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Dorsal hand veins features extraction and recognition by correlation coefficient

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ABSTRACT

One of the most convenient biometrics approaches for identifying a person is dorsal hand veins recognition. In recent years, the dorsal hand veins have acquired increasing attention because of its characteristics such as universal, unique, permanent, contactless, and difficulty of forging, also, the veins remain unchanged when a human being grows. The captured dorsal hand veins image suffers from the many differences in lighting conditions, brightness, existing hair, and amount of noise. To solve these problems, this paper aims to extract and recognize dorsal hand veins based on the largest correlation coefficient. The proposed system consists of three stages: 1) preprocessing the image, 2) feature extraction, and 3) matching. In order to evaluate the proposed system performance, two databases have been employed. The test results illustrate the correct recognition rate (CRR), and accuracy of the first database are 99.38% and 99.46%, respectively, whereas the CRR, and accuracy of the second database are 99.11% and 99.07% respectively. As a result, we conclude that our proposed method for recognizing dorsal hand veins is feasible and effective.

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1. INTRODUCTION

Traditional recognition techniques such as passwords, personal identification numbers (PINS), magnetic swipe cards, keys, and smart cards offer extremely limited security and are unreliable, hence biometrics are becoming increasingly popular in the research community [1], [2]. Biometrics are being developed to ensure more dependable security by analyzing human biological, physical, and behavioral features. Fingerprint, hand geometry, iris, faces, and handwritten signature are the most common biometric characteristics that have been used. Researchers have recently become interested in dorsal hand vein pattern biometrics, which is growing rapidly. Outside of surgical intervention, the vascular patterns in the back of the hand are anatomically unique [3]–[5]. Veins are blood carrying vessels that are intertwined with muscles and bones. The vascular system's main role is to give oxygen to every body part [6], [7]. Veins are located under the skin and cannot be viewed with naked eyes. Researchers are attracted to it because of Its uniqueness, stability, and resistance to forgery, because of these characteristics, it is a more reliable biometric for personal identification [8], [9]. Hand vein patterns are divided into two categories: dorsal veins and palm veins. This research uses the dorsal veins to recognize and identify people. Every person has a unique dorsal vein pattern, thus, twins do not have the same hand dorsal vein pattern. As a result, this property of uniqueness is required to build a biometric system, depending on the dorsal vein pattern of the hand. Other characteristics of the dorsal hand vein: the first is invariance, as the human dorsal hand vein is essentially constant; the second is difficult to forge, as the dorsal vein is a biological characteristic; and the third is that the detection method is friendly, as the dorsal vein characteristics are internal features that are difficult to damage [10], [11].

The process of extracting dorsal vein from hand image facing many problems such as poor lighting, thickness of the skin, presence of hair, contrast adjustment, contrast enhancement, eliminating noise, extracting the region of interest (dorsal veins), and extract discriminating features. The databases used to test the performance of the proposed system contain volunteers in different age groups, and there is also a difference in gender, skin color, and the amount of hair in the dorsal veins area. It was found that the difference in age, gender, and skin color has no effects on the process of vein extraction, but the existing hair affects the quality of the image. Thus, this paper aims to produce an effective method for extracting dorsal veins from hand images and recognizing persons using correlation coefficient.

The remaining sections of the paper are organized as: section 2 focuses on the related work. The layout of the proposed dorsal hand veins recognition system is described in section 3. The results and discussion are explained in section 4. Finally, the conclusions of this paper are introduced in section 5.

2. RELATED WORK

Researchers have been attracted to the uniqueness of dorsal vein patterns because of their potential for use in personal identification and verification. Many studies have been conducted on the identifying of dorsal hand veins. In terms of recognition and efficiency, these studies vary from the suggested approach. Yan *et al.* [12] suggested a method for extracting features from an image of the dorsal vein. After the image has been preprocessed by normalization of gray image and filtering enhancement, the texture features of the gray image are extracted using the global gist features. Finally, using a K neighbor classifier for personal identification. The proposed method is effective, with a proper recognition rate of 96.7%. Pontoh *et al.* [13] proposed a method to extract features using local line binary pattern (LLBP). LLBP straight-line structure allows it to extract robust characteristics from images. The fuzzy K-nearest neighbors (KNN) classifier is used in the recognition step since it does not require any learning algorithms and hence reduces processing time. The test results indicated that the LLBP technique is reliable for feature extraction from the dorsal vein, when the recognition accuracy is 98%. Rabie *et al.* [14] presented a method for recognizing dorsal palm vein patterns. There are two methods presented. The first method employed principal component analysis (PCA) to extract characteristics from the hand images, followed by a recognition phase using a multi-layer perception (MLP) neural network. The second method, known as bag of features (BOF), adopted speeded-up robust features (SURF) to extract local characteristics from the training set to select the interest points, which were subsequently clustered in a representative group. In the classification step, the support vector machine (SVM) approach is applied. The experiments show that BOF is substantially more accurate than PCA and MLP, with an accuracy rate of 98%. Wang *et al.* [15] presented a method for recognizing dorsal veins based on bit plane and block mutual information. To begin, the gray image was converted to eight-bit planes to remove brightness and noise interference in the upper bit planes and lower bit planes, respectively. Second, the texture of each bit plane of the dorsal hand vein was defined using a block technique, and the mutual information between the blocks was estimated as texture characteristics to solve the difficulties of rotation and size. When compared to the scale-invariant feature transform (SIFT) technique, the proposed method can improve the recognition rate from 86.60% to 93.33%. Vairavel *et al.* [16] presented several methods for extracting features such as the local binary pattern (LBP), histogram of oriented gradients (HOG), and weber local descriptor (WLD), and performance is evaluated in terms of KNN classification accuracy. The WLD method has an accuracy up to 98%, the LBP method has 96% of recognition accuracy, and the HOG method, when compared to both, has the best recognition accuracy up to 99.00%. Rajalakshmi *et al.* [17] introduced a method to extract features from the dorsal hand vein pattern depending on the LBP and repeated line tracking algorithm. Artificial neural network (ANN) is used to perform recognition and authentication. Arduino and global system for mobile (GSM) technologies are utilized to allow users to establish their own security preferences. Thus, with a 99.1% accuracy rate, this method is the most accurate.

3. PROPOSED SYSTEM

In this study, we present a new method for extracting and recognizing dorsal hand veins that using the correlation coefficient in the matching process. The suggested dorsal hand veins recognition system is demonstrated in Figure 1. It has three stages: 1) preprocessing, 2) feature extraction, and 3) matching. Each stage is composed of many steps that are used to identify each test sample and determine whether it belongs to the same person or not.

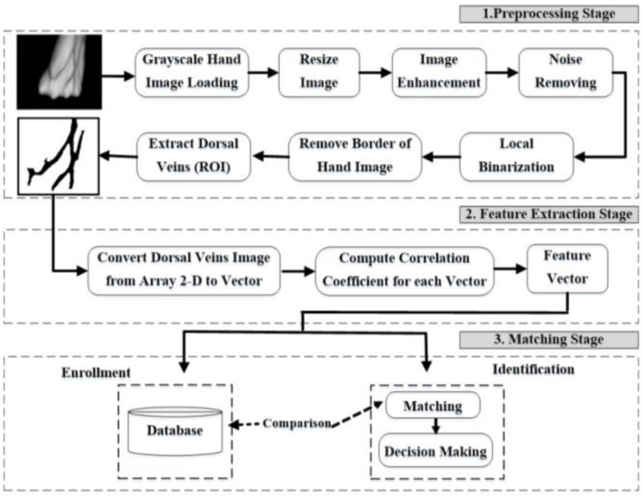


Figure 1. The layout of the proposed system

3.1. Preprocessing stage

The captured natural vein image contains a huge amount of unnecessary information such as hair, skin, flesh, and bone structures. Additionally, the image is damaged because of external lighting effects and sensor noise. Also, the feature extraction and matching stage depend on the quality of the dorsal hand veins image. Thus, preprocessing stage is the main stage to preserve the quality of the image and it consists of seven steps, which are:

a) Step 1: grayscale hand image loading
   This step loads the grayscale hand image from file.
b) Step 2: resize image
   Image resizing can be achieved by changing the dimensions of the image to a uniform size 256×256.
c) Step 3: image enhancement
   This step implies getting a clearer image. The basic steps required in the dorsal hand veins enhancement process are mentioned.

– Contrast adjustment

Min-max linear contrast adjustment is known as contrast stretching and used linear stretching of the pixel’s values as an attempt to improve the contrast of the image. In the min-max linear contrast stretching, anew defined set of values that use the complete range of possible brightness values are utilized to specify the original minimum and maximum values of the data to fall within the new range. The applied mapping function for this type can be found in (1); it maps the minimum grey level G_{min} in the image (I) to zero and the maximum grey level G_{max} to 255, the other grey levels are remapped linearly between 0 and 255 [18].

$$I(x,y) = 255\left(\frac{I(x,y)-Min}{Max-Min}\right) \quad (1)$$

Where the pixel intensity is $I(x,y)$, Max indicates the highest value of the image brightness and Min indicates the lowest value of the image brightness. Figure 2 presents the result of applying min-max linear contrast adjustment on the tested image selected from the database, where: Figure 2(a) explains the original grayscale image and Figure 2(b) explains the adjustment contrast of tested image to improve the brightness of the dorsal veins in the hand image. Thus, the dorsal veins of the hand became more prominent than the skin area.

– Contrast enhancement

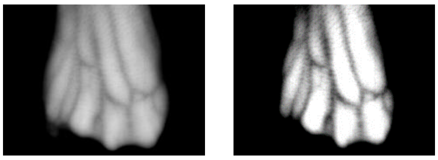
After adjust the contrast, it is important to enhance the image contrast. Thus, contrast limited adaptive histogram equalization (CLAHE) is used to improve the image’s contrast. In contrast limited histogram equalization (CLHE), on the other hand, the histogram is truncated at a certain threshold before equalization is applied. CLAHE is an adaptive contrast histogram equalization method that improves image contrast by applying CLHE to small data segments termed tiles rather than the complete image. Bilinear interpolation is then used to sew the neighboring tiles back together in a smooth manner. Noise amplification can be avoided if the contrast in the homogenous region is limited [19]–[21]. Figure 3 illustrates the result of applying CLAHE on the output image from the previous step, also note that the veins in the image resulting from applying CLAHE are darker, but the background of veins are brighter, thus improving the brightness of the image.

d) Step 4: noise removing

Thus, after contrast enhancement, we need to remove noise from hand image. Firstly, the median filter is applied. The median filter is a non-linear smoothing technique for reducing-edge blur; the main idea is to replace the current point in the image with the median of the brightness in its neighborhood as shown in Figure 4(a), then Gaussian blur filter is performed to eliminate the noise remaining on the veins area, such as hair and the difference in skin patterns as shown in Figure 4(b).

e) Step 5: local binarization

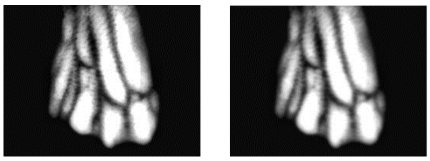
The process of converting an image to binary depends on the selection of a local thresholding value. Local threshold selection depends on the local mean intensity (first-order statistics) in the neighborhood of each pixel. In local thresholding, we need to specify whether the foreground pixels are dark or bright, in the proposed system, the foreground pixels are darker than the background pixels as explained in Figure 5(a) represents an estimate of average background illumination. Then, this local thresholding is used to convert the image to the binary, as shown in Figure 5(b) the veins are black and the background is white.



(a) (b)

Figure 2. Result of contrast adjustment: (a) original image and (b) contrast adjust

Figure 3. The result of applying CLAHE



(a) (b)

Figure 4. Result of noise removing: (a) median filter and (b) gaussian filter

(a) (b)

Figure 5. Result of local thresholding and binarization: (a) thresholding image and (b) binary image

f) Step 6: remove border of hand

The resulting image from the binary step contains a border surrounding the veins area, thus, we need to delete this border. In this step, we need to determine 8 connected components for each pixel in the binary image. In a binary image, a connected component is a group of pixels that are connected with the same values. Then we calculate the area for each group, which means the number of actual pixels in each group. Then, we find the largest area because it represents the largest object in the binary image, and it represents the larger border that surrounds the area of the veins. After that we determine the contour of the largest object, noting that the largest object has black color and the area around it is has white color as shown in Figure 6(a) where the contour and surrounding area is marked in red color for illustration, so we change the color of the area surrounding the contour to a black color so that it becomes the largest object in the image, thus the black border surrounding the area of the dorsal veins has been deleted as shown in Figure 6(b).

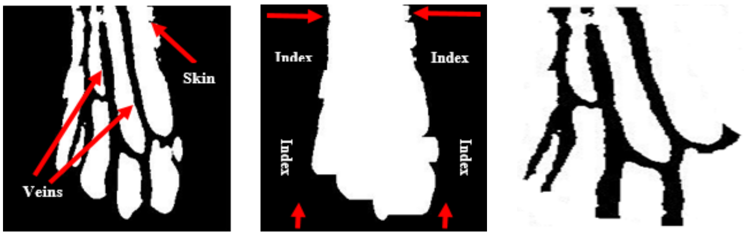
g) Step 7: extract dorsal veins (region of interest (ROI))

The main aim of this step is to extract the area of interest, i.e. the dorsal vein area, so we need to build a binary mask from the image resulting from the previous step, which contains the veins and the background that is black in color and the skin area is white as shown in Figure 7(a). Thus, we need to extract the dorsal veins from the background and skin area. The process of constructing the binary mask is done by checking each row, if the row pixel values are zero, the row values will remain zero, but, if the row pixel values are not zero, it finds the minimum and maximum index of the row to set the value of one between indexes of the row as shown in Figure 7(b).

(a) (b)

Figure 6. Result of remove border of hand: (a) determine border and (b) remove border

The process of extracting dorsal vein is achieved by scanning the binary mask image from the left side to the beginning of the binary mask and the right side to the end of the binary mask, also scan the binary mask from the bottom, these scanned areas have the black color as shown in Figure 7(b). Where the red arrows explain these areas, then we take the index for these areas surrounding the binary mask image, which have the black color, and replace these values with white color in the binary image that illustrated in Figure 7(a). Thus, the background becomes white while the dorsal veins of the hand are black as shown in Figure 7(c). Thus, the area of the dorsal veins is obtained to extract the distinctive features.



(a) (b) (c)

Figure 7. Result of extraction dorsal veins: (a) binary image, (b) binary mask, and (c) dorsals vein (ROI)

3.2. Feature extraction stage

After extracting dorsal veins from the hand image, we focus on obtaining the vein pattern features. This process involves two steps as described.

– Convert extracted dorsal veins image from array two dimensional 2-D to vector as shown in Figure 8.

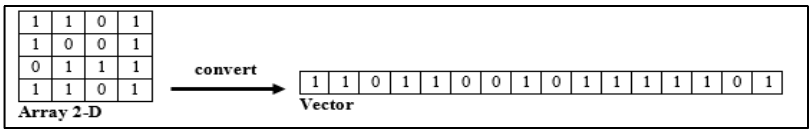


Figure 8. Convert array to vector

– Compute the correlation coefficient for each vector as the (2) [22].

$$C = \frac{\sum_{i=1}^{N}(a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_{i=1}^{N}(a_i - \bar{a})^2}\sqrt{\sum_{i=1}^{N}(b_i - \bar{b})^2}} \quad (2)$$

Where N represents the sample size, ai and bi denote the ith data values, and $\bar{a}$, $\bar{b}$ denote the mean values. The coefficient (C) has a value that varies from -1 to +1, close values to +1 indicate a high positive correlation, close values to -1 indicate a strong negative correlation, and values close to 0 indicate no correlation.

3.3. Matching stage

To recognize an image, you must first check to see if it exists in the database. When someone wants to access the system, an image of the dorsal veins is taken, known as the test image. Then processed and compared to the all feature vector stored in the database. The similarity measure is determined using a correlation coefficient which is computed from the test image and compared with the all correlation coefficients computed from images stored in the database.

4. RESULTS AND DISCUSSION

The performance of the proposed dorsal veins recognition system is evaluated using two databases. Each image is a grayscale that is stored as tif 24 bit/pixel (bit depth). The first database, called database 1, was taken from 138 persons, for each person 4 images per hand, thus the total of images are 1104. The second database comprises 113 persons, for each person 3 images per hand, thus the total of images are 678. The time between data collected in database session 1 and database session 2 is two months. These databases are publicly available in [23]. Figure 9 explains the samples of one person select from database 1 and has 4 images for left and 4 images for right. Figure 9(a) left_1, Figure 9(b) left_2, Figure 9(c) left_3, Figure 9(d) left_4, Figure 9(e) right_1, Figure 9(f) right_2, Figure 9(g) right_3, and Figure 9(h) right_.

The efficiency and accuracy of the proposed system are evaluating using two metrics are correct recognition rate (CRR) and accuracy which are described.

– CRR is the proportion of correctly identified samples to the total samples evaluated as the (3) [24].

$$CRR = \frac{Number\ of\ Correct\ Identified\ Images}{Total\ Number\ of\ test\ Images} \times 100\% \tag{3}$$

– Accuracy is representing the ratio of correct predictions as the (4) [25], [26].

$$Acc = (TP + TN)/(TP + TN + FP + FN) \tag{4}$$

The numbers of true positive, true negative, false positive, and false negative are represented as true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN), respectively.

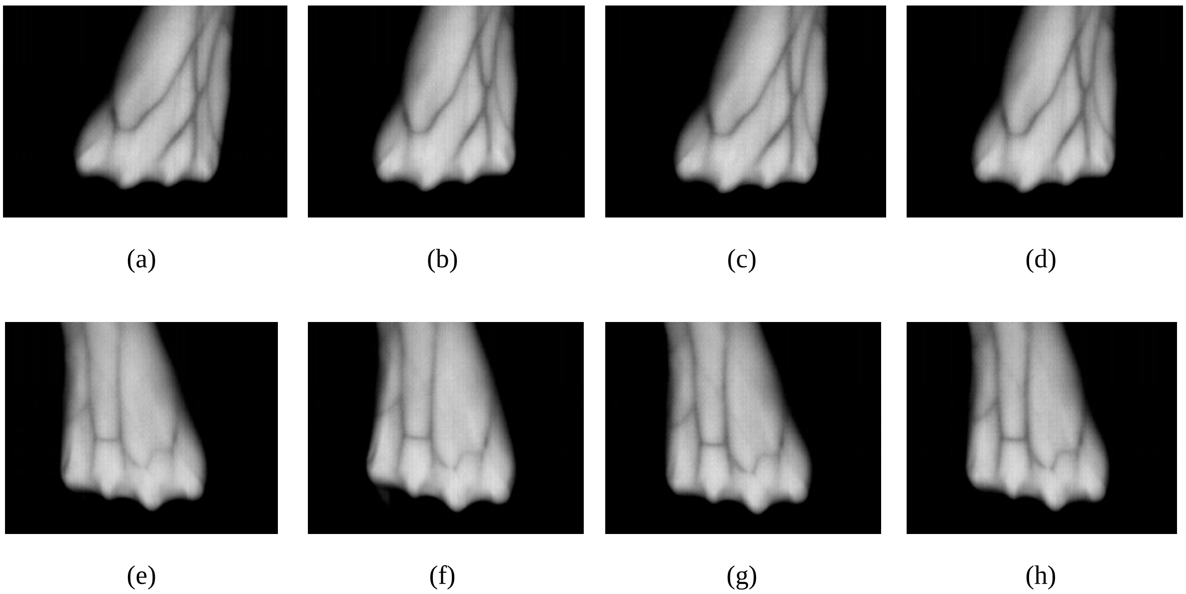


Figure 9. Samples for one person from database 1: (a) left_1, (b) left_2, (c) left_3, (d) left_4, (e) right_1, (f) right_2, (g) right_3, and (h) right_4

The process of recognition is done by passing each sample of the database through all the stages of the proposed system until we reach to compute the correlation value for each sample of the database, then we take the correlation value of the first sample from the first person and comparing it with the correlation values for all samples stored in the database, after that compute the largest correlation value for each sample and saved it with the sample that belongs to it, also, the same steps are done for all database samples.

As previously known, every eight samples represent a person or class in database 1, we choose the highest correlation value from these eight samples, because this value represents the best matching value of the test sample with the corresponding sample registered in the database. After that verified whether it really belongs to this person or not. Thus, the value of the correlation coefficient of the test sample that is identical to the samples of the correct person ranges between 0.7, 0.8, and 0.9, while the value of the correlation coefficient of the test sample that is identical to the samples of another person from the database ranges between 0.4, 0.5, and 0.6, but the value of 0.3 represents the value of the correlation for a test sample from outside the database, it means that a person who is not registered in the database.

The experimental results show that the CRR and accuracy for the first database are 99.38% and 99.46% respectively. But, the CRR and accuracy for the second database are 99.11% and 99.07% respectively. Thus, the first database gives better results than the second database as presented in Table 1.

Table 2 explains the comparison of our proposed method with many previously published studies and shows that it has better results than other existing experiments. The results listed in Table 2 also shows that the proposed method gives a higher correct recognition rate and accuracy than other previous studies. Therefore, it has been proved the efficiency of our proposed system.

Table 1. Show results of CRR and accuracy for the two databases

No. of database	Total of samples	CRR%	Accuracy%
Database 1	1104	99.38%	99.46%
Database 2	678	99.11%	99.07%

Table 2. Compared CRR and accuracy with previous experiments

Reference	Total of samples	CRR%	Accuracy%
[12]	210	96.7%	-
[13]	300	-	98.00%
[15]	2000	93.33%	-
[16]	2040	98.52%	99.00%
[17]	480	-	99.10%
Our proposed with database 1	1104	99.38%	99.46%
Our proposed with database 2	678	99.11%	99.07%

5. CONCLUSION

In this paper, we proposed an effective method for extracting and recognizing the dorsal hand veins. The databases used to test the performance of the proposed system contain volunteers in different age groups, and there is also a difference in gender, skin color, and the amount of hair in the dorsal veins area. It was found that the difference in age, gender, and skin color has no effects on the process of vein extraction, but the existing hair affects the quality of the image, so it was eliminated in the preprocessing stage in the proposed system and preserved the image quality. The experimental results showed that the largest correlation coefficient helped to better recognize persons. Two databases have been used to evaluate the performance of the proposed system. The test results illustrate the CRR and accuracy for database 1 are 99.38% and 99.46%, respectively, whereas the CRR and accuracy for database 2 are 99.11% and 99.07% respectively.

REFERENCES

[1] L. Wang and G. Leedham, “Near- and Far- Infrared Imaging for Vein Pattern Biometrics,” *2006 IEEE International Conference on Video and Signal Based Surveillance*, 2006, pp. 52-52, doi: 10.1109/AVSS.2006.80.

[2] P. Ramsoful and M. H. -M. Khan, “Feature Extraction Techniques for Dorsal Hand Vein Pattern,” *Third International Conference on Innovative Computing Technology (INTECH 2013)*, 2013, pp. 49-53, doi: 10.1109/INTECH.2013.6653722.

[3] C. L. Deepika and A. Kandaswamy, “An Algorithm for Improved Accuracy in Unimodal Biometric Systems through Fusion of Multiple Feature Sets,” *ICGST-GVIP Journal*, vol. 9, no. 3, pp. 33-40, 2009. [Online]. Available: https://static.aminer.org/pdf/PDF/000/349/519/multiscale_feature_extraction_of_finger_vein_patterns_based_on_curvelets.pdf

[4] J. -C. Lee, “Dorsal Hand Vein Recognition based on EP-Tree,” *2015 14th IAPR International Conference on Machine Vision Applications (MVA)*, 2015, pp. 402-405, doi: 10.1109/MVA.2015.7153214.

[5] Y. Wang, K. Li, L. -K. Shark, and M. R. Varley, “Hand-dorsa Vein Recognition Based on Coded and Weighted Partition Local Binary Patterns,” *2011 International Conference on Hand-Based Biometrics*, 2011, pp. 1-5, doi: 10.1109/ICHB.2011.6094331.

[6] D. Huang, Y. Tang, Y. Wang, L. Chen, and Y. Wang, “Hand-Dorsa Vein Recognition by Matching Local Features of Multisource Keypoints,” *IEEE Transactions on Cybernetics*, vol. 45, no. 9, pp. 1823-1837, 2015, doi: 10.1109/TCYB.2014.2360894.

[7] M. H. -M. Khan and N. A. M. Khan, “A New Method to Extract Dorsal Hand Vein Pattern using Quadratic Inference Function,” *International Journal of Computer Science and Information Security (IJCSIS)*, vol. 6, no. 3, pp. 26-30, 2009. [Online]. Available: https://arxiv.org/ftp/arxiv/papers/1001/1001.1966.pdf

[8] L. Chen, H. Zheng, L. Li, P. Xie, and S. Liu, “Near-infrared Dorsal Hand Vein Image Segmentation by Local Thresholding Using Grayscale Morphology,” *2007 1st International Conference on Bioinformatics and Biomedical Engineering*, 2007, pp. 868-871, doi: 10.1109/ICBBE.2007.226.

[9] A. M. Badawi, "Hand Vein Biometric Verification Prototype: A Testing Performance and Patterns Similarity," in *Proc. of the 2006 International Conference on Image Processing, Computer Vision, and Pattern Recognition*, 2006, vol. 1, [Online]. Available: https://www.researchgate.net/publication/220808848_Hand_Vein_Biometric_Verification_Prototype_A_Testing_Performance_and_Patterns_Similarity

[10] H. Wan, L. Chen, H. Shong, and J. Yang, "Dorsal Hand Vein Recognition Based on Convolutional Neural Networks," *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2017, pp. 1215-1221, doi: 10.1109/BIBM.2017.8217830.

[11] A. Singh, H. Goyal, Amar, and A. K. Gautam, "Human Identification Based on Hand Dorsal Vein Pattern using BRISK and SURF Algorithm," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 9, no. 4, pp. 2168-2175, 2020, doi: 10.35940/ijeat.D9059.049420.

[12] J. Yan, L. Chong, and T. Li, "A method of Dorsal Hand Vein Identification," *Tenth International Conference on Digital Image Processing (ICDIP)*, 2018, vol. 10806, pp.1-6, doi: 10.1117/12.2503068.

[13] F. J. Pontoh, J. Y. Sari, A. A. Ilham, I. Nurtanio, "Multispectral Dorsal Hand Vein Recognition Based on Local Line Binary Pattern," *Journal of Computer Sciences and Information*, vol. 11, no. 2, pp. 95-102, 2018, doi: 10.21609/jiki.v11i2.576.

[14] S. M. Rabie, H. M. Ebied, and S. Bayoumi, "Analysis of Dorsal Palm Vein Pattern Recognition System," *2019 Ninth International Conference on Intelligent Computing and Information Systems (ICICIS)*, 2019, pp. 92-98, doi: 10.1109/ICICIS46948.2019.9014833.

[15] Y. Wang, H. Cao, X. Jiang, and Y. Tang, "Recognition of Dorsal Hand Vein Based Bit Planes and Block Mutual Information," *Sensors*, vol. 19, no. 17, 2019, doi: 10.3390/s19173718.

[16] K. S. Vairavel, N. Ikram, and S. Mekala, "Performance Analysis on Feature Extraction using Dorsal Hand Vein Image," *Soft Computing*, vol. 23, pp. 8349-8358, 2019, doi: 10.1007/s00500-019-03991-8.

[17] N. Rajalakshmi, Ramsakar. M. P., and P. Manimegalai, "An Efficient Dorsal Hand Vein Recognition Security System using Arduino and GSM Technology," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 8, no. 6S3, pp. 1577-1581, 2019, doi: 10.35940/ijeat.F1290.0986S319.

[18] H. Ayad, N. F. Hassan, and S. Mallallah, "A Modified Segmentation Approach for Real World Images Based on Edge Density Associated with Image Contrast Stretching," *Iraqi Journal of Science*, vol. 58, no. 1A, pp. 163-174, 2017. [Online]. Available: https://ijs.uobaghdad.edu.iq/index.php/eijs/article/view/6237.

[19] N. M. Sasi and V. K. Jayasree, "Contrast Limited Adaptive Histogram Equalization for Qualitative Enhancement of Myocardial Perfusion Images," *Engineering*, vol. 5, no. 10B, pp. 326-331, 2013, doi: 10.4236/eng.2013.510B066.

[20] S. W. Chin, K. G. Tay, C. C. Chew, A. Huong, and R. A. Rahim, "Dorsal Hand Vein Authentication System using Artificial Neural Network," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 21, no. 3, pp. 1837-1846, 2021, doi: 10.11591/ijeecs.v21.i3.pp1837-1846.

[21] Q. A. A. Hadi, "Vein Palm Recognition Model using Fusion of Features," *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 18, no. 6, pp. 2921-2927, 2020, doi: 10.12928/TELKOMNIKA.v18i6.16149.

[22] S. Kumar and I. Chong, "Correlation Analysis to Identify the Effective Data in Machine Learning: Prediction of Depressive Disorder and Emotion States," *International Journal of Environmental Research and Public Health (IJERPH)*, vol. 15, no. 12, 2018, doi: 10.3390/ijerph15122907.

[23] F. W. -Bernal, B. N. -Álvares, and P. Vizcaya, "A Database of Dorsal Hand Vein Images," *arXiv*, pp. 1-4, 2020. [Online]. Available: https://arxiv.org/pdf/2012.05383.pdf (retrieved from: https://github.com/wilchesf/dorsalhandveins)

[24] A. M. J. Abbas and L. E. George, "Palm Vein Recognition and Verification System Using Local Average of Vein Direction," *International Journal of Scientific and Engineering Research*, vol. 5, no. 4, pp. 1026-1033, 2014. [Online]. Available: https://www.ijser.org/researchpaper/Palm-Vein-Recognition-and-Verification-System.pdf

[25] H. Khusnuliawati, C. Fatichach, and R. Soelaiman, "Multi-feature Fusion Using SIFT and LEBP for Finger Vein Recognition," *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 15, no. 1, pp. 478-485, 2017, doi: 10.12928/TELKOMNIKA.v15i1.4443.

[26] L. H. Albak, R. R. O. Al-Nima, and A. H. Salih, "Palm Print Verification Based Deep Learning," *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 19, no. 3, pp. 851-857, 2021, doi: 10.12928/TELKOMNIKA.v19i3.16573.

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