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Dorsal hand vein authentication system using artificial neural network

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ABSTRACT

Biometric feature authentication technology had been developed and implemented for the security access system. However, the known biometric features such as fingerprint, face and iris pattern failed to provide ideal security. Dorsal hand vein is the features beneath the skin which makes it not easily be duplicated and forged. It was expected to be used in biometric authentication technology to achieve an ideal accuracy with the uniqueness of its characteristics. In this study, 240 images of 80 users were obtained from Bosphorus Hand Vein Database. The images were then pre-processed by cropping ROI, mean filtering, CLAHE enhancing and histogram equalizing. The ROI was then segmented by implementing binarization. The local binary pattern (LBP) features were then extracted from the binarized image. The extracted features were sent to an artificial neural network (ANN) for the classification of the images. The training result shows that the LBP features and ANN can recognize the dorsal hand vein pattern quite well with 90% recognition rate. The NN net was then utilized in the MATLAB GUI program for testing 100 images (80 trained images of 80 users and 20 untrained images of 20 users) from the Bosphorus Hand Vein Database. The results revealed 100% accuracy in their matching result.

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1. INTRODUCTION

Biometric feature authentication technology had been developed and implemented for the security access system. Biometric is defined as the term used in computer science to refer to the field of mathematical analysis of human features such as fingerprint, palm, finger veins, eyes, voice, signature, gait and DNA [1]. By comparing to the traditional personal verification method, such as password, PINS, magnetic swipe cards, keys and smart cards which only offer limited security and are unreliable. Biometric feature authentication technology offers a more reliable and secure performance as biometric features are hard to forge and relatively easy to use [2].

From the past studies, the biometric features such as fingerprint, iris and face that used in the current biometric recognition still fail to provide a highly secure environment. The fingerprint could be produced by a gelatin mould to fool the fingerprint reader, the brightness of the surroundings will affect the detection of iris pattern besides the different view of the face captured increases the difficulty to recognize a face [3].

Biometric authentication systems based on dorsal hand vein patterns had gained attention in recent years due to their physiological properties which are unique, universal and immune to the imposter attacks [4]. Dorsal hand vein is one of the vascular patterns at the back of the hand. This characteristic has made dorsal hand vein not easily to be damaged, wore, duplicated and counterfeited as it is beneath the skin [5, 6]. Apart from this, the dorsal hand vein is believed to be different for every individual, even the twins will have different vein pattern [5]. By comparing to fingerprints, iris and face, the dorsal hand vein provides higher security in the biometric recognition system.

Past studies [2, 7-12] suggested imaging sensors such as a complementary metal-oxide-semiconductor (CMOS) or charged-coupled device (CCD) camera, scanner and webcam with the aid of an infrared source or a neutral density filter. Nevertheless, some researchers preferred to use valid databases, such as a dorsal hand vein image database from [13], North China University of Technology (NCUT) hand dorsal vein database [14], general primary data source (GPDS) [15] and Bosphorus Hand Vein Database [16, 17].

In the image pre-processing stage, obtaining region of interest (ROI), enhancing and denoising images are essential to make the vein pattern easily to be detected at the next segmentation stage. Some researchers implemented algorithms, such as devising datum points [2], Knuckle extraction [2, 11, 18], grey normalization methods [10] to extract ROI of dorsal hand vein. Among the techniques to enhance the ROI, include histogram equalization techniques like contrast limited adaptive histogram equalization (CLAHE) [19], adaptive histogram equalization (AHE) [11, 20, 21] and equalized histogram [4]. Meanwhile, researchers applied Wiener filter, smoothing filter, median filter and 2-D Gaussian filter to reduce the noise in the image [3, 22-24].

In the effort to segment out the dorsal vein patterns from the image, a thresholding technique such as local dynamic or adaptive threshold with morphological operation [4, 9, 24, 25] was proposed. Binarization was also recommended in [16] as it segments out the ROI into white and the black part is the background. By referring to the past studies, local binary pattern (LBP) was suggested to extract the features of dorsal hand vein pattern [3, 5, 10]. LBP, a simple yet efficient texture operator labels the pixels of the images by thresholding the neighbourhood of each pixel and consider the result as a binary number.

Classification is required in a biometric recognition system to identify and recognize the class of images. Winner-takes-all-rule [6] which means that the value ‘1’ indicates the correct class, while the value ‘0’ indicates the incorrect class and cross-entropy error was used to detect errors. K-nearest neighbor (KNN), support vector machine (SVM), Random forest [26] and Mahalanobis distance [25] were used to classify the images by the past researches.

Even though different techniques for a dorsal hand vein recognition were proposed in the past, there is a need for a higher accuracy system. This is because, according to the previous study, the accuracy of the existing approach is limited to the range 51 - 98%, or an error range of 2-49%. Thus, this study intends to perform dorsal hand vein pattern recognition using LBP features and develop a dorsal hand vein authentication system using artificial neural network (ANN) besides evaluating the performance accuracy of the dorsal vein pattern authentication system.

2. RESEARCH METHOD

In this work, the dorsal hand vein pattern authentication using ANN was categorized into two phases, that were training phase and authentication phase. The workflow of this paper is displayed in Figure 1. Bosphorus Hand Vein Database which has a total of 1575 hand images from 100 users under different conditions as seen in Table 1 was employed in this study.

Table 1. Classification of images

Number	Conditions	Left-hand	Right-hand	Number of images
1	Normal (N)	3 images per user	3 images per user	600
2	After carrying a 3kg-bag for 60s (B)	3 images per user	-	300
3	After squeezing an elastic ball (closing and opening) for 60s (A)	3 images per user	-	300
4	After cooling the hand by holding the ice pack on the surface of the back of the hand. (I)	3 images per user	-	300
5	After a time-lapse ranging from two months to five months.	-	-	75

In this project, 100 users' left-hand images under different conditions ((34 users from N-condition, 34 users from A- condition and 32 users from I- condition) were selected. The N- condition, A- condition and I- condition will cover hand vein conditions during tensed and relaxed conditions. Among the 100 users, 80 users were selected to act as genuine users, while the rest 20 users were used to act as the imposters. Thus, in the training phase, a total of 240 images of 80 genuine users was used. Whereas, in the authentication phase, 100 images (80 images from 80 genuine users and 20 images from 20 imposters) were used for testing.

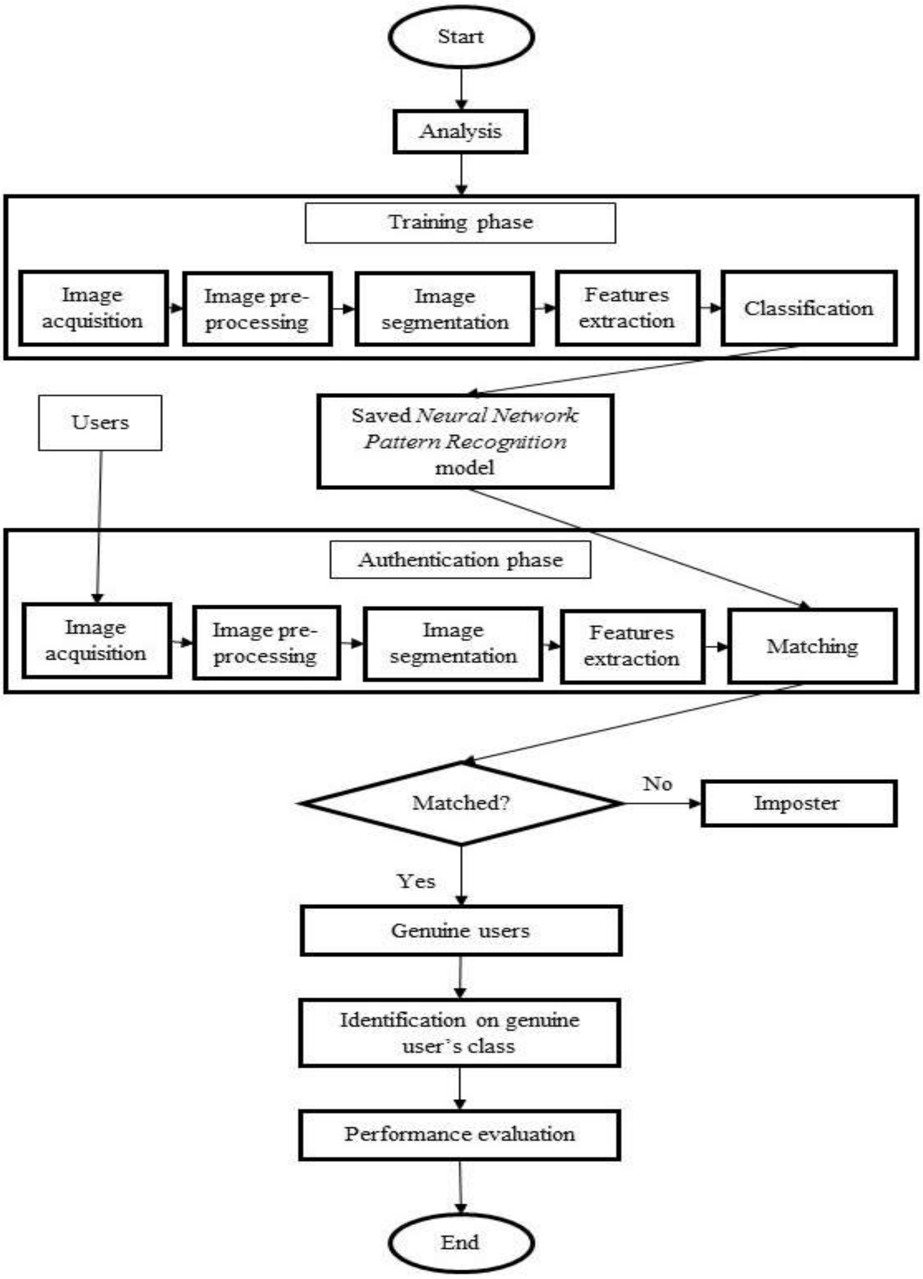

Figure 1. Flowchart of dorsal hand vein pattern authentication system using ANN

In the pre-processing stage, the images were cropped from 300×240 pixels into 60×60 pixels to obtain ROI. After cropping the images, mean filter, CLAHE enhancement and histogram equalization were applied to the cropped ROI to denoise, enhance and contrast the images respectively. The equalized image was then binarized to segment out the vein pattern. Feature extraction was done by extracting the LBP features which consists of 236 features from the binarized image.

To classify the class of the hand vein images, ANN was created by using Neural Network Pattern Recognition Pattern App from Matlab 2019b as shown in Figure 2. The 2-layered feedforward NN consists of one input with 236 neurons, one hidden layer with 240 neurons, one output layer with 80 neurons and one output which consists of 80 neurons. The hidden layer contains weight, bias and tan-sigmoid transfer function, whereas the output layer has a softmax transfer function on top of weight and bias.

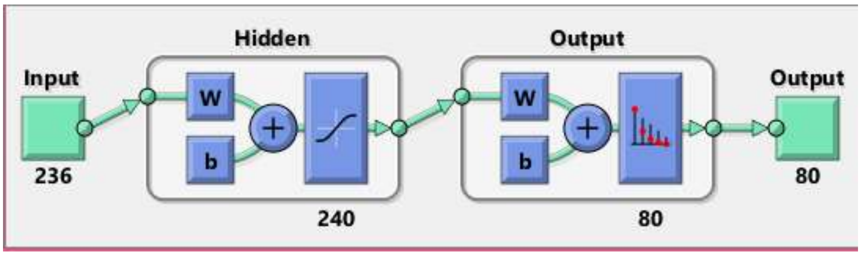

Figure 2. Structure of ANN

Each input neuron X_i will be multiplied with its corresponding weight W_i in the hidden layer. Summation of the product of each input neuron X_i and its weight W_i together with a bias b is called a net, $net = \sum_{i=1}^{n} X_i W_i + b$. The net will be inputted into the tan-sigmoid transfer function to give the continuous output between 0 and 1.

$$Y_i = f(\sum_{i=1}^{n} X_i W_i + b) \tag{1}$$

The tan-sigmoid transfer function is given by $f(x) = \frac{1}{1+e^{-x}}$. The output from the hidden layer will be multiplied with the corresponding weight in the output layer. Summation of the product of output from the hidden layer and corresponding weight W_i together with a bias b in the output layer gives a new net. Later the new net will be passed to the softmax transfer function to give the final output, $Z_i = g(\sum_{i=1}^{n} Y_i W_i + b).$ The softmax transfer function is a normalized exponential function given by

$$g(y)_i = \frac{e^{y_i}}{\sum_{i=1}^{k} e^{y_i}} \tag{2}$$

The input in this study is the LBP features (236 features ×240 images) and the target data (80 classes × 240 images) or equivalent to the dimension of 80 rows x 240 columns. Target was constructed according to the class of images where the binary value '1' denotes true class and the binary value '0' denotes false class. In other words, each column of target data contains '0' values except '1' at the corresponding class.

To train the network for classification, the 240 images were randomly divided into 90% training, 5% validation and 5% testing. Initially, the weight is randomly assigned, later the error between the predicted output and target will be calculated. The weight will be adjusted to minimize the errors using the scaled conjugate gradient (SCG) backpropagation algorithm [27] during the training process. The SGS algorithm combines both conjugate gradient (CG)and Levenberg-Marquardt algorithms to avoid time-consuming line search in CG algorithm.

The performance of the trained NN was measured using recognition rate, false rejection rate (FRR) and false acceptance rate (FAR) as below. In the training process, FR means a correct class was not identified, while FA indicates wrong class or for example, class 1 is identified as another class, etc.

$$\text{Recognition rate} = \frac{\text{number of recognizedi mages}}{\text{total number of images}} \times 100\% \tag{3}$$

$$FRR = \frac{\text{number of unrecognized images}}{\text{total numberof images}} \times 100\% \tag{4}$$

$$FAR = \frac{\text{number of misclass}}{\text{total number of images}} \times 100\% \tag{5}$$

The trained NN net was then saved to be used at the matching stage of the authentication phase. The workflow of the training phase can be represented in Figure 3. In the authentication phase, a graphic interface user (GUI) program was developed. 80 trained images of 80 users and 20 untrained images of 20 users which were directly selected from the Bosphorus Hand Vein Database were tested using this GUI. The images were sent to the image pre-processing to go through the mean filter, CLAHE enhancement and histogram equalization. Binarization was adopted to the pre-processed images. The LBP features of the binarized images were then extracted and matched with the trained NN net. The results of matching would be a genuine case or imposter case. For the genuine case, identification of the genuine user was done. The workflow of the authentication phase could be represented in Figure 4.

The performance analysis of the dorsal hand vein authentication will be calculated as given in the following Table 2. From Table 2, TA denotes true acceptance, FA denotes false acceptance, FR denotes false rejection and TR denotes true rejection. The meaning of TA, FA, FR and TR is given in Table 3.

To compare the performance of NN from Neural Net Pattern Recognition with other classifiers, machine learning algorithms from Classification Learner in App Matlab 2019 was used. In Classification Learner App, Input (236 x 240) and Target (80 x 240) in Neural Net Pattern Recognition App were supplied in a matrix only (237 x 240). In this case, the last row is Target which is not in binary number as before but labeled 1, 2, 3,…,80 to indicate the class. There are decision tree (DT), Discriminant Analysis, Logistic Regression (LR), Naïve Bayes, support vector machine (SVM), Nearest Neighbor and ensemble classifiers in Classification Learner App.

Table 2. Confusion matrix

	Genuine user	Imposter	
Acceptance(A)	TA	FA	Acceptance precision = $\frac{TA}{TA+FA}$
Rejection (I)	FR	TR	Rejection precision = $\frac{TR}{TR+FR}$
	Sensitivity=Recall $\frac{TA}{TA+FR}$	Specificity= $\frac{TR}{TR+FA}$	Accuracy= $\frac{TA+TR}{TA+TR+FA+FR}$

Table 3. The definition on the expressions

Expression	Name	Definition
TA	True acceptance	Genuine user with true class.
TR	True rejection	Imposter with no class.
FA	False acceptance	Genuine user with wrong class or imposter with wrong class.
FR	False rejection	Genuine user with no class.

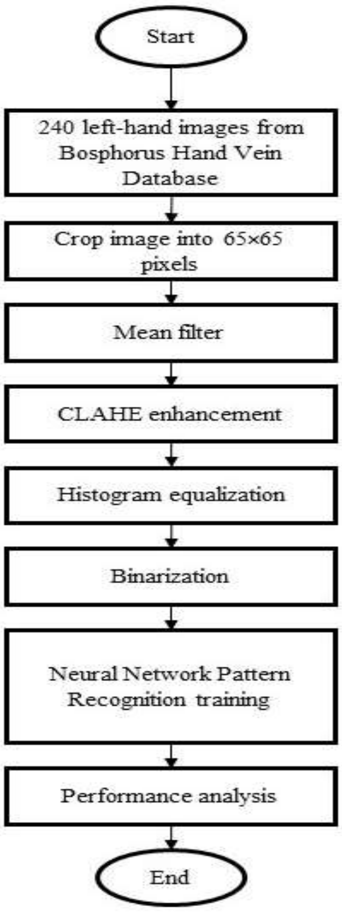

Figure 3. The workflow of the training phase of the dorsal hand vein authentication system using ANN

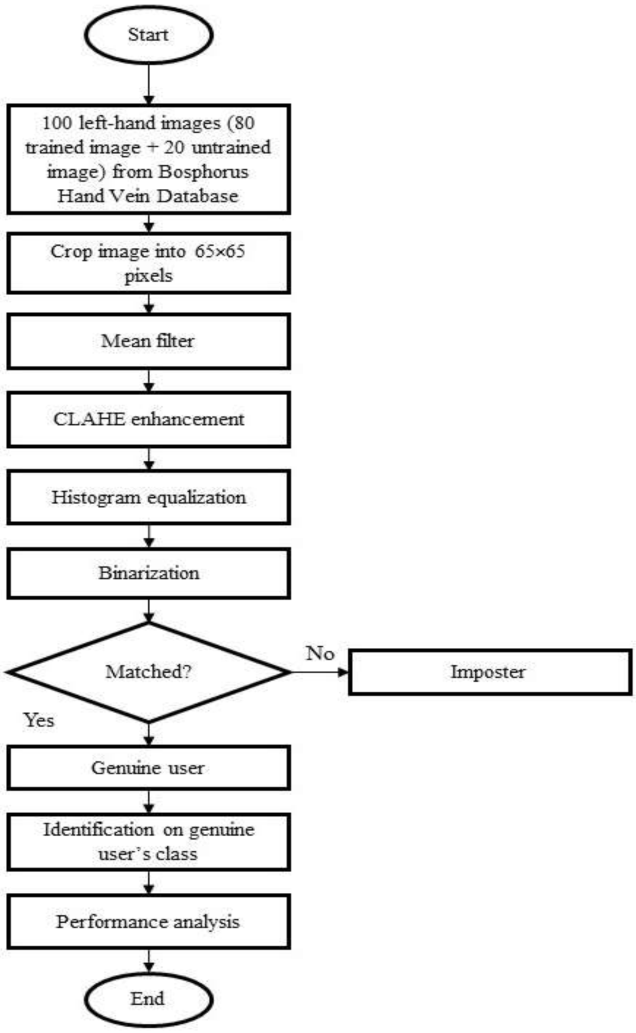

Figure 4. The workflow of the authentication phase in dorsal hand vein authentication system using ANN

3. RESULTS AND DISCUSSION

This section discusses the results during the training phase and the authentication phase.

3.1. Training phase

This subsection focuses on the performance analysis of the training phase. The confusion matrix for the 80 classes in the training phase is shown in Figure 5. Columns represent target (real) class, whereas rows indicate output (predicted) class from ANN. The main diagonal of the confusion matrix shows the recognized classes. Yellow color indicates all 3 training images at that particular class were correctly identified, green color denotes 1 image out of 3 images was recognized while blue color stands for 2 images per 3 images were correctly recognized. The total recognized images are 216 out of 240, hence there is 24 images were unrecognized. From these 24 unrecognized classes, 3 are misclass as shown in red color at the off-diagonal in the confusion matrix. Thus, the performance parameters were calculated and tabulated as shown in Table 4. The recognition rate of the dorsal hand vein using LBP features and ANN is 90%. Figure 6 proves that the highest accuracy obtained using Classification Learner App is 20% from the KNN classifier. The significant difference of accuracy obtained in ANN and KNN may due to different labeling of target in both classifiers. On top of that, ANN allows retrain NN until the desired accuracy is obtained, but the Classification Learner App does not allow retrain. Besides, the accuracy results at each run in Classification Learner are different and not stable. Thus, Ann which yields a higher recognition rate was adopted to build the dorsal hand vein authentication system.

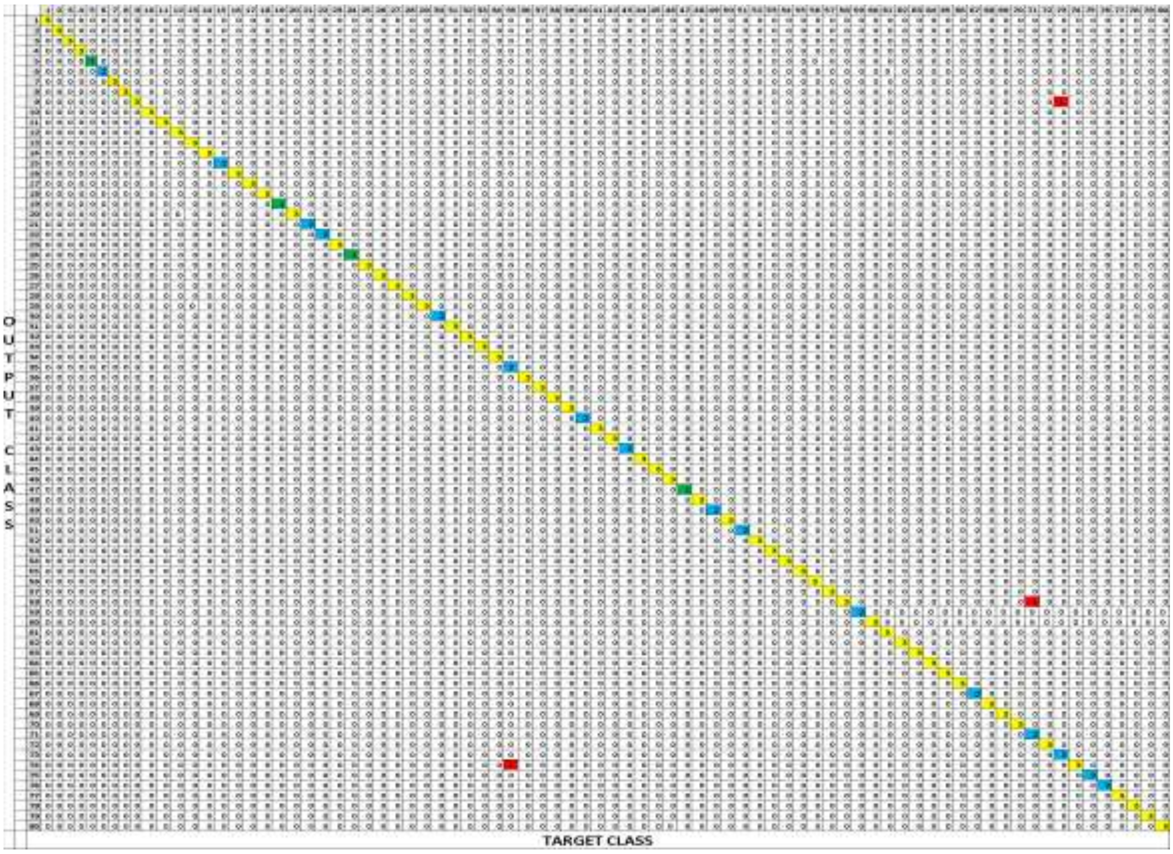

Figure 5. Confusion Matrix

Table 4. Performance analysis of the classification using ANN

Performance parameters	Percentage (%)
Recognition rate	90.00
Precision	98.63
FRR	10
FAR	1.25

Figure 6. Accuracy of KNN

3.2. Authentication phase

This subsection discusses the developed dorsal hand vein pattern authentication system and the matching results. 100 images included 80 trained images and 20 untrained images were tested in the GUI program to validate the performance of the developed system. The GUI in Figure 7 and Figure 9 lets users select an image from the database. Once, each button of the Image Cropping, Mean Filter, CLAHE Enhancement, Histogram Equalization and Image Binarization buttons are selected respectively, the corresponding images are portrayed. Later, when, the Feature Extraction button is clicked, the LBP features will be extracted from the binarized image. Lastly, if the Matching button is pushed, the extracted LBP features will be matched with the imported NN net from the training phase. The result of the matching will be popped up as seen in Figures 8-9. Figure 7 displays the resultant images for a genuine user and its matching status is shown in Figure 8. The imposter case is displayed in Figure 9 if the developed system failed to verify the users. The performance of the result was tabulated in Table 5. From Table 5, the accuracy of the developed GUI program was 100%, which proves that the system is successfully developed.

Figure 7. The resultant images with the identification of a genuine user

Figure 8. The message box of ‘Genuine user!’ pops up during the genuine case

Figure 9. The resultant images with the identification of imposter user

Table 5. Performance on the GUI program

Performance parameters	Percentage (%)
Accuracy	100.00
Precision	100.00
Sensitivity	100.00
Specificity	100.00

4. CONCLUSION

In this work, dorsal vein pattern authentication was divided into two phases, which are the training phase and the authentication phase. To achieve the first objective, 240 training images from 80 users were acquired from the Bosphorus Hand Vein Database. Then, image processing methods were implemented to segment out the ROI followed by denoising, enhancement and binarization to obtain vein patterns. Later, the

LBP features of the binarized dorsal vein pattern were gained. The LBP features were sent into the Neural Net Pattern Recognition App in Matlab 2019b to classify the vein pattern. The recognition rate, FRR and FAR using ANN model is 90%, 10% and 1.25%. The trained ANN net model with LBP features was saved to the authentication phase. A GUI program was developed in the authentication phase with the aid of the NN net model to enable users to test their image. To evaluate the performance accuracy of the dorsal vein pattern authentication system, 100 images of 100 users were input and tested using the developed GUI. The accuracy of the testing and validation of the authentication system is 100%. In a nutshell, this work shows a standard procedure of biometric authentication systems starts from image processing, image enhancement, segmentation, features extraction to ANN classification. The developed GUI system able to be modified to be used in real life as it is convenient and highly secure. Nevertheless, a practical biometric authentication systems process must be started with hardware development of the image acquisition process which is not covered in this study.

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REFERENCES

[1] M. Singaram, P. Preveena, J. Sabitha and M. Shalini, " Dorsal Hand Vein Authentication System," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 8, pp. 2566-2571, 2019.

[2] Y. Wang, K. Li and J. Cui, "Hand-dorsa Vein Recognition Based on Partition Local Binary Pattern," in *International Conference on Signal Processing, ICSP 2010, IEEE*, pp. 1671-1674, 2010.

[3] M. M. N. M. Heenaye and R. K. A. Subramanian, "Study of Dorsa Vein Pattern for Biometric Security," *University of Mauritius Research Journal*. 2009, vol. 15, pp. 17-25, 2009.

[4] Y. Wang, Y. Fan, W. Liao, K. Li, L. K. Shark and M. R. Varley, "Hand Vein Recognition Based on Multiple Keypoints Sets," *2012 5th IAPR International Conference on Biometrics, IEEE*,. pp. 367-371, 2012.

[5] K. Wang, Y. Zhang, Z. Yuan, and D. Zhuang, "Hand Vein Recognition Based on Multi Supplemental Features of Multi-Classifier Fusion Decision,"*2006 IEEE International Conference on Mechatronics and Automation. IEEE*, pp. 1790-1795, 2006.

[6] M. Rajalakshimi, V. Ganapathy, and R. Rengaraj, "Palm-Dorsal Vein Pattern Authentication Using Convolution Neural Network (CNN)," *International Journal of Pure and Applied Mathematics*, vol. 116, pp. 525-532, 2017.

[7] R. Raghavendra, J. Surbiryala, and C. Busch, "Hand Dorsal Vein Recognition: Sensor, Algorithms and Evaluation," *2015 IEEE International Conference on Imaging System and Techniques (IST), IEEE*, pp. 1-6, 2015.

[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, IEEE*, pp. 868-871, 2007.

[9] P. Ramsoful and M. H. M. Khan, "Feature Extraction Technique for Dorsal Hand Vein Pattern," *Third International Conference on Innovative Computing Technology (INTECH 2013), IEEE*, pp. 49-53, 2013.

[10] A. Queslati, N. Feddaoui, and K. Hamrouni, "Identity Verification through Dorsal Hand Vein Texture Based on NSCT Coefficients," *2017 IEEE/ACS 14th International Conference on Computer Systems and Application (AICCSA), IEEE*, pp. 781-787, 2018.

[11] S. Bhosale, and M. R. Jadhav, "Dorsal Hand Vein Pattern Recognition System Based on Neural Network," *2017 International Conference of Electronics, Communication and Aerospace Technology (ICECA). IEEE*, pp. 52-55, 2017.

[12] P. Gupta, and P. Gupta, "Multibiometric Authentication System Using Slap Fingerprints, Palm Dorsal Vein and Hand Geometry," *IEEE Transactions on Industrial Electronics*, vo1. 65, pp. 9777-9784, 2018.

[13] M. Shahin, A. Badawi, and M. Kamel. Biometric Authentication Using Fast Correlation of Near Infrared Hand Vein Patterns. *International journal of biomedical sciences* 2007. Vol. 2, no. 3, pp. 141-148, 2007.

[14] X. Li, D. Huang, R. Zhang, Y. Wang, and X. Xie, "Hand dorsal vein recognition by matching Width Skeleton Models," *2016 IEEE International Conference on Image Processing. (ICIP), IEEE*, pp. 3146-3150, 2016.

[15] A. H. H. Alasadi and M.H. Dawood, "Dorsal hand-vein images recognition system based on grey level co-occurrence matrix and Tamura features," *International Journal of Applied Pattern Recognition*, vol. 4, pp. 207-226, 2017.

[16] B. Belean, M.Streza, S. Crisan, and S. Emerich, "Dorsal hand vein pattern analysis and Neural Network for biometric authentication system," *Studies in Informatics and Control*, vol. 26, pp. 305-314. 2017.

[17] Bosphorus Hand Database. DotNetNuke Corporation. [2010; 2019 October 2], available from http://bosphorus.ee.boun.edu.tr/hand/Home.aspx

[18] A. Kumar, and K.V. Prathyusha, "Personal authentication using hand vein triangulation and knuckle shape," *IEEE Transactions on Image Processing*, vol. 18, pp. 2127-2136, 2009.

[19] S. Kulkarni, and M. Pandit, "Biometric Recognition System based on Dorsal Hand Veins," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 5, pp. 18899-18905, 2016.
[20] R. Malutan, S. Emerich, S. Crisan, O. Pop, and L. Lefkovits, "Dorsal hand vein recognition based on Riesz Wavelet Transform and Local Line Binary Pattern," *2017 3rd International Conference on Frontiers of Signal Processing (ICFSP), IEEE*, pp. 146-150, 2017.
[21] Z. Honarpisheh and K. Faez, "An efficient dorsal hand vein recognition based on firefly algorithm," *International Journal of Electrical and Computer Engineering (IJECE),* vol. 3, pp. 30-41, 2013.
[22] S. Sanchit, M. Ramalho, P. L. Correia, and L. D. Soares, "Biometric identification through palm and dorsal hand patterns," *2011 IEEE EUROCON-International Conference on Computer as a Tool, IEEE*, pp. 1-34, 2011.
[23] S. Zhao, Y. Wang, and Y. Wang, "Extracting Hand Vein Patterns from Low-Quality Images: A New Biometric Technique Using Low-Cost Devices," *Fourth International Conference on Image and Graphics (ICIG 2007), IEEE*, pp. 667-671, 2007.
[24] D. Sandhiya and B. Thiyaneswaran, "Extraction of dorsal palm basilic and cephalic hand vein features for human authentication system," *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), IEEE*, pp. 2231-2235, 2018.
[25] M. U. Akram, H. M. Awan, and A. A. Khan, "Dorsal hand vein based person identification," *2014 4th International Conference on Image Processing Theory, Tools and Applications (IPTA), IEEE*, pp. 1-6, 2015.
[26] Gopal, S. Srivastava, S. Bhardwaj, and S. Bhargava, "Fusion of palm-phalanges print with palmprint and dorsal hand vein," *Applied Soft Computing Journal,* vol. 47, pp. 12-20, 2016.
[27] M.F. Moller, "A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning," *Neural Networks*, vol. 6, pp. 525-533, 1993.

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