNN design.
- There should be an effective pattern matching criteria for a reliable output.
- The CNN developed should be less complex so that it can be fitted into a small scale device.
- The system should have anti spoofing mechanisms to detect presentation attacks.
- Proper optimizations of the training algorithm of CNN can yield high performance.
- The CNN developed should be useful for practical applications

IV. CONCLUSION

Biometric authentication using finger vein is of great importance due to its unique characteristics. This paper had presented several finger vein recognition methods using convolutional neural networks. From the analysis we can conclude that feature extraction using CNN can tremendously increase the performance of the system. A finger vein verification system should be reliable, secure, accurate, stable and should be able to embed on a small scale device. For creating such a system several modifications and optimizations should be made to improve the performance parameters such as high accuracy, low learning rate, reduced training and testing time, low EER etc. We can notice that greater results are achieved with the use of CNN. Insuffi-cient training data is one of major concern, so better strategies should be adopted for solving such issues. Preprocessing techniques are not very much needed for CNN but an efficient ROI extraction method will effectively improve the accuracy of the system. An efficient presentation attack detection algorithm should also be incorporated for preventing spoofing attacks and thereby ensuring the security of the system. Thus by analyzing all these approaches we can come to a conclusion that CNN based finger vein verification can give a better result with more training samples ,necessary preprocessing techniques such as image enhancement, ROI extraction etc and a suitable pattern matching technique which is reliable, less time consuming and accurate..All these with an anti spoof mechanism can form an efficient biometric identifier which can be used in all applications where security is needed.

REFERENCES

1. Radzi, S.A., Hani, M.K., Bakhteri, R.: “Finger-vein biometric identification using convolutional neural network”, Turk. J. Electr. Eng. Comput. Sci., 2016.
2. Itqan K.S., Syafeeza A.R., Gong F.G., Mustafa N., Wong Y.C., Ibrahim M.M. ,”User Identification System Based on Finger-Vein Patterns Using Convolutional Neural Network”, ARPN J. Eng. Appl. Sci. 2016;11:3316–3319. 24, (3), pp. 1863–1878.
3. Hong, H.G.; Lee, M.B.; Park, K.R. “Convolutional Neural Network-Based Finger-Vein Recognition Using NIR Image Sensors”. Sensors 2017, 17, 1297.
4. Meng.G;Fang.P;Zhang.B, ”Finger vein recognition based on Convolutional neural network, In proceedings of the MATECWeb of Conferences”,Zhuhai,China,23-24September2017;EDPSciences:Les Ulis, France.2017; Volume 128.p.04015.
5. Wenjie Liu, Linjun SunLiping Zhang, Peng Chen, “Finger vein recognition based on deep learning” 12th IEEE conference on industrial electronics and applications,2017.

6. Qin.H;El-Yacoubi.M.A, "Deep representation based feature extraction and recovering for finger vein verification", IEEE Trans.Inf Forensics Secur,2017,12,1816-1829.
7. Fang, Y.; Wu, Q.; Kang, W. A "Novel finger vein verification System based on two-stream convolutional network learning", Neurocomputing, 2018.
8. Shuyi Li; Haigagng Zhang; Jinfeng Yang, "Finger vein recognition based on local graph structural coding &CNN, Proceedings", Volume 11069, Tenth International Conference on Graphics and Image Processing 2018.
9. Xie, C.; Kumar, A. "Finger Vein Identification Using Convolutional Neural Network and Supervised Discrete Hashing, In Deep Learning For Biometrics"; Springer: Cham,Switzerland, 2018; pp. 109–132.
10. Rig Das, Emanuela Piciucco, Patrizio Campisi, Emanuele Maiorana, "Convolutional Neural Network For Finger Vein Based Biometric Identification", In Proceedings of the MATECWeb of Conferences,Zhuhai, China, 23–24 September 2018; EDP Sciences: Les Ulis, France, 2018; Volume 128.
11. Subha Fairuz , Mohamed Ahmed Elsheikh, "Pretrained based CNN model to identify finger vein, Bulletin of Electrical Engineering and Informatics" Vol. 8, No. 3, September 2019, pp. 855~862.
12. Manjith Singh,Sunil Kumar Singla ,"Convolutional Neural Network Based Deep Feature Learning for Finger-vein Identification", in Proceedings of the 2019 2nd International Conference on Electronics and Electrical Engineering Technology.
13. Tugce Arican, "Optimisation of a patch-based finger vein verification with a convolutional neural network", In Proceedings of the IEEE International Workshop on Information Forensics and Security (WIFS), Rome, Italy, 16– 19 November 2019; pp. 1–6.
14. Manish Agnihotri , Aditya Rathod , Daksh Thapar , Gaurav Jaswal, Kamlesh Tiwari and Aditya Nigam , "Learning Domain Specific Features using Convolutional Autoencoder: A Authentication Case Study using Siamese Triplet Loss Network", 8th International Conference on Pattern Recognition Applications and Methods, At Prague, Czech Republic 2019.
15. Ehsaneddin Jalilian ,Andreas Uhl , "Improved CNN-Segmentation Based Finger Vein Recognition Using Automatically Generated and fused training labels, Handbook of Vascular Biometrics" pp 201-223,2019.
16. Su Tang ; Shan Zhou ; Wenxiong Kang ; Qiuxia Wu ; Feiqi,Deng, "Finger vein verification usina a Siamese CNN, IET Biometrics Volume: 8" , Issue: 5 , 9 2019.
17. Liu, T., Xie, J.B., Yan, W., et al.: "An algorithm for finger-vein segmentation based on modified repeated line tracking",Imaging Sci. J., 2013, 61, (6), pp.491502.
18. Miura, N., Nagasaka, A., Miyatake, T.: "Extraction of finger-vein patterns using maximum curvature points in image profiles", IEICE Trans. Inf. Syst., 2007, 90, (8), pp. 1185–1194.
19. Rosdi, B.A., Shing, C.W., Suandi, S.A.: "Finger vein recognition using local line binary pattern", Sensors, 2011, 11, (12), pp. 11357–11371.
20. Yang, G., Xiao, R., Yin, Y., et al.: "Finger vein recognition based on personalized weight maps", Sensors, 2013, 13,(9), pp. 12093–12112.
21. Yu, C.-B., Qin, H.-F., Cui, Y.-Z., et al.: "Finger-vein image recognition combining modified Hausdorff distance with minutiae feature matching", Interdiscip. Sci. Comput. Life Sci., 2009, 1, (4), pp. 280–289.
22. Liu, F., Yang, G., Yin, Y., et al.: "Singular value decomposition based minutiae matching method for finger vein recognition", Neurocomputing, 2014, 145, pp. 75–89.
23. Vega, A.P.; Travieso, C.M.; Alonso, J.B. "Biometric personal identification system based on patterns created by finger veins", In Proceedings of the 2014 International Work Conference on Bio-inspired Intelligence (IWOBI), Liberia, Costa Rica, 16–18 July 2014; pp. 65–70.
24. Raghavendra, R.; Busch, C. "Presentation attack detection algorithms for finger vein biometrics: A comprehensive study", In Proceedings of the 2015 11th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), Bangkok, Thailand, 23–27 November 2015; pp. 628–632.
25. Yang, J.; Shi, Y. "Finger–vein ROI localization and vein ridge enhancement Pattern Recognit. Lett." 2012, 33, 1569–1579.
26. Wang, M.; Tang, D. "Region of interest extraction for finger vein images with less information losses". Multimed. Tools Appl. 2017, 76, 14937–14949.
27. Zheng, H.; Ye, Y.; Liu, S.; Ni, N.; Zhang, Y.; Huang, H.; Li,W. "Parameter adjustment of finger vein recognition algorithms. In Proceedings of the Identity, Security and Behavior Analysis (ISBA)", 2017 IEEE International Conference, New Delhi, India, 2017; pp. 1–8.
28. Ezhilmaran, D.; Joseph, P.R.P. "A Study of Feature Extraction Techniques and Image Enhancement Algorithms for Finger Vein Recognition. Int.", J. PharmTech Res. 2015, 8, 222–229.
29. Xie, S.J.; Lu, Y.; Yoon, S.; Yang, J.; Park, D.S. "Intensity variation normalization for finger vein recognition using a guided filter based singe scale retinex.", Sensors 2015, 15, 17089–17105.
30. Kauba, C.; Reissig, J.; Uhl, A. "Pre-processing cascades and fusion in finger vein recognition", In Proceedings of the 2014 International Conference of the Biometrics Special Interest Group (BIOSIG), Darmstadt, Germany, 10–12 September 2014; pp. 1–6.

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