WJCMS

Wasit Journal of Computer and Mathematics Science

Journal Homepage: https://wjcm.uowasit.edu.iq/index.php/WJCM

e-ISSN: 2788-5879 p-ISSN: 2788-5879

Finger Vein Recognition Using Deep Learning Technique

Sahar Wahab khadim[1,*], Hussain k. Ibrahim[2] and Ameen majid shadhar[3]

[1]Ministry of Education, Karkh Second Directorate of Education, Iraq
[2]Computer Sciences and information Technology College, Wasit University, Iraq
[3]Ministry of Education, Wasit Education Directorate,

*Corresponding Author: Sahar Wahab khadim

DOI: https://doi.org/10.31185/wjcm.Vol1.Iss2. 43
Received: March 2022; Accepted: May 2022; Available online: June 2022

ABSTRACT: Due to their combination of security and economic viability, finger vein biometrics have gained considerable traction in recent years. They have the advantage of being the least vulnerable to identity theft because veins are present beneath the skin, as well as being unaffected by the ageing process of the user. To address the ever-increasing need for security, all of these variables necessitate working models. Using face recognition and AI-based biometrics has become a hot subject in law enforcement because of the accidental demographic bias it introduces into the process. Biometric prejudice, on the other hand, has far-reaching implications that transcend into everyday situations. When an ATM transaction or an online banking transaction is compromised by a fake positive or negative verification, it makes it simpler for fraudsters to carry out their criminal activities. The veins of a fingertip were the subject of this research project's investigation. Deep convolutional neural network models were utilised to extract features from two widely-used and freely-available datasets of finger veins. Finger vein identification as a unique biometric approach has received a lot of attention recently. Accuracy of greater than 98 percent is reached with the deployment of multi-class categorization. The binary classification based model has a 97.51 percent accuracy rate. The total outcomes and their effectiveness are fairly good with the implementation situations. Deep learning, an end-to-end technique that has demonstrated promising results in domains like face recognition and target detection, may be useful for finger vein recognition.

Keywords: Deep Learning, Finger Vein Detection, Finger Vein Analysis using Deep Learning

1. INTRODUCTION

To authenticate a person's identification, a biometric authentication system measures certain physical traits or behaviors of the person's body in real-time. Iris scanners, for example, use biometric data to create digital representations of a person's identity. Accordingly, biometric authentication systems may identify or validate the individual by comparing the data to other biometric records in the database using algorithms. Biometric authentication systems have two primary modes of operation: identification and verification. The input data is compared to all known patterns in the database in the identification mode. It is possible to determine if this individual is in the database using the system. Biometric input data is compared to a single person's unique pattern when in verification mode. If they're not the same person, it's a way to stop many individuals from using the same identity [1, 2].

Biometric identification systems, like those shown in movies and science fiction, can be deceived by phoney resources. The Hassassin in Dan Brown's novel "Angels & Demons" chopped off Leonardo's eye to steal the antimatter that was locked behind a door with retina scanners [3, 4]. Retinal fingerprints are unique to each individual, yet hackers can still find a method to get around them. The amount of protection provided by various biometric features also varies. It is

*Corresponding author: Saharwahab2001@gmail.com

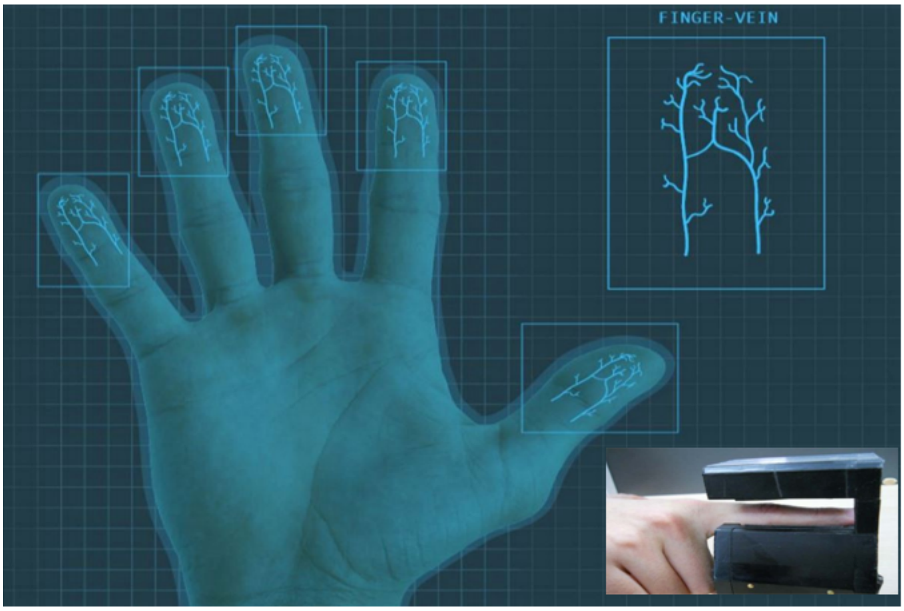

FIGURE 1. **Finger Vein Recognition Patterns.**

more difficult to deceive the finger-vein based biometric verification system that the work is discussing today since it only recognizes the unique patterns of finger-veins beneath the skin of the live individual [5, 6].

Key Points in Finger Vein and Research Statement

Finger-vein data is gathered with the use of specialized capturing equipment. Near-infrared light, a lens, a light filter, and picture capturing technology make up the bulk of this capture apparatus. Finger veins are invisible to the naked eye because they are hidden beneath the surface of the skin. Near-infrared light, which may penetrate through human tissue, is used in this gadget [7, 8]. Near-infrared light is also blocked by pigments like hemoglobin and melanin [9].

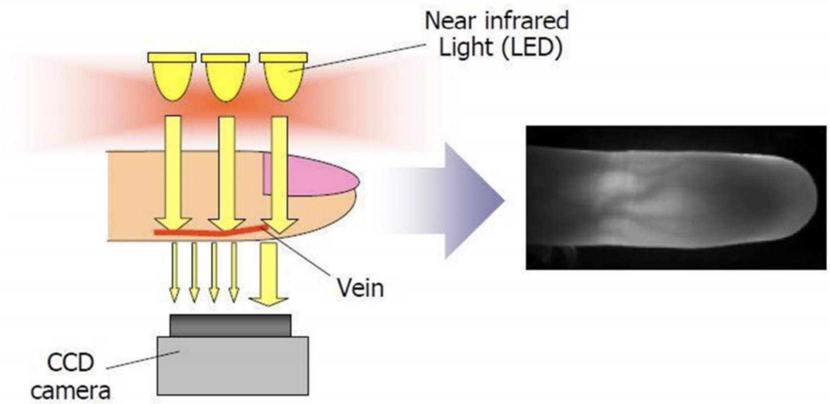

FIGURE 2. **Finger Vein Data Capturing**

Finger vein biometrics uses a person's individual vein patterns to determine their identity. Biometrics derived from the blood vessels beneath the skin is also known as vascular biometrics. Using near-infrared light or visible light causes haemoglobin — the iron-containing protein all have in our blood — to change colour. This means that the reader is able to scan the vein patterns of the individual user. In the cloud, the vein pattern is kept in an encrypted digital format [10].

A near-infrared reader device has been in use for more than a decade for access control systems (people entering a building) and ATMs (people withdrawing money). To identify people on internet services, finger vein biometrics proved its versatility when the world became more connected than it is today [11].

Finger vein biometrics can be used as a primary or a secondary method of authentication for internet services. This is an example of multi-factor authentication (MFA), which involves two factors: a password or social media login (the first factor), and a finger vein authentication (the second factor) [12–14].

Table 1. Modalities with Biometrics

Biometrics	Long-term Stability	Data Size	Cost	Accuracy	Security Level
Finger Vein	High	Medium	High	High	High
Fingerprint	Low	Small	Low	Medium	Low
Face	Low	Large	High	Low	Low
Iris	Medium	Large	High	High	Medium
Voice	Low	Small	Medium	Low	Low
Hand Geometry	Low	Large	High	Low	Low

2. RESEARCH ASPECTS AND METHODOLOGY:

To recognize photos of 10 handwritten digits, the earliest neural networks LeNet were used, but nowadays, convolutional neural networks (CNNs) are widely renowned for their ability to categorize 1000 images in the ImageNet database. Conventional computer vision algorithms are often outperformed by CNNs because they are excellent at automatically extracting characteristics from pictures [15].

Consider finger-vein identification as an image classification issue. The use of CNNs to solve the finger-vein identification problem must be intriguing! To meet the demands of biometric authentication systems, what kind of tests should conduct? It is common practice to first extract features, and then utilize that information to determine the distance between them. The distribution of feature distances is used to establish a threshold. If the gap between the two traits is more than a certain threshold, they are not considered to be the work of the same author. As long as the gap between these two traits is less than the threshold, they are classified as belonging to the same individual [16–20].

FIGURE 3. Interior Analytics on Finger Veins

Finger-vein databases are available from a number of research institutions. SDUMLA-HMT has provided us with the finger-vein dataset that is utilised.

Here would like to thank Shandong University's MLA Lab for creating the SDUMLA-HMT Database for the work [21]. 106 persons had their finger-vein pictures recorded in this collection. Index, middle and ring fingers of both hands were snatched by the thugs. There are six images on each finger. The total number of photos is 3,816. Images are in the "bmp" format and have a resolution of 320x240 pixels.

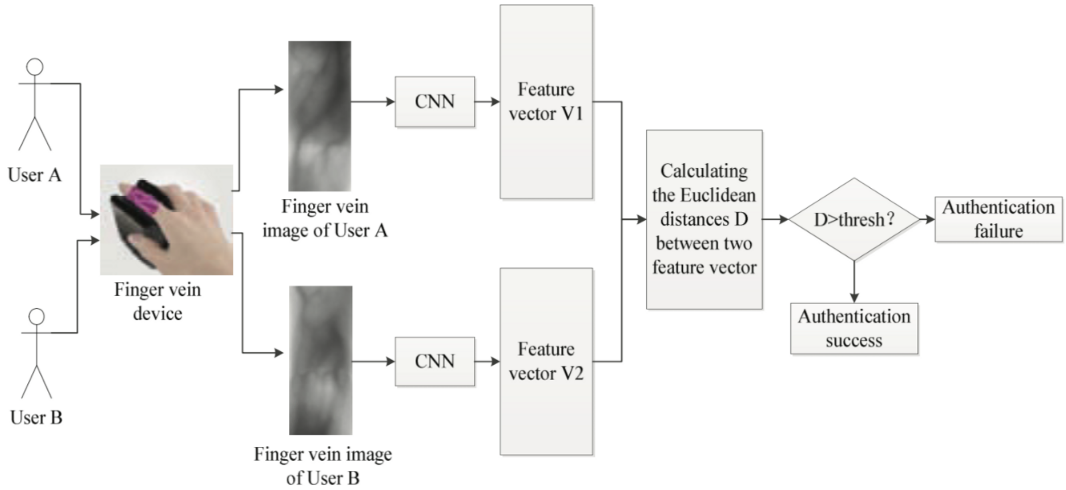

FIGURE 4. **Analytics Patterns and Methodology.**

Image capture includes not only a person's finger, but also the background, which is often a camera. In order to preserve the finger portion of the image and eliminate the backdrop, it is necessary to extract ROI. It's necessary to determine the ROI's upper and lower bounds [22, 23].

Finger-vein Detection using Transfer Learning:

Large datasets need the use of CNN models with a large number of parameters. Complex CNN models need a long time and a lot of resources to train from the beginning. To begin training from scratch in most circumstances, there is not enough data. Another factor to consider is 'overfitting. Insufficient data and a sophisticated model both increase the risk of model overfitting [24, 25].

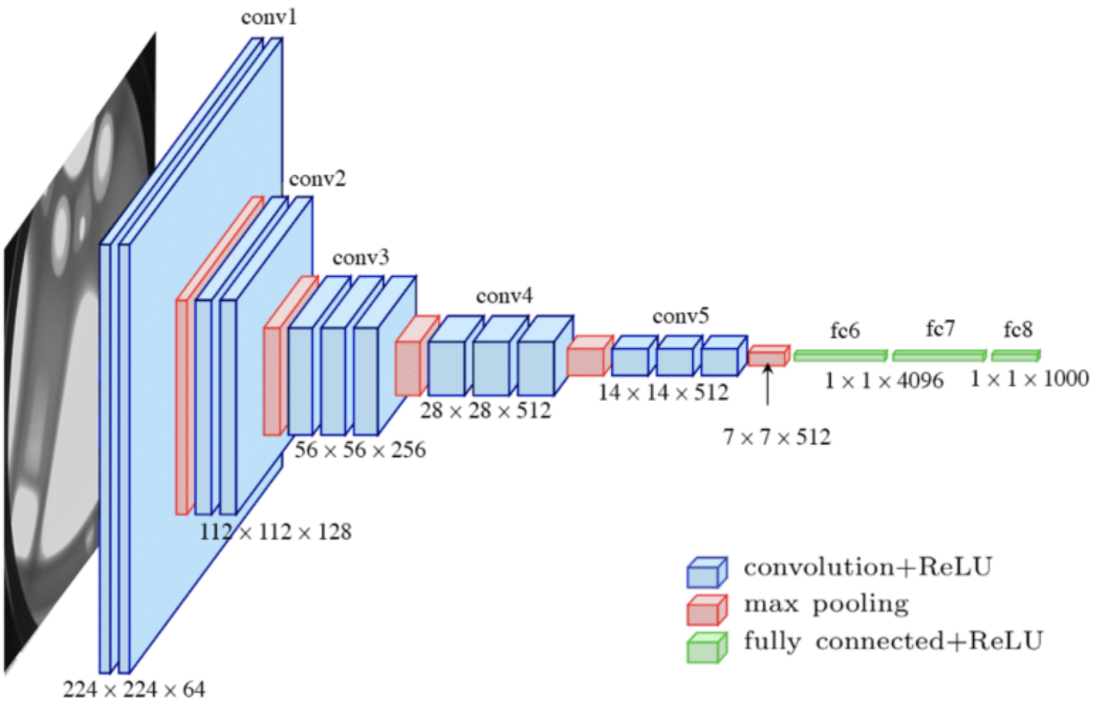

FIGURE 5. **Architecture of Deep Learning Model for Finger Vein Recognition.**

This challenge can be solved with the help of transfer learning [26, 27]. The goal of Transfer Learning is to use an existing model (one that has been pre-trained on a significant quantity of data) in a new context. Using a model pre-trained on a big dataset of cats and dogs, that can categorize elephants and monkeys or cartoon cats and dogs, for example.

A pre-trained model may not perform as well when applied to other domains or tasks because it was trained without input from the original one. There are often two options available to us. It's possible to think of the pre-trained CNN as an extractor of features. Extracted features can be used as input for a linear classifier. The fine-tuning approach, on the other hand, is frequently used to fine-tune certain high-level layers [28–34]. The early layers of features are more general in nature. However, the more detailed information from the original datasets may be found in the following layers. It's possible that freezing the earliest layers may yield characteristics that can be applied to a wide range of jobs. The work may produce even more specific characteristics in our datasets by fine-tuning the next layers [21, 35–37].

3. RESULTS AND OUTCOMES

In our investigation, we used two alternative models. In a multi-class classification model, the first model is used to identify the second model is a binary classification model used to verify the results The binary classification model uses photographs of differences as inputs. Both models have been fine-tuned using a pre-trained VGG-16 model. In these models, ROIs are not preprocessed. Experiments using ROI data models were also conducted, however the results were not as anticipated. Low-quality datasets and unconfirmed image quality make it impossible to reliably classify classes.

Model Type Levels	**Achieved**	**Accuracy**
Multi-Class Classification	98.12 %	
Binary Classification	97.51 %	

The projected approach with multi-class classification is quite effective and giving better results as compared to the classical binary classification.

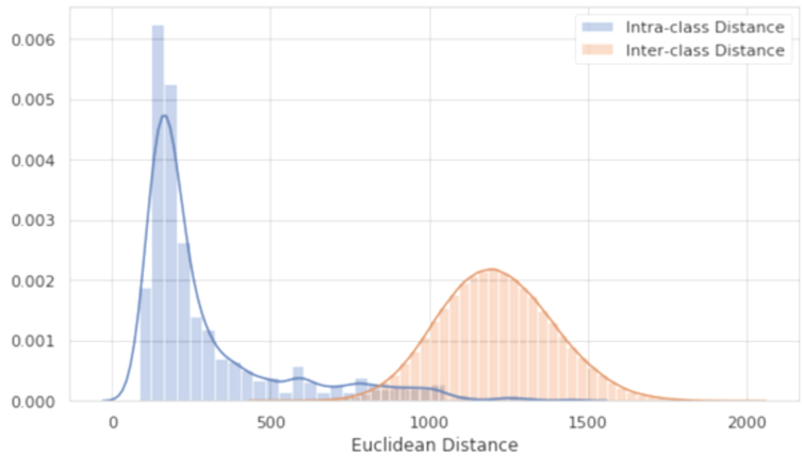

FIGURE 6. Performance Evaluation of the Projected Approach.

A model that uses Euclidean distance as the distance between features will provide results that are difficult to explain. Differential images of the same and dissimilar classes, as well as interclass and intraclass distances, are employed in this study. How to describe the distance between two images in simple terms might be a challenge. It's helpful to take photos of the differences between two photographs so you can see just how big the disparity is. Using the Euclidean distance between feature sites as a measurement is unnecessary in this scenario. So, in the binary classification problem, it is possible to calculate FAR and FRR with relative ease According to how many samples match, FRR (false negative) and FAR (false positive) are defined. The FAR and FRR were calculated based on the forecast's probability. A very low error rate (ERR).

Deep learning, as all know, is data-driven. The quality of the data is critical to the success of an experiment. The results are encouraging, despite the poor quality of the dataset utilised. Paper-referenced findings were not met by either the identification or verification models' final outcomes. When compared to other models, deep learning approaches are easier to apply and do not need extensive feature handling and engineering. According to some previous research, still have room for improvement when it comes to pre-processing data, building models, and selecting hyper-parameters.

4. CONCLUSION

Security has grown increasingly crucial in recent years. The Finger Vein Authentication System has attracted our interest due to its robustness, consistency, and high level of performance. Biometrics, such as fingerprint and iris biometrics, have a lower level of reliability. Finger vein authentication removes the possibility of tampering since it relies on the fact that each person's veins are distinct, even if they are identical twins, and reside beneath the skin their whole lives. In recent years, a number of deep learning algorithms have greatly increased the ability to recognize finger vein patterns. Finger vein authentication and the deep learning approaches used to build the Finger Vein Recognition system are the major objectives of this manuscript.

FUNDING

None

ACKNOWLEDGEMENT

None

CONFLICTS OF INTEREST

The author declares no conflict of interest.

REFERENCES

[1] Y. Fang, Q. Wu, and W. Kang, "A novel finger vein verification system based on two-stream convolutional network learning," *Neurocomputing*, vol. 290, pp. 100–107, 2018.
[2] M. & Ferguson, R. & Tina Ak, Lee, & H Yung-Tsun, and K. Law, "Automatic localization of casting defects with convolutional neural networks," 2017.
[3] H. G. Hong, M. B. Lee, and K. R. Park, "Convolutional Neural Network-Based Finger-Vein Recognition Using NIR Image Sensors. Sensors (Basel)," 2017.
[4] W. Liu, W. Li, L. Sun, L. Zhang, and P. Chen, "Finger vein recognition based on deep learning," *12th IEEE conference on industrial electronics and applications (ICIEA)*, pp. 205–210, 2017.
[5] O. A. Hassen, "Improved Approach for Identification of Real and Fake Smile using Chaos Theory and Principal Component Analysis," *Journal of Southwest Jiaotong University*, vol. 54, 2019.
[6] Y. Liu, J. Ling, Z. Liu, J. Shen, and C. Gao, "Finger vein secure biometric template generation based on deep learning," *Soft Computing*, vol. 22, no. 7, pp. 2257–2265, 2018.
[7] G. Meng, P. Fang, and B. Zhang, "Finger vein recognition based on convolutional neural network," *MATEC Web of Conferences EDP Sciences*, 2017.
[8] T. D. Pham, Y. H. Park, D. T. Nguyen, S. Y. Kwon, and K. R. Park, "Nonintrusive Finger-Vein Recognition System Using NIR Image Sensor and Accuracy Analyses According to Various Factors. Sensors (Basel)," 2015.
[9] H. Qin and M. A. El-Yacoubi, "Deep representation-based feature extraction and recovering for finger-vein verification," *IEEE Transactions on Information Forensics and Security*, vol. 12, no. 8, pp. 1816–1829, 2017.
[10] A. Hassen, A. A. Abdulhussein, M. Saad, Z. A. Darwish, S. Othman, Y. A. Tiun, and Lotfy *Towards a Secure Signature Scheme Based on Multimodal Biometric Technology: Application for IOT Blockchain Network*, vol. 12, pp. 1699–1699, 2020.
[11] S.-H. Database. http://mla.sdu.edu.cn/info/1006/1195.htm.
[12] K. & Shaheed, Id, & Hangang, & Liu, Yang, & Gongping, Qureshi, & Imran, and Gou, "Jie & Yin, Yilong. information A Systematic Review of Finger Vein Recognition Techniques. Information (Switzerland)," 2018.
[13] A. Ansam and H. K. Ibrahim, "A Pragmatic Review and Analytics of Gait Recognition Techniques in Biometric Domain of Research," *International Journal of Computing and Business Research (IJCBR)*, vol. 10, no. 3, pp. 1–9, 2020.
[14] G. K. Sidiropoulos, P. Kiratsa, P. Chatzipetrou, and G. A. Papakostas, "Feature Extraction for Finger-Vein-Based Identity Recognition," *Journal of Imaging*, vol. 7, no. 5, pp. 89–89, 2021.
[15] K. & Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," 2014.
[16] A. Jain, A. Ross, and S. Prabhakar, "An introduction to biometric recognition," *IEEE Trans. Circ. Syst. Video Tech*, vol. 14, pp. 4–20, 2004.
[17] A. K. Jain, J. Feng, and K. Nandakumar *Computer*, vol. 43, pp. 36–44, 2010.
[18] Z. Guo, D. Zhang, L. Zhang, and W. Zuo, "Palmprint verification using binary orientation co-occurrence vector," *Patt. Recogn. Lett*, vol. 30, pp. 1219–1227, 2009.
[19] K. Ito, H. Nakajima, K. Kobayashi, T. Aoki, and T. Higuchi, "A fingerprint matching algorithm using phase-only correlation," *IEICE Trans. Fundament. Electron. Commun. Comput. Sci*, pp. 87–682, 2004.
[20] A. Abu, N. A. Abidin, Z. Z. Darwish, and S. M, "A New Descriptor for Smile Classification Based on Cascade Classifier in Unconstrained Scenarios," *Symmetry*, vol. 13, no. 5, pp. 805–805, 2021.
[21] Y. Yin, L. Liu, and X. Sun, "SDUMLA-HMT: A Multimodal Biometric Database," in *The 6th Chinese Conference on Biometric Recognition (CCBR 2011)*, vol. 7098, pp. 260–268, 2011.

[22] L. Zhang, L. Zhang, D. Zhang, and H. Zhu *Ensemble of local and global information for finger-knuckle-print recognition*, vol. 44, 1990.
[23] N. Miura, A. Nagasaka, and T. Miyatake, "Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification," *Mach. Vision Appl*, vol. 15, pp. 194–203, 2004.
[24] T. Yanagawa, S. Aoki, and T. Ohyama, "Human finger vein images are diverse and its patterns are useful for personal identification," *MHF Preprint Ser*, vol. 12, pp. 1–7, 2007.
[25] H. O. A. Abu, N. A. Abidin, Z. Z. Darwish, and S. M, "Realistic Smile Expression Recognition Approach Using Ensemble Classifier with Enhanced Bagging," *CMC-Computer Materials & Continue*, vol. 70, no. 2, pp. 2453–2469, 2022.
[26] Y. B. Zhang, Q. Li, J. You, and P. Bhattacharya, "Palm Vein Extraction and Matching for Personal Authentication," in *Proceedings of the 9th International Conference on Advances in Visual Information Systems*, pp. 154–164, 2007.
[27] C. B. Yu, H. F. Qin, L. Zhang, and Y. Z. Cui, "Finger-vein image recognition combining modified hausdorff distance with minutiae feature matching," *J. Biomed. Sci. Eng*, vol. 2, pp. 261–272, 2009.
[28] W. Song, T. Kim, H. C. Kim, J. H. Choi, H. J. Kong, and S. R. Lee, "A finger-vein verification system using mean curvature," *Patt. Recogn. Lett*, vol. 32, pp. 1541–1547, 2011.
[29] E. C. Lee and K. R. Park, "Image restoration of skin scattering and optical blurring for finger vein recognition," *Opt. Lasers Eng*, vol. 49, pp. 816–828, 2011.
[30] E. C. Lee, H. Jung, and D. Kim, "New finger biometric method using near infrared imaging," *Sensors*, vol. 11, pp. 2319–2333, 2011.
[31] A. Abter, S. O. Abdulhussein, A. A. Darwish, S. M. Ibrahim, Y. M. Sheta, and W, "Nature-Inspired Level Set Segmentation Model for 3D-MRI Brain Tumor Detection," *CMC-COMPUTERS MATERIALS & CONTINUA*, vol. 68, no. 1, pp. 961–981, 2021.
[32] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Trans. Patt. Anal. Mach. Intell*, vol. 24, pp. 971–987, 2002.
[33] B. Zhang, Y. Gao, S. Zhao, and J. Liu, "Local derivative pattern versus local binary pattern: Face recognition with high-order local pattern descriptor," *IEEE Trans. Image Process*, vol. 19, pp. 533–544, 2010.
[34] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," *IEEE Trans. Image Process*, vol. 19, pp. 1635–1650, 2010.
[35] L. Nanni, A. Lumini, and S. Brahnam, "Local binary patterns variants as texture descriptors for medical image analysis," *Artif. Intell. Med*, vol. 49, pp. 117–125, 2010.
[36] A. Petpon and S. Srisuk, "Face Recognition with Local Line Binary Pattern," in *Proceedings of the Fifth International Conference on Image and Graphics*, pp. 533–539, 2009.
[37] G. Yang, X. Xi, and Y. Yin, "Finger vein recognition based on a personalized best bit map. Sensors (Basel)," 2012.