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# Enhancing Biometric Authentication with Convolutional Neural Networks for Finger Vein and Palm Recognition

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#### ABSTRACT

This research study describes a complex way of improving biometric identification systems that use Convolutional Neural Networks (CNNs) to analyze and distinguish finger veins and palm patterns. Using different datasets for each biometric characteristic, the study methodically preprocesses the photos using approaches such as scaling to consistent scales, improving image quality through restoration, and limiting noise interference to generate the best input for neural processing. These stages are crucial to ensure that CNNs can correctly extract and categorize the unique features of each biometric trait.

The CNN models used in this work are specially designed to enhance feature extraction while improving classification accuracy. These models can discover and learn complicated patterns in biometric data using deep learning techniques, which are required for accurate authentication. The pre-processed images are fed into the CNN, which uses multiple convolutional and pooling layers to recognize and understand the unique identifiers included in both palm and vein images.

Authentication is accomplished by examining both palm and vein photos from the same person. This dual-modality technique improves the system's security characteristics by minimizing the chance of spoofing, as well as the general reliability of the authentication process. By combining these two biometric markers, the system can make more informed decisions, resulting in fewer false positives and negatives.

The ability of CNNs to recognize these complicated biometric patterns demonstrates deep learning technology's potential to revolutionize security procedures. The findings of this investigation show a significant improvement in authentication accuracy, indicating CNN's capacity to handle the complexities of biometric data successfully.

Overall, this research highlights the considerable advances gained in biometric authentication technologies through the use of CNNs. The dual-modality approach not only provides a more secure and trustworthy means of identity verification but also establishes a new industry standard, potentially leading to larger applications in other security-sensitive domains.

Keywords: advanced biometric authentication, CNN technology, vein and palm recognition, deep learning enhancement, dual-modality security system, biometric analysis precision, noise reduction techniques, image quality restoration.

#### 1. INTRODUCTION

The primary objective of this research is to enhance biometric authentication by implementing Convolutional Neural Networks (CNNs) for finger vein and palm recognition. The study begins by focusing on palm recognition, which involves using a dataset of palm images. To ensure consistency, the images undergo initial pre-processing steps such as image resizing. Subsequently, CNN classification is employed to accurately categorize the palm images based on their unique patterns. The aim is to improve the overall accuracy of biometric authentication.

In parallel, vein recognition utilizes a dataset of vein images. Similar pre-processing steps, including image resizing, restoration, and noise removal, are applied to optimize the quality of the vein images. These processed vein images are then subjected to CNN classification, which contributes to the precision of biometric authentication.

The overarching goal of this study is to achieve successful authentication when both palm and vein images correspond to a single individual. Any discrepancy between the two sets of images results in authentication failure. By strategically combining the strengths of palm and vein biometrics and leveraging the capabilities of CNNs, this research aims to enhance the accuracy of biometric authentication systems, thereby bolstering security in various applications.

A significant global security concern revolves around the recognition of specific attributes within the realm of smart recognition. Despite the creation of numerous algorithms in recent years to tackle this security issue, there remains a pressing need for swift and efficient biometric identification. Biometric recognition entails the automatic identification of individuals based on their morphological and behavioural characteristics. Various biometric techniques have been developed based on these anatomical and behavioural traits, encompassing fingerprint, palm print, hand veins, finger veins, palm veins, foot vein, iris, gait, DNA recognition, palate recognition, voice recognition, facial expression, heartbeat, signature, body language, and face shape. These biometric recognition techniques can be distinguished by utilizing extrinsic biometric features

like palm prints, iris scans, fingerprints, and faces, as well as intrinsic biometric features such as palm veins, hand veins, and finger veins. Extrinsic features are more conspicuous and possess certain drawbacks compared to intrinsic traits. For example, the extraction of iris characteristics can be affected by high light intensity on the retinal surface. Similarly, variations in brightness, facial expression, blood vessel obstruction, and positioning can impact the accuracy of face identification. Finger veins, a unique vein pattern in the fingers, are distinct for each individual and are concealed beneath the skin where red blood cells flow. This vascular biometric, known as finger vein identification, relies on the distinctive blood vessel patterns beneath the finger skin for identification purposes. Among various identification methods, using fingerprints as a biometric form of identification stands out as the most efficient method.

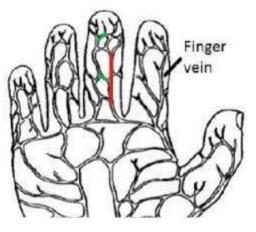


Fig.1. Finger vein structure

Finger vein recognition, also referred to as finger vein authentication, is an innovative biometric technology that utilizes the distinct patterns of veins beneath the skin's surface to verify individuals. This emerging field of biometrics has garnered considerable interest due to its exceptional accuracy, security, and non-intrusive nature. In contrast to conventional biometric methods like fingerprint or iris recognition, which rely on external characteristics, finger vein recognition examines the vascular patterns, providing a more robust and dependable form of authentication. The veins in the finger, being internal and shielded by the skin, are less prone to damage, wear, or deterioration, enhancing the longevity and reliability of this biometric modality. As technology progresses, finger vein recognition shows potential in various applications, including access control, financial transactions, healthcare, and more. This introductory overview seeks to explore the principles, technological advancements, applications, and potential obstacles associated with finger vein recognition, highlighting the increasing significance and versatility of this biometric technology in our interconnected and security-conscious world.



Fig 2. Palmer Region

The palm, also referred to as the palmar region, denotes the inner surface of the hand that lies between the wrist and fingers. It encompasses a range of anatomical characteristics, such as the palm lines (dermatoglyphics), which consist of creases, ridges, and unique patterns specific to each individual. These palm lines, commonly known as palm prints, develop during fetal development and remain relatively unaltered throughout a person's lifetime, rendering them suitable for biometric identification objectives.

Palm prints are extensively utilized in biometric authentication systems due to their distinctiveness and stability. The distinctive patterns present on the palm surface, including loops, whorls, and arches, facilitate precise identification and verification of individuals. Biometric systems employ imaging devices like cameras or scanners to capture palm prints, and advanced algorithms analyze the captured images to extract distinctive features for identification purposes.

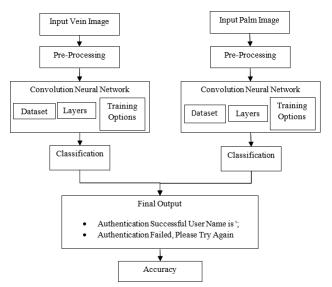
Palm recognition technology finds application in various domains, including access control, identity verification, and forensic investigations. It offers several advantages over alternative biometric modalities, such as fingerprints, including a larger surface area for capturing biometric data and reduced vulnerability to wear and damage.

In conclusion, palm recognition technology plays a pivotal role in enhancing security and efficiency across diverse industries and sectors, ranging from banking and finance to healthcare and law enforcement. Its reliability, accuracy, and user-friendly nature make it a valuable tool for identity authentication and verification purposes.

## 2.LITERATURE REVIEW

Finger-vein-based biometric technology has garnered significant attention and has shown notable progress in enhancing personal identification performance. This article aims to present a comprehensive overview of the current finger-vein-based biometric methods, covering the four key steps of finger-vein recognition methods: image acquisition, image preprocessing, feature extraction, and matching. Following a brief discussion on image acquisition and preprocessing, the feature extraction methods are categorized into template-based, representation-based, and learning-based methods. Additionally, the article delves into the analysis and discussion of deep-learning-based methods. In order to enhance the security of the Internet of Things (IoT), this proposes a finger study vein-based personal authentication method that explores competitive orientations and magnitudes from finger vein images. Finger vein recognition has demonstrated itself as a dependable and promising solution for biometric-based personal authentication. The stable and intricate piecewise line features present in finger vein images can effectively represent finger vein patterns for personal authentication. The study introduces an efficient local descriptor for finger vein feature extraction, known as the histogram of competitive orientations and magnitudes (HCOM). This method involves extracting two types of local histograms from a finger vein image and fusing them together to adequately represent competitive information: the histogram of competitive orientations (HCO) and the local binary pattern histogram derived from the image of competitive magnitudes (referred to as HCMLBP).

# 3. SYSTEM DESIGN:



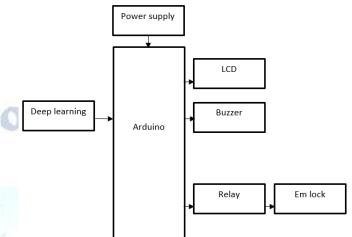
#### A.PROPOSED BLOCK DIAGRAM:

## Figure 1. Proposed Method Block Diagram

The present study utilizes a methodology that consists of two primary components: palm recognition and vein recognition. These components employ Convolutional Neural Networks (CNNs) to enhance the process of biometric authentication. In the case of palm recognition, a dataset containing palm images is utilized, and pre-processing steps, such as image resizing, are performed to ensure uniformity. The resized images are then inputted into a CNN for classification, to accurately identify and authenticate individuals based on their palm patterns. Similarly, for vein recognition, a dataset comprising vein images is employed. Pre-processing steps, including image resizing, restoration, and noise removal, are applied to improve the quality and clarity of the images. The processed vein images are then to CNN classification subjected for accurate classification. The final step involves comparing the results obtained from palm and vein recognition. If both the palm and vein images belong to the same individual, the authentication process is considered successful. However, if there is a discrepancy between the two sets of images, the authentication is deemed unsuccessful. This methodology effectively combines the advantages of both palm and vein biometrics, utilizing CNNs to achieve a robust and precise biometric authentication system.

# **B.CIRCUIT IMPLEMENTATION:**

The circuit implementation of proposed system has been created as shown in figure.2



# Figure 2. Circuit Implementation C. Developed Hardware prototype

The developed prototype (see Figure 3) has been tested for different finger veins and palms.

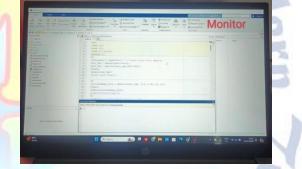


Figure 3. Developed Hardware prototype

# D. PROTOTYPE FOR THE PROPOSED SYSTEM

The prototype for the proposed system is designed as shown in below figure .4

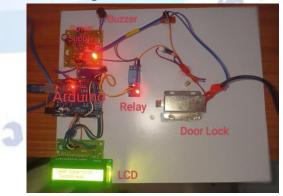
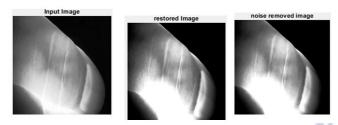
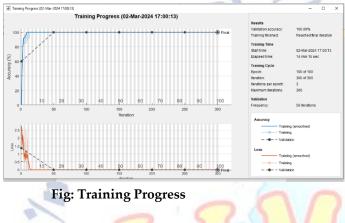


Figure 4. Prototype for the proposed system

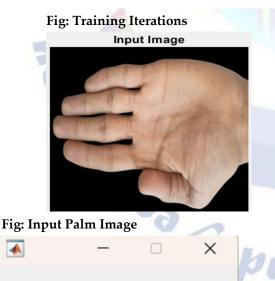
## 4. EXPERIMENTAL RESULTS



Input Vein Image Restored Image Noise Removed Image



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						Mini harak				Mini harak				Base Learning
Lpoch	1	iteration	1		5		1		1		1		5	
			1	(nn:mm:ss)	1	Accuracy	1	Accuracy	1	Loss	1	Loss		Rate
										0.0551				
	1													0.0010
17	1	50	1	00:02:16	1	100.00%		100.00%	1	3.7003e-06		4.9473e-06	1	0.0010
34	1	100	1	00:04:35	1	100.00%	I.	100.00%	1	5.2549e-06	1	3.4452e-06	1	0.0010
50	1	150	1	00:06:54	1	100.00%	I.	100.00%	1	2.5082e-06	1	2.8134e-06	1	0.0010
67	1	200	Т	00:09:08	T.	100.00%	I.	100.00%	Т	7.1526e-08	T.	2.4081e-06	1	0.0010
84	Т.	250	÷.	00:11:37	÷.	100.00%	i.	100.00%	÷.	1.8740e-06	i.	2.1100e-06	1	0.0010
100		300		00:14:14		100.00%	1	100.00%		2.3270e-06		1.8954e-06		0.0010
	Epoch 1 17 34 50 67 84	Epoch       1   17   34   50   67   84	aining on single CPU. tiializing input data Epoch   Iteration 1   1 17   50 34   100 50   150 67   2200 84   250	aining on single CFU. titalizing input data no Epoch   Iteration   1   1   1   17   50   34   100   50   150   67   200   84   250	hining on single CPU. Italizing input data normalization. Epoch   Iteration   Time Elepsed   I   1   0010010 1   1   00100104 1   1   00100104 34   100   00102126 35   100   00106154 67   220   00101137	sining on single CPC. Itializing input data normalization. Epoch   Iteration   Time Elopsed             (hrmmiss)   1   1   00:00:004   17   50   00:002:16   34   100   00:002:16   35   150   00:005:05   67   200   00:01:057   68   250   00:01:157	hining on single CPU. Italizing input data normalization. Epoch   Teration   Time Elopsed   Mini-batch   (hhimmiss)   Accuracy 1   1   00:00:04   0.000 17   50   00:00:15   100:005 34   100   00:01:55   100:005 50   110   100   00:05:55   100:005 67   220   00:05:05   100:005 64   220   00:01:157   100:005	sining on single CPU. Itializing input data normalization: Epoch   Iteration   Time Elapsed   Mini-batch     (himmss9)   Accuracy   1   1   00:00104   0.0004   17   50   00:02116   100:0004   34   100   00:04135   100:004   50   150   00:04135   100:004   67   200   00:06108   100:004   64   250   00:011137   100:004	nining on single CPU. Italizing input data normalization. Epoch   Terzion   Time Elapsed   Mini-batch   Validation   (hhrmmise)   Accuracy   Accuracy   1   1   00100104   0.000   600000 17   50   00102126   00.000   000005 34   100   0010355   100.000   100.005 50   150   00105154   100.000   100.005 67   220   0010518   100.000   100.005	sining on single CFU. Itializing input des normalization. Epoch   Iteration   Time Elapsed   Mini-betch   Validation     (hhimmiss)   Accuracy   Accuracy   1   1   00:00:004   0.00%   60:00%   17   50   00:0216   100:00%   100:00%   34   100   00:04:35   100:00%   100:00%   55   150   00:06:54   100:00%   100:00%   67   200   00:06:54   100:00%   100:00%   64   250   00:01:137   100:00%   100:00%	nining on single CFU. Italizing input data normalization. Epoch   Teration   Time Elapsed   Mini-batch   Validation   Mini-batch   (hhimmism)   Accuracy   Loss     1   1   00100104   0.0004   Accuracy   Loss   1   1   00100104   0.0004   000.004   2.7551   1   5 0   00102116   100.004   100.004   5.2545e-00   34   100   00104155   100.004   100.004   5.2545e-00   5 0   150   00104154   100.004   100.004   7.1526e-00   6   2 20   0010418   100.004   100.004   7.1526e-00   6   2 20   00101137   100.004   100.004   7.1526e-00	sining on single CFU. Italizing input data normalization. Epoch   Iteration   Time Elapsed   Mini-hatch   Validation   Mini-hatch     himmiss   Accuracy   Loss   1   1   00:00:04   0.00%   Accuracy   Loss   1   1   00:00:04   0.00%   00.00%   2.7551   17   50   00:02126   100.00%   100.00%   3.7008-06   34   100   00:06153   100.00%   100.00%   5.2556-06   50   150   00:0656   100.00%   100.00%   2.5082-06   67   200   00:06150   100.00%   100.00%   1.8768-08   64   250   00:011137   100.00%   100.00%   1.8748-06	nining on single CFD. Italizing input data normalization. Epoch   Iceration   Time Elapsed   Mini-batch   Validation   Mini-batch   Validation   (hhimmiss)   Accuracy   Accuracy   Loss   Loss   1   1   00100104   0.0004   60.0004   2.7551   1.9694 17   50   00100126   100.004   100.004   5.2598-06   3.4452-00 34   100   00104155   100.004   100.004   5.2598-06   3.4452-00 50   150   00104515   100.004   100.004   5.2598-06   3.4452-00 67   200   0010918   100.004   100.004   7.1526-06   2.4038-06 67   200   00191137   100.004   100.004   7.1526-06   2.4038-06	ating on single CPU. Italizing input data normalization. Epoch   Teratin   Time Elegand   Mini-batch   Velidation   Mini-batch   Velidation     (hhimmiss)   Accuracy   Loss   Loss   1   1   00100104   0.000   60.000   2.7551   1.3684   17   50   00102126   100.000   100.000   3.7083-06   4.94783-06   34   100   00106155   100.000   100.000   5.25849-06   3.4652-06   50   150   00106155   100.000   100.000   5.25849-06   3.4652-06   67   200   0010615   100.000   100.000   1.52682-08   2.0318-06   64   250   0011137   100.000   100.000   1.00.000   1.74740-06   2.1008-06





**Fig: Final Output** 

vein\_output =

'Raghavendra'

The classified Vein output is : 97.586667

palm\_output =

'Raghavendra'

The classified Palm output is : 99.106667



Fig Access Granted so the lock will get open



Fig Access is Not Granted so the lock will not open and the buzzer gets on, LEDs will blink



Biometric Security System for Vein and Palm Matching Our innovative biometric security system uses vein and palm recognition technologies to improve access control measures. When an individual's vein and palm patterns correspond to the stored data:

Access Granted: The LCD screen will indicate "Access Granted," signifying that you have permission to enter. Additionally, the door lock will automatically unlock, allowing for easy admission.

However, if the vein and palm patterns do not match. Access Not Granted: The LCD screens will flicker, notifying the user of the mismatch. Simultaneously, the buzzer will alert and alarms will sound, highlighting the security violation.

This powerful solution provides safe access control by integrating biometric verification with instant notification of illegal attempts.

# **5. CONCLUSION**

To summarize, this research showcases the efficacy of Convolutional Neural Networks (CNNs) in enhancing biometric authentication through finger vein and palm recognition. By utilizing datasets of palm and vein images and employing pre-processing techniques like image resizing, restoration, and noise removal, the proposed methodology achieves superior image quality and clarity. The CNN classification process accurately identifies and categorizes palm and vein patterns, resulting in enhanced authentication accuracy. The comparison of palm and vein recognition outcomes enables a robust authentication process, where successful authentication occurs when both palm and vein images correspond to the same individual. The findings of this study emphasize the potential of integrating palm and vein biometrics and leveraging CNNs to fortify biometric authentication systems. Furthermore, the methodology demonstrates scalability and adaptability for implementation in various real-world applications, providing a dependable solution for access control and identity verification. Overall, this research contributes to the advancement of biometric authentication technologies and underscores the significance of employing advanced machine learning techniques to enhance security and reliability in authentication processes.

#### **Conflict of interest statement**

Authors declare that they do not have any conflict of interest.

#### REFERENCES

- [1] Anil, K.J.; Arun, A.R.; Nandakumar, K. Introduction to Biometric; Springer: Berlin, Germany, 2011.
- [2] Mishra, K.N.; Mishra, K.N.; Agrawal, A. Veins Based Personal Identification Systems: A Review. Int. J. Intell. Syst. Appl. 2016, 10, 68.

- [3] Qin, H.; He, X.; Yao, X.; Li, H. Finger-vein verification based on the curvature in Radon space. Expert Syst. Appl. 2017, 82, 151–161.
- [4] Syazana-Itqan, K.; Syafeeza, A.R.; Saad, M.N.; Hamid, N.A.; Saad, W.H.M. A review of finger-vein biometrics identification approaches. Indian J. Sci. Technol. 2016, 9.
- [5] Lu, Y.; Wu, S.; Fang, Z.; Xiong, N.; Yoon, S.; Park, D.S. Exploring finger vein based personal authentication for secure IoT. Future Gener. Comput. Syst. 2017, 77, 149–160.
- [6] Viet Dung Nguyen, Anh Tu Tran "Finger Vein Pattern Extraction Improvement by Enhance Maximum Curvature and Frangi Filter" in IEEE Computer Science, Electronics and Communication Engineering, Page no: 4133-4157, Volume 13, Issue 4, 2022.
- [7] George Kumi Kyeremeh, Mohamed Abdul-Al, Nabeel Abduljabbar, "Finger vein Recognition" in International Journal of Advanced Computer science and applications (IJACSA), Page no: 3489-3510, Volume 13, Issue 5, 2022.
- [8] T. Sathish Kumar, Pachaivannan Partheeban, S. Rajes Kannan "Finger Vein based Human Identification and Recognition using Gabor Filter" in IEEE Computer Science, Page no: 5456-5480, Volume 9, Issue 2, 2022.
- [9] N. Elhaddad, M. E. Elhamdadi, and A. E. Hassanien "Finger Vein Recognition Using Deep Convolutional Neural Networks" in IEEE Biometrics and Security, Page no: 4789-5000, Volume 7, Issue 6, 2021.
- [10] Jialiang Peng a, Ahmed A. Abd El-Latif b, Qiong Lim c, Xiamu Niu c "Multimodal biometric authentication based on score level fusion of finger biometrics", in IEEE Authentication and Informatics, Page no 3456-3480, Volume 4, Issue 9, 2019.
- [11] Beining Huang, Yanggang Dai, Rongfeng Li, Darun Tang and Wenxin Li "Finger-vein Authentication Based on Wide Line Detector and Pattern" in IEEE Finger Vein Recognition, Page no: 5679-6000, Volume 5, Issue 9, 2019.
- [12] Wenchng Yang, Song Wang , Jiankun Hu " Securing Deep Learning Based Edge finger vein Biometrics with Binary decision Diagram "in IEEE transactions on industrial Informatics , Page no: 4244-4253, Volume 15, Issue 7 , July 2019. 38
- [13] J. Yang, Y. Shi, and G. Jia, "Finger-vein image matching based on adaptive curve transformation," Pattern Recogn., vol. 66, pp. 34–43, Jun. 2017.
- [14] Wenchng Yang, Song Wang, Jiankun Hu "Securing Deep Learning Based Edge finger vein Biometrics with Binary decision Diagram" in IEEE transactions on industrial Informatics, Page no: 4244-4253, Volume 15, Issue 7, July 2019.
- [15] Dyaneshwari P.Wagh , H.S.Fadewar and G.N. Shinde, "Biometric finger vein Recognition methods for Authentication", Advances in Intelligent systems and computing, AISC, Volume 1025, Oct 2019.
- [16] Sapkale, M.; Rajbhoj, S.M. A biometric authentication system based on finger vein recognition. In Proceedings of the 2016 International Conference on Inventive Computation Technologies (ICICT),
- Coimbatore, India, 26–27 August 2016; Volume 3, pp. 1–4. [17] Kulkarni, S.; Raut, R.D.; Dakhole, P.K. A Novel Authentication
- [17] Kukami, S., Kaut, K.D., Dakhole, F.K. A Novel Authentication System Based on Hidden Biometric Trait. Procedia Comput. Sci. 2016, 85, 255–262.
- [18] Miura, N.; Nagasaka, A.; Miyatake, T. Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification. Mach. Vis. Appl. 2004, 15, 194–203.

- [19] VERA Finger Vein Data Base. 2014. Available online: https://www.idiap.ch/dataset/vera-fingervei (accessed on 18 August 2018)
- [20] Liu, Z.; Song, S. An embedded real-time finger-vein recognition system for mobile devices. IEEE Trans. Consum. Electron. 2012, 58.

