

DOI: <http://doi.org/10.32792/utq.jceps.12.02.34>

Dorsal Hand Vein Image Recognition: A Review

Maha A. Rajab¹

Dr. Kadhim M. Hashim²

¹ Department of Biology Science, College of Education for Pure Sciences /Ibn AL-Haitham, University of Baghdad, Iraq

² Imam Ja,afar AI-Sadiq University, Nasiriyah, Iraq

Received 30/11/2022 Accepted 16/12/2022 Published 01/12/2022



This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/).

Abstract:

Subcutaneous vascularization has become a new solution for identification management over the past few years. Systems based on dorsal hand veins are particularly promising for high-security settings. The dorsal hand vein recognition system comprises the following steps: acquiring images from the database and preprocessing them, locating the region of interest, and extracting and recognizing information from the dorsal hand vein pattern. This paper reviewed several techniques for obtaining the dorsal hand vein area and identifying a person. Therefore, this study just provides a comprehensive review of existing previous theories. This model aims to offer the improvement in the accuracy rate of the system that was shown in previous studies and to evaluate test samples and training samples for person identification using distance criteria or neural networks.

Keywords: biometrics, CNN, deep learning, VGG Net-16

Introduction:

An effective method for personal identification and authentication is biometric technology. In computer science, the study of unique human characteristics through quantitative analysis is known as biometrics. Over the past few decades, the global security market for biometric solutions has grown at an accelerated rate, driven mostly by rising demands for public protection against terrorist activities, complex crimes, and electronic fraud [1], [2]. The unique information found in human biometric characteristics, such as face images, hand vein patterns, fingerprints, palmprints, retinal information, handwriting, signatures, and gait, is the basis for biometric identity verification technologies. Dorsal vein recognition is one of them that is the most reliable method of identifying a person [3], [4]. The hand vein patterns can be visualized as a vast network of blood vessels under a person's skin. Even with identical twins, the under-the-skin vein pattern varies greatly from person to person and is stable over an extended length of time. Blood is transported through the veins from one area of the body to another, hence the vein network is widely dispersed throughout the body. For biometric authentication and identification, the veins on the hands' fingers, palms, and dorsal surfaces can be easily collected using near-infrared light [5], [6].

Veins are located under the skin and are not visible to the human eye. Researchers are interested in it due to its distinctiveness, durability, and resistance to forgery. Because of these features, it is a more reliable biometric for identifying individuals. In contrast to the acquisition of fingerprints and facial

features, the vein image is unaffected by the state of the skin, temperature, or humidity. The dorsal vein pattern is employed in the non-invasive hand vein biometrics approach to confirm people's identities. Additionally, the pattern of the veins is stable, meaning that even when a person grows, the veins' shapes do not alter [7], [8].

The remainder of the paper is divided into the following sections: Section 2 focuses on the dorsal hand vein pattern. Section 3 describes the related work. Finally, part 4 introduces the paper's conclusions.

3. DORSAL HAND VEINS PATTERN

The network of blood veins beneath a person's skin is known as their vein pattern, as depicted in figure 1. Vein patterns were first proposed as a kind of biometric technology in 1992. Vein patterns are sufficiently varied between people, stable, unaffected by aging, and show no obvious changes in adults when seen. According to popular belief, even identical twins have different blood vein patterns [9]. In contrast to other biometric qualities, Vein patterns offer a particularly unique way to distinguish yourself from other biometric features that are acquired externally, such as face or fingerprint, as they are buried inside the human body. Internal veins give the systems a high level of security and guarantee that they are unaffected by the condition of the skin on the exterior (e.g. dirty hand) [10].



Figure1. Dorsal hand veins [10]

4. RELATED WORKS

Over the past several years, numerous recognition methods utilizing hand vein biometrics have been created. Many scientists are currently focused on creating new, improved biometric systems using a variety of features. Accordingly, dorsal hand vein patterns are a more recent characteristic that is utilized to identify a person due to their distinctiveness, dependability, durability, and difficulty to fake. Numerous methods for extracting the dorsal hand vein from an image and identifying a person have been developed. One of the most crucial deep learning techniques that use intense training of numerous layers is convolutional neural networks (CNN). This technique is very effective and popular for usage with images. Convolution, pooling and fully linked layers make up the three primary layers of a CNN network. Images of dorsal hand veins may be recognized by CNN with high accuracy. Numerous studies have used the dorsal hand vein recognition system as their focal point. The dorsal vein can be extracted from the image using several different methods that have been developed for this purpose as described below:

- Ramsouf et al. [11] suggested a technique for creating a biometric security system based on a configuration that effectively captures dorsal hand vein images. The image is then thinned using several preprocessing techniques. An essential step in a biometric identification system is feature extraction. Three types of features extracted which are including the Hough lines transform, the Pixel by Pixel Method, and the Directional Coding Method, have been investigated and put into practice. Mahalanobis distance and correlation percentage have been utilized for matching.
- Premalatha et al. [12] proposed an innovative method for identifying dorsal hand vein patterns from information on the dorsal hand veins at the grey level. In this study, the features are extracted using a Gabor filter quadrature pair that computes locally in a window for each pixel position. Six frequency coefficients are quantized and utilized to create a descriptor code for the

neighborhood. A histogram is produced for each pixel that describes the local pattern after these local descriptors are decorrelated using the whitening process. The minimum distance is used for the classification stage.

- Lee et al. [13] A bank of directional filters with a variety of orientations has been proposed in order to extract vein patterns. Line-based vein features are then encoded into binary code using the minimum directional code. In addition, a large amount of the vein image's non-vein areas are ineffective for recognizing veins. To increase accuracy, the variance of the minimum directional filtering response image is evaluated to identify non-vein locations, which are then referred to as non-orientation codes. Lee [4] proposed a technique to extract minute details from the dorsal hand vein, such as endpoints and the distance between the two endpoints as measured along the image's edge. Additionally, it is suggested to use the end-points-tree (EP-tree) to improve matching efficiency and assess these end points' discriminatory potential for the purpose of personal verification.
- Kumar et al. [14] developed an approach based on a local image descriptor that is created from a stack of naturally occurring image patches that are statistically independent in filter response. It generates binary code for each pixel by linearly projecting the natural image patches onto an image subspace and thresholding the coordinates to make them binary. The ROI of the dorsal hand vein image, which is divided into 17 overlapping rectangular sections, is subjected to the 12 preconfigured filters that were learned from a small sample of real images. Each of these regions receives a unique binarized statistical image feature descriptor computation. The recognition rate is calculated using the KNN classifier and fivefold cross-validation. The trial outcomes demonstrate that the City block distance measure performs.
- Wang et al. [15] presented an enhanced Bag of Visual Words (BoVW) model to investigate the dorsal hand vein recognition issue. To be more specific, before building a visual dictionary, firstly, use K-means++ to get a few clustering center points for each image category, and each center point stands for a visual word. Secondly, created a visual dictionary by combining all of the word categories. Last but not least, optimized the visual dictionary by removing redundant terms using the mutual information method. The suggested approach was evaluated on image databases assembled under loose conditions, and the findings demonstrate that the enhanced model has great robustness, limited computational complexity, and a more prominent representation of each image class, which can result in superior performance.
- Alasadi et al. [16] suggested a technique that calls for the presence of a human operator in order to design and implement a dorsal hand-vein recognition system that can recognize individuals based on their veins and can segment veins. Firstly, the dorsal vein image is preprocessed to extract ROI, and then features based on wavelet transform, GLCM, and Tamura features are retrieved. MDC classifier is utilized for classification in the end.
- BELEAN et al. [17] proposed a method for user authentication based on dorsal hand vein pattern analysis and multi-layer perception neural network classification. Rotation invariant Hough transforms and clustering-based segmentation and mathematical morphology are two separate methods used for image processing. Both methods produce binary images that include the vein pattern. In order to extract the final features, which are independent of hand rotation and distance from the camera lens during acquisition, the vascular structure matching to hand image samples taken from the same user is employed. These features are utilized to train the neural network and to determine if the new input images correspond to one of the genuine subjects or not.
- Yan et al. [18] designed a method to solve the shortcomings of losing detail about vein anatomy and the incorrect assessment of feature points in the current algorithms. This algorithm will extract the global Gist feature from the dorsal hand veins image. The preprocessing is done by image gray normalization pretreatment and filtering improvement. The global Gist characteristics of the gray dorsal hand veins image are retrieved as the texture features. The K-Nearest Neighbor

(KNN) classifier was then used to determine the individual's identification. Using a self-created dorsal vein picture database, this technique was finally confirmed.

- Pontoh et al. [19] developed a technique based on employing the Local Line Binary Pattern (LLBP) to extract features from the input dorsal veins image. The dorsal hand vein image will be recognized well because the LLBP's straight-line design to extract distinct features from photos with indistinct veins. Since the fuzzy K-NN classifier does not require a learning algorithm, it is used at the recognition step to reduce processing time.
- Oueslati et al. [20] developed a technique for identifying people based on the texture of the dorsal hand veins. The method consists of four steps: the first involves applying a pre-processing phase to the image contrast in order to produce a better quality dorsal hand vein image, followed by the extraction of the region of interest (ROI), secondly, proposing a novel encoding method based on Nonsampled Contourlet Transform (NSCT) and phase response information; and the third step is dividing the resulting image into local regions, after which statistical descriptors are calculated in each block. Then, determine the similarity between two dorsal hand veins by computing the modified Hamming distance between templates.
- Arora et al. [21] suggested employing fingertips and finger valley key points to extract the region of interest (ROI). Based on information set theory, new features and a new classifier are suggested. The information set is derived from a fuzzy set by applying the information-theoretic entropy function to express the uncertainty in the attribute and information source values. The new feature types include the vein effective information (VEI), vein energy feature (VEF), vein sigmoid feature (VSF), Shannon transform feature (STF), and composite transform feature (CTF). Using the Frank t-norm and the entropy function, the Improved Hanman Classifier (IHC) is created from the training and test feature vectors.
- Premavathi et al. [22] proposed a framework for a biometric classification system by projecting dorsal hand vein patterns using the local binary pattern (LBP) and local tree pattern (LTP) feature descriptor components together. To create a useful classification system, the K-nearest classification approach is analyzed with various proximity measure calculations. As a similarity metric between the training and testing images, this approach employs several distance metrics, including Chi-square, Cityblock, Euclidean, and Murkowski. The test findings show that Chi-square distance measurement works better than other distance measures.
- Wang et al. [23] proposed a technique for recognizing the dorsal hand veins based on bit plane and block mutual information. First, the grayscale input image of the dorsal hand vein was transformed to eight-bit planes to avoid interference from both brightness and noise inside the higher bit planes and lower bit planes respectively. Second, to address the issues of rotation and size, the texture of each bit plane of the dorsal hand vein was characterized using a blocking technique, and the mutual information between blocks was computed as texture features using three different modes. The studies were then conducted across multiple devices. The first gadget was used for registration, while the second was for recognition. The proposed technique can increase the recognition rate of the dorsal hand vein when compared to the Scale-invariant feature transform (SIFT) algorithm.
- Nie et al. [24] proposed a new hyperspectral hand vein identification technology. First, a new hyperspectral acquisition device is created to create a database of 53 spectra from the dorsal hand. From all of the spectral images of the dorsal hand, a region of interest was then extracted. Then, both the dorsal hand texture and the vein features were extracted using the partitioned local binary pattern, which was used for feature representation. In order to perform recognition, the nearest neighborhood classifier was used.
- Zulpe et al. [25] presented a technique for identifying the dorsal hand vein pattern. The vein skeleton extraction with low distortion is crucial for increasing the recognition ratio. After several steps including size and gray normalization, Gaussian low pass and wiener filtering, adaptive thresholding segmentation, area thresholding, morphological opening and closure, conditional

thinning, and spurs pruning, our technique first acquires a clean, minimally distorted skeleton. The feature vector is then retrieved using the seven corrected moment invariants of the vein skeleton. Finally, KNN is used to train and recognize the feature vector.

- Arora et al. [26] explored the use of dorsal vein images and histogram of oriented gradients. After pre-processing, the region of interest is identified from dorsal hand vein images using the feature descriptor histogram of oriented gradients (HOG). By following the stages of the HOG algorithm, which extracts edge information from the images, interesting features are calculated. Even in raw images, edges are significant features that hold crucial information. The nearest neighbor classifier is used for classification.
- Lefkovits et al. [27] demonstrated a convolutional neural network-based technique for recognizing dorsal hand veins (CNN). It is used and compared with two CNNs that have been fully trained on the most significant modern deep-learning architectures (AlexNet, VGG, ResNet, and SqueezeNet). The transfer learning and finetuning techniques are devoted to dorsal hand vein-based identification. Different pre-processing approaches are necessary to perform, which motivated us to research the effects of several image quality improvement strategies, including Gaussian smoothing, inhomogeneity correction, contrast-limited adaptive histogram equalization, ordinal image encoding, and coarse vein segmentation based on geometrical considerations.
- Vairavel et al. [28] proposed a technique to construct a high acknowledgment rate, accessible dorsal vein design dependant individual acknowledgment framework. Features such as LBP (Local Binary Pattern), HOG (Histogram of Oriented Gradients), and WLD (Weber Local Descriptor) are extracted from the dorsal image, and the technique of Chisquare, Cityblock, Euclidean, and Minkowski is used for recognition speeds. KNN is employed for classification.
- Chin et al. [29] explains how to extract features from gray-level co-occurrence matrices (GLCMs) and statistical methods employing artificial neural networks (ANN) to recognize dorsal hand veins. The images were preprocessed by cropping the region of interest (ROI), followed by utilized of mean filtering, contrast enhancement, and histogram equalization. Then, the binarization method is used to segment the ROI into segments. Afterward, the segmented ROI was used to extract the statistical and GLCM features. These features are passed to ANN for classification.
- Nadiya et al. [30] proposed a technique for identifying the hand's dorsal veins. First, undesirable noise is removed from the input image of the dorsal hand vein. Utilizing an expanded variant of Local Binary Pattern (LBP) known as the Orientation of LBP (OLBP), the directional feature is retrieved from the preprocessed image. The feature extracted with OLBP is represented in binary format so that the Hamming distance can be used to match the features.
- ALASHIK et al. [31] suggested a system for identifying people to a system that uses the deep convolutional neural network (CNN) while developing the visual intermediate activation layer. The network is trained to extract features directly without pre-processing the original images in this system. The proposed method uses a transfer learning model using CNN models (DenseNet, ResNet) to extract and classify both features.
- SAYED et al. [32] proposed a real-time, effective dorsal hand identification system to attain high frame rates and good outcomes. A smartphone is utilized to gather our dataset and is attached to a contactless device that comprises an infrared LED and a universal serial bus (USB)camera. To boost the frame rate and enhance real-time performance, simple algorithms were used to process the collected images. K-nearest neighbors (K-NN) matching is used in the feature detection and extraction technique together with an orientation of FAST and rotation of BRIEF (ORB) to match features.
- Nozaripour et al. [33] proposed a new dorsal hand vein recognition system that is robust against rotation. The negative impacts of hand rotation during image capture are largely offset by adjusting the length and angle of the sides to select ROI. ROI in each shot will therefore vary in size and shape depending on how much the hand has rotated. However, because the dorsal hand

vein patterns have the same direction distribution, we classify using the kernel method on sparse representation. Therefore, the majority of samples with various classes but the same direction distribution will be correctly identified. By combining these two methods, it is possible to develop a methodology that effectively counters hand rotation for identifying dorsal hand veins.

- Sari et al. [34] suggested a technique based on the Local Binary Patterns (LBP) approach. LBP is utilized as a feature extraction technique to enhance the vein's texture feature for maximum accuracy and processing speed. The Fuzzy K-Nearest Neighbor (Fuzzy K-NN) method is used to recognize dorsal hand vein images.
- Hasan et al. [35] suggested a technique centered on identifying hand gestures by using the dorsal hand veins. The research aims to develop a unique method for tracking and identifying hand vein rotation using fuzzy neural networks. The change in orientation was treated as a gesture and measured. The methods were tested with rotations ranging from -45 to +45. Both clockwise and counterclockwise rotations were discernible to us with success.
- ALASHIK et al. [36] proposed a method based on utilizing Deep learning (DL) and generative adversarial networks (GANs). Deep learning and GAN are combined to create a DL-GAN. The adversarial network (DL-GAN) approach is designed to boost the proportional value of the authentication process. Dorsal hand veins with biometric physical traits are utilized to verify identities. For choosing hand dorsal features, a multistep procedure is performed, including preimage processing and successfully recognizing individuals. Based on the data gathered from the dorsal hand vein images, the deep learning productive anti-network approach is employed to accurately identify people.
- Kumar et al. [37] suggested a technique based on using a convolution neural network (CNN) to recognize dorsal veins. Four types of datasets (good, medium, and low quality) and augmented images are used to fine-tune the VGG Net-16 model in addition to using the pre-trained version (between the two images from genuine matching or false matching). Dorsal hand vein images of the left and right hands are included in each of the four datasets. The suggested model's performance is compared to those of current transfer learning work as well as other CNN models like VGG Face and VGG-19 (with and without fine-tuning).
- NAYEBI et al. [38] presented a dorsal hand vein pattern-based biometric identification system. Sample data has been used from the literature to test the relevant system. By adding noisy data to the data collection, the total amount of data was increased. SVM, ANN, LDA + KNN, and CNN algorithms were used to classify the preprocessed images. It has been found that using CNN yields the maximum identification accuracy and that the CNN approach performs better than other methods.
- Mohaghegh et al. [39] suggested a fully automated, Convolutional Neural Network (CNN) for biometric identification technique based on dorsal hand images. Two related datasets, the 11k Hands and IITD dorsal hand databases are used to experimentally compare the identification performance of three different CNN architectures: AlexNet, ResNet50, and ResNet152. A transfer learning approach is used to adjust the CNNs' final output layers to correspond to the number of classes contained in the datasets.
- Kefeng Li et al. [40] presented an approach based on the fusion of ResNet and Histograms of Oriented Gradients (HOG) features, in which the residual structure of ResNet is fed with the shallow semantic data generated by primary convolution and HOG features for full fusion and, ultimately, classification is done based on using KNN classifier.

Table 1 presents the results obtained from previous studies concerned with the topic of extracting the dorsal hand veins, and these results include the number of persons, the total number of dorsal hand vein images, accuracy, Correct Recognition Rate (CRR), False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER).

Table1. Summarized the results of previous research work.

References	Person	Total Dorsal Veins	Accuracy%	CRR%	FAR%	FRR%	EER%
[11] (2013)	100	500	-	-	-	0.03%	-
[12] (2014)	102	2040	-	100%	-	-	-
[13] (2014)	214	4280	99%	-	-	-	-
[4] (2015)	214	4280	-	99.64%	-	-	-
[14] (2015)	102	2040	-	99.80%	-	-	-
[15] (2017)	42	420	85.95%	-	-	-	-
[16] (2017)	100	400	92%	-	-	-	-
[17] (2017)	15	60	-	-	-	-	0.83%
[18] (2018)	15	210	-	96.7%	-	-	-
[19] (2018)	50	300	98%	-	-	-	-
[20] (2018)	102	1020	-	99.96%	-	-	-
[21] (2018)	103	1030	92.2%	-	-	-	-
[22] (2018)	102	2040	-	95.10%	-	-	-
[23] (2019)	50	2000	-	93.33%	-	-	-
[24] (2019)	120	31,800	99.00%	-	-	-	-
[25] (2019)	100	1200	-	97.75%	-	-	-
[26] (2019)	100	500	-	-	91.2	-	-
[27] (2019)	102	2040	99.00%	-	-	-	-
[28] (2020)	50	204	-	98.33%	-	-	-
[29] (2020)	80	240	99.32%	-	-	-	-
[30] (2020)	50	400	-	98.4%	-	0.07%	-
[31] (2020)	502	4650	82.509 %	-	-	-	-
[32] (2021)	100	2200	-	-	-	-	4.33%
[33] (2021)	100	1200	-	96.25	-	-	-
[34] (2021)	50	200	90.67%	94%	-	-	-
[35] (2021)	-	192	93.00%	-	-	-	-
[36] (2021)	190	11076	98.36%	-	-	-	2.47%
[37] (2021)	400	8000	99.60%	-	-	-	-
[38] (2021)	100	4000	99.64%	-	-	-	-
[39] (2021)	190	11076	99.9%	-	-	-	-
[40] (2022)	110	2200	-	93.47%	-	-	-

5. CONCLUSION

Automated biometrics-based personal identification has gained attention in pattern recognition due to the increasing security concern. Due to its great reliability, vein identification has recently received more attention. After reading various research articles, we were familiar with the dorsal vein authentication process in general and its corresponding method. The methods for identifying a person by their dorsal hand veins are all summarized in the literature. There is still an opportunity for improvement despite the existence of several existing methods for dorsal vein recognition. Various global and local techniques are used, including SIFT, SURF, PCA, LBP, and many more to extract features from images of the dorsal

hand veins and then pass those features to KNN, CNN, deep learning, and many other techniques to perform the classification process.

REFERENCES

- [1] **M. Rajalakshmi, V. Ganapathy, and R. Rengaraj**, "Palm-dorsal vein pattern authentication using convoluted neural network (CNN)," *Int J Pure Appl Math*, vol. 116, no. 23, pp. 525-532, 2017.
- [2] **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*, vol. 21, no. 3, pp. 1837-1846, 2021.
- [3] **S. H. Benziane and A. Benyettou**, "Anisotropic diffusion filter for dorsal hand vein features extraction," *International Journal of Biology and Biomedicine*, vol. 1, pp. 27-31, 2016.
- [4] **J.-C. Lee**, "Dorsal hand vein recognition based on EP-tree," in *2015 14th IAPR International Conference on Machine Vision Applications (MVA)*, 2015, pp. 402-405: IEEE.
- [5] **A. Singh, H. Goyal, and A. K. G. Amar**, "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.
- [6] **N. Charaya and P. Singh**, "Human Authentication Based On Dorsal Hand Veins: A Review," *vol*, vol. 119, pp. 2175-2185, 2015.
- [7] **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, 2014.
- [8] **M. H. M. Khan and N. A. M. Khan**, "A new method to extract dorsal hand vein pattern using quadratic inference function," *arXiv preprint arXiv:1001.1966*, 2009.
- [9] **B. Sontakke, V. Humbe, and P. Yannawar**, "Dorsal hand vein authentication system: a review," *Journal of Scientific Research and Development*, vol. 6, no. 5, pp. 511-514, 2017.
- [10] **N. A. Al-johania and L. A. Elrefaei**, "Dorsal hand vein recognition by convolutional neural networks: feature learning and transfer learning approaches," *International Journal of Intelligent Engineering and Systems*, vol. 12, no. 3, pp. 178-91, 2019.
- [11] **P. Ramsiful and M. H.-M. Khan**, "Feature extraction techniques for dorsal hand vein pattern," in *Third International Conference on Innovative Computing Technology (INTECH 2013)*, 2013, pp. 49-53: IEEE, 2013.
- [12] **K. Premalatha and A. Natarajan**, "A dorsal hand vein recognition-based on local gabor phase quantization with whitening transformation," *Defence Science Journal*, vol. 64, no. 2, p. 159, 2014.
- [13] **J.-C. Lee, T.-M. Lo, and C.-P. Chang**, "Dorsal hand vein recognition based on directional filter bank," *Signal, Image and Video Processing*, vol. 10, no. 1, pp. 145-152, 2016.
- [14] **K. Premalatha and A. Natarajan**, "Hand vein pattern recognition using natural image statistics," *Defence Science Journal*, vol. 65, no. 2, p. 150, 2015.
- [15] **Y. Wang and S. Dong**, "Dorsal Hand Vein Recognition Based on Improved Bag of Visual Words Model," in *Chinese Conference on Biometric Recognition*, 2017, pp. 203-212: Springer.

- [16] **A. H. H. Alasadi and M. H. Dawood**, "Dorsal Hand-vein Images Recognition System based on Grey Level Co-occurrence Matrix and Tamura," *Int. J. Applied Pattern Recognition*, vol. 4, no. 3, p. 207, 2017.
- [17] **B. Belean, M. Streza, S. Crisan, and S. Emerich**, "Dorsal hand vein pattern analysis and neural networks for biometric authentication," *Studies in Informatics and Control*, vol. 26, no. 3, pp. 305-314, 2017.
- [18] **J. Yan, L. Chong, and T. Li**, "A method of dorsal hand vein identification," in *Tenth International Conference on Digital Image Processing (ICDIP 2018)*, 2018, vol. 10806, pp. 1578-1583: SPIE.
- [19] **F. J. Pontoh, J. Y. Sari, A. A. Ilham, and I. Nurtanio**, "Multispectral dorsal hand vein recognition based on local line binary pattern," *Jurnal Ilmu Komputer dan Informasi*, vol. 11, no. 2, pp. 95-102, 2018.
- [20] **A. Oueslati, N. Feddaoui, and K. Hamrouni**, "A Human Identification Technique Through Dorsal Hand Vein Texture Analysis Based on NSCT Decomposition," in *International Conference on Soft Computing and Pattern Recognition*, 2018, pp. 183-193: Springer.
- [21] **P. Arora, S. Srivastava, M. Hanmandlu, and S. Bhargava**, "Robust authentication using dorsal hand vein images," *IEEE Intelligent Systems*, vol. 34, no. 2, pp. 25-35, 2018.
- [22] **C. Premavathi and P. Thangaraj**, "Efficient Hand-dorsa Vein Pattern Recognition using KNN classification with Completed histogram CB in TP Feature Descriptor," *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 7, no. 4S, pp. 50-55, 2018.
- [23] **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, p. 3718, 2019.
- [24] **W. Nie, B. Zhang, and S. Zhao**, "A novel hyperspectral based dorsal hand recognition system," in *Proceedings of the 2019 11th International Conference on Machine Learning and Computing*, 2019, pp. 362-367.
- [25] **N. Zulpe and B. Sontakke**, "A Dorsal Hand Vein Pattern Recognition using Invariant Moment," *International Journal of Computer Sciences and Engineering*, vol.7, no. 3, 2019, pp.563-566.
- [26] **P. Arora, G. Chaudhary, and S. Srivastava**, "Exploiting Oriented Gradient Histogram for Dorsal Vein Recognition," in *2019 Twelfth International Conference on Contemporary Computing (IC3)*, 2019, pp. 1-4: IEEE.
- [27] **S. Lefkovits, L. Lefkovits, and L. Szilágyi**, "CNN approaches for dorsal hand vein based identification," *Computer Science Research Notes*, 2019.
- [28] **K. Vairavel, R. Nevetha, and S. Mekala**, "Certain investigation on feature extraction in dorsal hand vein image," in *IOP Conference Series: Materials Science and Engineering*, 2020, vol. 764, no. 1, p. 012039: IOP Publishing.
- [29] **S. W. Chin, K. G. Tay, A. Huong, and C. C. Chew**, "Dorsal Hand Vein Pattern Recognition Using Statistical Features and Artificial Neural Networks," in *2020 IEEE Student Conference on Research and Development (SCORED)*, 2020, pp. 217-221: IEEE.
- [30] **K. Nadiya and V. P. Gopi**, "Dorsal Hand Vein Biometric Recognition Based on Orientation of Local Binary Pattern," in *2020 IEEE-HYDCON*, 2020, pp. 1-6: IEEE.

- [31] **K. Alashik, S. Hussin, R. YILDIRIM, and A. ALGUTTAR**, "Dorsal Hand Vein Identification Based on Deep Convolutional Neural Networks and Visualizing Intermediate Layer Activations," *Avrupa Bilim ve Teknoloji Dergisi*, pp. 512-521, 2020.
- [32] **M. I. Sayed, M. Taha, and H. H. Zayed**, "Real-Time Dorsal Hand Recognition Based on Smartphone," *IEEE Access*, vol. 9, pp. 151118-151128, 2021.
- [33] **A. Nozaripour and H. Soltanizadeh**, "Robust vein recognition against rotation using kernel sparse representation," *Journal of AI and Data Mining*, vol. 9, no. 4, pp. 571-582, 2021.
- [34] **J. Y. Sari, S. Bantun, and Z. Noorhasanah**, "Local Binary Patterns for Dorsal Hand Vein Recognition," *Proceeding KONIK (Konferensi Nasional Ilmu Komputer)*, vol. 5, pp. 235-239, 2021.
- [35] **H. S. Hasan and M. A. Al-Sharqi**, "Hand vein recognition with rotation feature matching based on fuzzy algorithm," *International Journal of Nonlinear Analysis and Applications*, vol. 12, pp. 951-958, 2021.
- [36] **K. M. Alashik and R. Yildirim**, "Human identity verification from biometric dorsal hand vein images using the DL-GAN method," *IEEE Access*, vol. 9, pp. 74194-74208, 2021.
- [37] **R. Kumar, R. C. Singh, and S. Kant**, "Dorsal hand vein-biometric recognition using convolution neural network," in *International Conference on Innovative Computing and Communications*, 2021, pp. 1087-1107: Springer.
- [38] **M. Z. NAYEBİ and Z. TURGUT**, "Dorsal Hand Veins Based Biometric Identification System Using Deep Learning," *Erzincan University Journal of Science and Technology*, vol. 14, no. 1, pp. 1-15.
- [39] **M. Mohaghegh and A. Payne**, "Automated biometric identification using dorsal hand images and convolutional neural networks," in *Journal of Physics: Conference Series*, 2021, vol. 1880, no. 1, p. 012014: IOP Publishing.
- [40] **J. Li, K. Li, G. Zhang, J. Wang, K. Li, and Y. Yang**, "Recognition of Dorsal Hand Vein in Small-Scale Sample Database Based on Fusion of ResNet and HOG Feature," *Electronics*, vol. 11, no. 17, p. 2698, 2022.