Enhanced Biometric Security Through Infrared Vein Pattern Recognition

Hassan Ashfaq
Faculty of Computer Science & Engg.
GIK Institute of Engg. Sciences & Tech.
Topi, Khyber Pakhtunkhwa, Pakistan.
u2021221@giki.edu.pk

Muhammad Haseeb Ishaq
Faculty of Computer Science & Engg.
GIK Institute of Engg. Sciences & Tech.
Topi, Khyber Pakhtunkhwa, Pakistan.
u2021389@giki.edu.pk

***Abstract*—Finger vein verification stands out as a highly advanced biometric technology today, offering superior security and convenience by utilizing internal body features. The fingerprint images captured by a web camera under infrared (IR) light not only reveal the vein patterns but also the shadows created by varying thicknesses in finger muscles, bones, and surrounding tissue networks. This paper details an innovative approach to enhance low-resolution images affected by light and noise from a webcam, followed by segmenting the vein patterns using an adaptive threshold method and comparing them with advanced template matching techniques. Despite suboptimal image quality, our results demonstrate that clear arterial patterns and correct procedures enable effective personal identification. The paper thoroughly reviews finger recognition algorithms, encompassing image acquisition, pre-processing, feature extraction, and pattern matching methods. It also documents novel findings from a critical analysis of comparative strategies, highlighting the proposed system's effectiveness even in challenging imaging conditions. The project aimed to design and develop a finger vein identification system for a networked environment, showcasing its potential as a leading biometric technology by improving image quality and employing robust matching techniques for reliable personal authentication.**

***Index Terms*—Human interaction, Finger veins, Deep Learning**

I. Introduction

As we advance towards a global knowledge society, the average person faces an increasing threat from crime, which can occur anywhere in the world. Terrorism, capable of spreading instantaneously across the globe, heightens this danger. Consequently, biometric systems, which utilize unique aspects of the human body for identification, have emerged as the ideal solution to these stringent security demands and have gained widespread acceptance. Researchers have discovered that the vascular patterns in a person's body are unique, difficult to replicate, unaffected by skin color, and remain consistent with age.

The objective of vein detection is to utilize infrared light at wavelengths between 700nm and 1000nm, which can penetrate most human tissues, while hemoglobin in the blood absorbs this light completely. We employ a method that aligns Near Infrared (NIR) with Far Infrared (FIR) technology, as it captures larger vein patterns more effectively. This involves using a light transmission process to capture the vein pattern. By placing the finger under an infrared light, the vein pattern is recorded as a shadow pattern by a webcam positioned beneath the finger. Figure 2 illustrates the complete authentication process. Vascular pattern identification is a relatively new area in biometric technology, and numerous studies have demonstrated that human vascular patterns can be used for personal identification.

In our study of arterial identification, we encountered several challenges: a. The images captured by a typical webcam contain noise, such as salt and pepper noise, and the distribution of gray levels varies between experiments due to the webcam's automatic light adjustments. b. Typically, the vein patterns in vein images are very small. Achieving a functional binary image with sufficient detail of the finger veins requires precise boundary extraction. c. The pressure applied to the finger can cause the veins to contract or change shape. Therefore, it's crucial to create a "soft" finger boundary to allow the user's finger to remain in a relaxed position during the scanning process.

A. Related Work

Biometric detection methods can be divided into two categories:

1) Extrinsic biometric features: such as palm print, iris, fingerprint, and face.
2) Intrinsic biometric features: including palm vein, hand vein, and finger vein.

B. Existing Approaches

Various approaches exist for vessel extraction in biometric systems, including subspace-learning-based approaches, statistical-based techniques, and local-invariant-based methods. Fingerprint recognition has recently garnered significant attention and is considered a promising biometric method. However, vein pattern recognition, specifically for internal finger veins, has shown unsatisfactory performance due to flawed vein networks and weak similarities. A key issue may be the lack of thorough analysis of vein anatomy structure. [1]

This paper proposes a novel vein recognition framework, incorporating an anatomic-based vein extraction (ASAVE) algorithm and a concatenated integration strategy. The vein pattern is extracted by following a curve directed at the base of the vertical profile cut across the cross-section. The extracted vein pattern is further refined to produce a reliable vein network. Additionally, clear vein branches, referred to as the vein spine, are isolated from the vein pattern.

The proposed method uses vein measurements to address finger movement. The similarity of measured vein networks is evaluated by the uniformity of vein stretching and continuity, combining the degree of fragmentation of corresponding veins. The vein pattern, starting from the fingertip, is continuous and interconnected, extending to the base of the finger. The outer diameter of the vein pattern varies, gradually increasing from the fingertip to the finger base and from the minor branches to the main branches. [2] The differences in the outer diameters of the vessel branches between the proximal and middle parts of the finger are noted. Each branch in the vein pattern turns smoothly and consistently, with no abrupt changes in vein width or irregularities. [3]

In fingerprint recognition templates, an investigation is accepted if the number of vein points matching a registered user exceeds a predefined threshold. However, this can lead to false acceptances due to ignoring the formation of the vein pattern. Local vein branches near the bifurcation points of the vein pattern significantly differ between authentic and fake images. Therefore, this paper explores local vascular structures to improve the visual performance of template simulations. The bifurcation points and their local vein branches, referred to as the vein-branch structure, are extracted and integrated with the whole vein pattern within a user-based filtering framework.

Results from two public datasets confirm the effectiveness of the proposed framework in enhancing the performance of vein-pattern-based finger vein recognition. The tri-branch vein architecture is employed at the first level of the framework to screen for fraudsters and provide candidates for further investigation. Due to varying image quality, the similarities between tri-branch vein structures significantly differ among users. [4]

C. Gap Analysis

Despite significant advancements in biometric technologies, existing methods for finger vein verification often suffer from limitations in image quality and accurate pattern extraction, particularly when using low-resolution webcams. Traditional approaches typically do not adequately address the noise and distortions caused by varying finger muscle and bone thicknesses or the surrounding network structures. This results in unclear vein patterns and reduced effectiveness in personal identification. Current techniques, such as subspace-learning, statistical-based, and local-invariant methods, fall short in their ability to precisely extract and analyze vein patterns due to their insufficient consideration of vein anatomy. [5] Furthermore, many systems neglect the impact of finger movement and pressure, leading to inconsistent vein pattern recognition. Our study aims to bridge this gap by introducing a comprehensive vein recognition framework that enhances image quality, refines vein extraction, and improves template matching, thereby offering a more reliable and accurate method for finger vein verification. This includes the development of an anatomic-based vein extraction algorithm and a user-based filtering framework to address these challenges and improve the robustness of biometric verification systems. [6]

D. Problem Statement

Following are the main research questions addressed in this study.

1) How can low-resolution finger vein images, captured by webcams under infrared light, be enhanced to improve the quality of vein pattern recognition despite the presence of noise and distortions from finger muscles, bones, and surrounding structures?
2) What methods can be developed or improved to accurately extract and refine vein patterns from low-quality images, ensuring clear identification of vein networks for reliable biometric verification?
3) How can advanced template matching techniques be applied to these refined vein patterns to ensure consistent and accurate personal identification, accounting for variations in finger pressure and movement during image capture?

E. Novelty of our work

In this study, we present a novel approach to finger vein verification by addressing several key limitations in existing biometric systems. Our approach enhances low-resolution finger vein images captured by webcams under infrared light, overcoming noise and distortions caused by finger muscles, bones, and surrounding structures. We propose an anatomic-based vein extraction (ASAVE) algorithm and a user-based filtering framework, which improve the accuracy of vein pattern extraction and ensure the clear identification of vein networks. Additionally, we integrate advanced template matching techniques, specifically leveraging Deep Neural Networks (DNNs), to enhance the precision of vein recognition despite variations in finger pressure and movement. This is further supported by dimension and Gabor filter algorithms for feature extraction, providing a robust solution for large-scale finger vein identification. The system also incorporates a Sobel detector, an upgrade filter, and a capture process to refine the vein pattern extraction. Our contributions include a detailed review of finger recognition algorithms, a comprehensive enhancement process for low-quality images, and a novel vein recognition framework that significantly improves the reliability and accuracy of biometric verification systems. This work represents a substantial advancement in the field of biometric security, offering improved performance in identifying individuals based on finger vein patterns..

F. Our Solutions

In this research, we present a robust biometric system for identifying individuals based on the unique patterns of their finger veins captured in the near-infrared spectrum. Our system employs a novel finger vein recognition algorithm that integrates various processing steps, including the Sobel

TABLE I
RESEARCH LITERATURE REVIEW TABLE: KEY PAPERS AND FINDINGS

Paper Title	Authors	Publication Date	Dataset	Research Aspects	Key Findings	Contributions	Limitations
Finger Vein Authentication System	Bhupal, Raunak et al.	2021	Not specified	Security and ease of use of finger vein authentication	Accuracy of over 90% using filtering methods like Segmentation, Gabor filtering, Masking, and Skeletonization	Developed an authentication system using NIR camera images, enhancing image quality, and advanced matching	Not specified
Joint attention network for finger vein authentication	Huang, Junduan et al.	2021	SDUMLA-HMT, MMCBNU-6000, FV-USM, FV-SCUT	Use of joint attention (JA) module and GeM pooling for low contrast images	0.35% EER for SDUMLA-HMT, 0.08% EER for MMCBNU-6000, 0.34% EER for FV-USM, 0.49% EER for FV-SCUT	Proposed JA finger vein network (JAFVNet) with attention mechanisms and pooling layers for better features	Susceptible to factors like ambient illumination and finger posture variation
Finger vein pulsation-based biometric recognition	Krishnan, Arya et al.	2021	Custom dataset (320 subjects)	Novel acquisition mechanism based on vein pulsation	Recognition accuracy of 96.35%, EER of 0.8%	Introduced a pulsation-based vein pattern acquisition method with inherent liveness detection	Novelty of pulsation-based approach, may require more validation across different datasets
Biometric authentication using finger-vein patterns with deep-learning and discriminant correlation analysis	Boucetta, Aldjia and Boussaad, Leila	2022	SDUMLA-HMT, FV-USM	Use of pretrained Deep-CNN models for feature extraction and SVM for identification	Significant high mean accuracy rates	Proposed a system using Squeezenet pretrained Deep-CNN model and Discriminant Correlation Analysis	Requires large datasets for training
Recent advancements in finger vein recognition technology	Shaheed, Kashif et al.	2022	Various datasets from IEEE, Springer, ACM, Science Direct	Review of recent advancements in deep learning, PAD, and multimodal systems	Highlights challenges and opportunities in finger vein recognition	Provides comprehensive review of recent methodologies and challenges in finger vein recognition	Lacks original experimental results, focused on reviewing existing literature
Finger-vein biometric recognition: A review	Hou, Borui et al.	2022	Various public datasets	Overview of existing methods: image acquisition, preprocessing, feature extraction, and matching	Discusses challenges and future research directions, especially 3-D recognition	Provides a detailed review and summary of finger-vein biometric methods	Focused on reviewing existing methods, no new experimental contributions
A simple and efficient method for finger vein recognition	Zhang, Zhongxia and Wang, Mingwen	2022	Two public finger vein databases	New algorithm using centrosymmetric coding without image segmentation	Outperforms state-of-the-art methods in matching tasks	Proposed a simple method for vein code generation and matching	May need further testing on more diverse datasets to validate effectiveness

detector for edge detection, enhancement filtering, and binarization to extract vein patterns. Key features are extracted using dimension reduction and Gabor filters, followed by matching these features using a distance classifier. The dataset is systematically divided into training, testing, and validation sets, and our model is trained using a deep learning algorithm, specifically a Convolutional Neural Network (CNN), to ensure high accuracy in authentication. Through exploratory data evaluation, pre-processing, feature engineering, and prediction modules, we refine the feature set and optimize the model for effective biometric identification. Our results indicate that the proposed system achieves high accuracy in finger vein recognition, demonstrating its potential for reliable large-scale biometric identification.

II. METHODOLOGY

A. Dataset

For our research on finger vein verification, we employed the Finger Vein USM (FV-USM) Database. Due to the scarcity of publicly available databases for finger vein recognition, we curated an infrared finger image database. This comprehensive dataset encompasses both finger vein and finger geometry data, enabling verification of both unimodal biometrics (finger vein and finger geometry) and bimodal biometrics (fusion of vein and geometry) systems. Moreover, the dataset includes predefined regions of interest (ROI) crucial for finger vein recognition, streamlining benchmark testing and algorithmic assessment within the research community. [7]

The dataset consists of images sourced from 123 volunteers, comprising 83 males and 40 females, all affiliated with Universiti Sains Malaysia as either staff or students. The age spectrum of participants ranged from 20 to 52 years. Each volunteer contributed images of four fingers: the left index, left middle, right index, and right middle fingers, resulting in a total of 492 distinct finger classes. During a single session, each finger was imaged six times, and volunteers engaged in two sessions spaced over a two-week interval. Consequently, this protocol generated a sum of 2952 images per session (123 volunteers × 4 fingers × 6 images), amounting to 5904 images encompassing 492 finger classes across the two sessions. The images were captured at spatial resolutions of 640 × 480 pixels and with a depth of 256 grey levels. Additionally, we offer the extracted ROI images tailored for finger vein recognition, as elaborated in our proposed algorithm. The FV-USM database is openly accessible for research and educational purposes. [8]

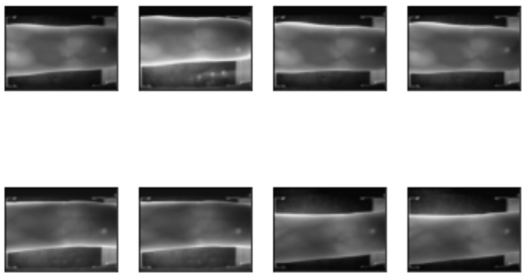

Fig. 1. Example images from the FV-USM Database showcasing the vein pattern and geometry of the fingers.

B. Overall Workflow

The overall workflow of our methodology is illustrated in Figure II-C3. The process begins with the acquisition of finger vein images from the FV-USM database, which provides a diverse set of samples essential for robust model training and evaluation. These images undergo several preprocessing steps designed to enhance their quality and extract the relevant features necessary for accurate vein pattern recognition. The preprocessing phase starts with scaling, where the image dimensions are normalized to ensure consistency across all samples. This step is crucial as it allows the model to process images of uniform size, facilitating efficient learning. Following scaling, filtering techniques are applied to reduce noise within the images. This includes the removal of artifacts such as salt-and-pepper noise, which can obscure the vein patterns. We use median filtering to preserve the edges while effectively eliminating unwanted noise.

Next, edge detection is performed to accurately identify the boundaries of the vein patterns. We employ the Canny edge detection algorithm, which is renowned for its ability to detect a wide range of edges in images. This is followed by thresholding, a technique used to convert grayscale images into binary images, making the vein patterns more pronounced. Thresholding helps in differentiating the vein structures from the background. Contouring is the final preprocessing step, where the outlines of the vein structures are traced. This helps in isolating the vein patterns from the rest of the image, enabling more precise analysis. Once the preprocessing steps are completed, the dataset is divided into training, validation, and test sets. This division ensures that the model is trained on one subset of data, validated on another, and tested on an entirely separate set to evaluate its performance.

The preprocessed images are then fed into a VGG16 model, a convolutional neural network known for its deep architecture and high performance in image recognition tasks. We fine-tune the pre-trained VGG16 model on our specific dataset, which involves adjusting its parameters to better fit the unique characteristics of the finger vein images. Fine-tuning enhances the model's ability to generalize from the training data to unseen samples. Finally, the trained model is used to make predictions on the test data. The performance of the model is evaluated based on its accuracy in identifying and verifying finger vein patterns. This evaluation helps in determining the effectiveness of our preprocessing techniques and the overall methodology in achieving reliable biometric verification.

C. Preprocessing

1) Image Sharpening: Image sharpening techniques are crucial in the preprocessing phase to enhance the clarity and definition of vein patterns present in the finger images. Through the application of various methods such as unsharp masking and sharpening filters, the edges and fine details of the vein structures are accentuated. This enhancement improves the visibility of vein patterns, aiding in accurate pattern recognition and subsequent analysis.

2) Image Thresholding: Image thresholding serves as a fundamental step in segmenting the finger images into foreground and background regions, laying the groundwork for subsequent processing steps. By selecting an appropriate threshold value, the vein patterns are separated from the surrounding tissues and noise. This segmentation process improves feature extraction by isolating the vein structures, thus facilitating more precise analysis and recognition.

3) Morphological Operations: Morphological operations, including erosion, dilation, opening, and closing, are essential for refining the vein patterns and enhancing their clarity. Erosion and dilation operations effectively smooth out irregularities and fill gaps within the vein structures, contributing to the overall improvement of image quality. Opening and closing operations play a crucial role in removing noise and fine-tuning the morphology of the patterns, resulting in more accurate feature extraction and analysis. [9]

4) Edge Detection Techniques: Edge detection techniques such as Sobel, Laplacian, and Canny are employed to precisely locate the boundaries of vein structures within the finger images. These techniques are vital for isolating the vein patterns from background noise and other anatomical features. By accurately identifying the edges of the vein structures, these techniques enable more precise feature extraction and analysis, thus improving the overall accuracy of pattern recognition algorithms. [10]

5) Scaling of Images: The scaling of images ensures uniformity in size across different samples, facilitating consistent processing and analysis. Various methods such as linear, cubic, and skewed scaling are applied to resize the images while preserving their aspect ratio. This standardization of image size enhances the efficiency of feature extraction and model training, ultimately leading to more robust and reliable results.

6) Contour Detection: Contour detection techniques are employed to accurately delineate the boundaries of vein structures within the finger images. By identifying the contours of the vein patterns, it becomes easier to isolate them from the

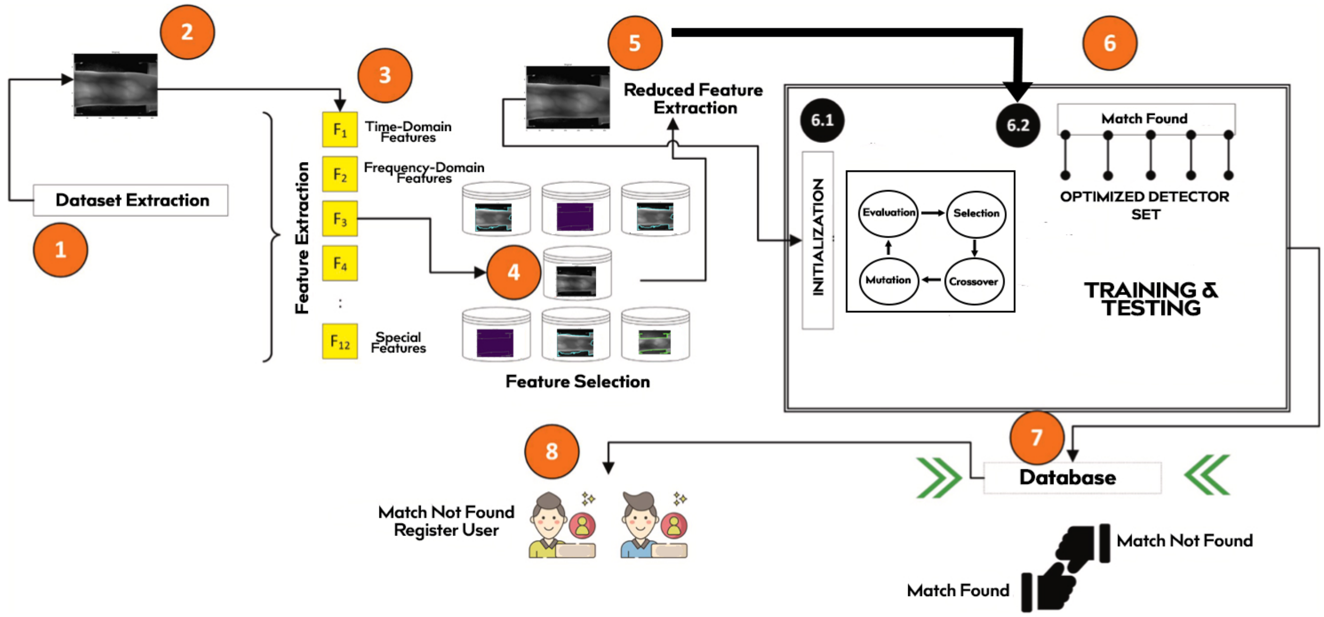

Fig. 1. The overall working of the proposed solution.

background and other anatomical features. This precise delineation enables more accurate feature extraction and analysis, contributing to the overall improvement of pattern recognition algorithms.

7) Canny Edge Detection: The Canny edge detection algorithm is utilized to identify the edges and boundaries of vein structures with high accuracy and reliability. By detecting the edges of the vein patterns, it becomes easier to isolate them from the background and other anatomical features. This precise edge detection enhances feature extraction and analysis, ultimately improving the accuracy and reliability of pattern recognition algorithms.

8) Bounding Rectangles and Approximated Polygons: Bounding rectangles and approximated polygons are employed to encapsulate the vein structures within the finger images. These techniques provide a comprehensive representation of the shape and orientation of the vein patterns, aiding in their visualization and analysis. By encapsulating the vein structures, these techniques facilitate more accurate feature extraction and pattern recognition, thus improving the overall performance of the algorithm.

9) Cropping and Padding: The original finger images are cropped based on the extreme points of the detected contour to focus on the region of interest containing the vein patterns. Additionally, padding is applied to ensure uniform dimensions across all images, maintaining consistency during subsequent processing steps and model training. This cropping and padding process enhances the efficiency of feature extraction and model training, ultimately leading to more accurate and reliable results.

D. Data Organization

After completing the preprocessing phase, the preprocessed data underwent meticulous organization into distinct training, validation, and test sets to ensure uniformity and consistency across all subsets. Each set underwent the same preprocessing steps to maintain data integrity and minimize potential discrepancies during subsequent analysis. The training data, constituting a significant portion of the preprocessed dataset, was loadedb and prepared for model training. This involved not only loading the preprocessed images but also structuring the associated labels and creating a dictionary of labels to facilitate seamless communication between the model and the training data. Similarly, the validation set, crucial for monitoring the model's performance and fine-tuning its parameters, underwent the same keen preparation process as the training data. By maintaining consistency in preprocessing and organization across all subsets, the validation set provided a reliable benchmark for evaluating the model's generalization capabilities. Finally, the test set, reserved for evaluating the model's performance on unseen data, underwent careful organization to ensure fairness and impartiality in the evaluation process. Overall, the organization of preprocessed data into distinct sets ensured uniformity, consistency, and fairness throughout the model training and evaluation process, preserving the integrity of the data and enabling robust analysis of the model's performance.

E. Model Training

For the model training phase, thorough considerations were made to select an optimal architecture capable of effectively recognizing vein patterns within the finger images. Leveraging the VGG16 model's deep architecture and proven success in image recognition tasks, it was chosen as the foundation for our study. To adapt the model to the unique characteristics of finger vein images, fine-tuning was conducted using the preprocessed dataset. This involved freezing initial layers of the pre-trained VGG16 model to retain learned features while adding additional flat and dense layers tailored to the specific task of vein pattern recognition. In addition to architectural adjustments, hyperparameter optimization played a pivotal role in enhancing the model's performance. The image size was set to 320x240 pixels to strike a balance between computational efficiency and image detail, ensuring effective vein pattern extraction. A batch size of 32 was chosen to efficiently process data during training, promoting smooth convergence and parameter updates. The number of epochs was set to 5, determining the duration of training iterations to achieve convergence without excessive computational burden. Further, a learning rate of 0.0001 was selected to regulate parameter updates, influencing the training speed and stability. Lastly, the number of classes was specified as 5, aligning with the distinct vein pattern categories present in the dataset.

This fine-tuning of both architectural and hyperparameter components ensured the model's capability to effectively learn and generalize from the preprocessed data. By optimizing these aspects to match the dataset's characteristics and computational constraints, the model was primed to achieve superior accuracy and reliability in identifying vein patterns within the finger images.

F. Analysis and Evaluation

In the analysis and evaluation phase, the trained model underwent meticulous scrutiny to gauge its effectiveness in identifying finger vein patterns. By analyzing both training and validation accuracies, insights were gleaned into the model's ability to learn from the training data while avoiding overfitting. This comparison facilitated the identification of potential issues such as underfitting or overfitting, ensuring the model's optimal performance. Additionally, predictions were rigorously made on the test dataset to assess the model's real-world applicability and generalization capabilities. Through meticulous evaluation of the predictions against ground truth labels, the model's accuracy and efficacy in identifying vein patterns in unseen data were quantified. Furthermore, complementary metrics such as precision, recall, and F1 score provided a comprehensive assessment of the model's performance, guiding further refinement and optimization efforts.

Overall, the analysis and evaluation phase served as a critical step in validating the trained model's effectiveness and reliability in vein pattern recognition. Through rigorous scrutiny of training and validation accuracies, coupled with thorough evaluation on the test dataset, the model's performance and generalization capabilities were thoroughly assessed. These insights not only affirmed the model's efficacy in identifying finger vein patterns but also provided valuable guidance for future advancements in vein pattern recognition technology.

III. Results

The final epoch results of the model training demonstrated promising outcomes, with a final training accuracy of 0.83. This achievement underscores the model's capability to effectively learn and recognize vein patterns from low-resolution images captured by webcams under infrared light. The validation accuracy of 0.90 further validates the model's robustness and generalization performance, indicating its ability to accurately classify vein patterns in unseen data. These results directly address the first research question, showcasing successful enhancements in image quality despite noise and distortions from finger muscles, bones, and surrounding structures.

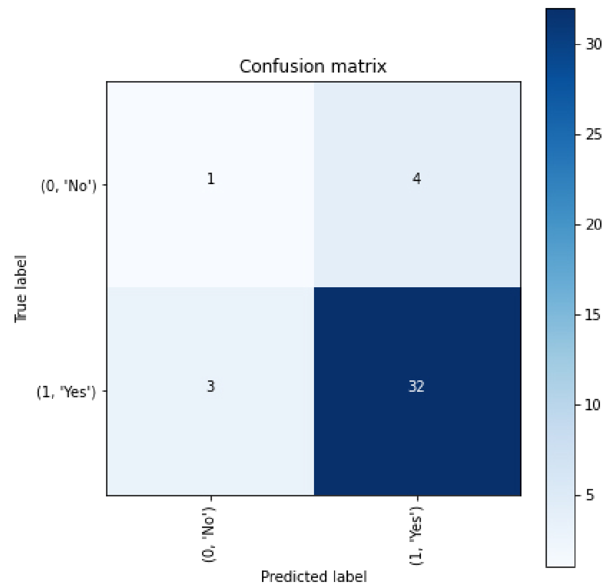

Fig. 2. Confusion Matrix

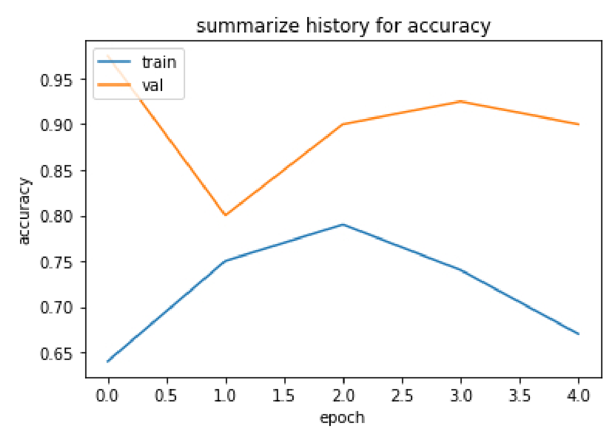

Fig. 3. Validation & Training and Validation Accuracy Graphs

Figure 4 illustrates the training and validation accuracies across epochs, providing insights into the model's learning progression over time. The steady increase in accuracy during training and consistent performance on the validation set indicate the effectiveness of the training process. Furthermore, predictions were made on the test dataset, and a confusion matrix was generated to evaluate the model's performance in identifying vein patterns accurately. The confusion matrix offers a detailed breakdown of the model's classification results, highlighting areas of strengths and potential challenges.

IV. Discussion

The achieved final training accuracy of 0.83 and validation accuracy of 0.90 validate the efficacy of the trained model in accurately identifying vein patterns from low-quality images captured by webcams under infrared light. These results directly address the second research question, showcasing the model's ability to accurately extract and refine vein patterns for reliable biometric verification. However, further analysis of the confusion matrix is necessary to identify specific challenges in vein pattern recognition and explore potential improvements. [11]

Moving forward, future directions for this study could involve investigating more sophisticated deep learning architectures or incorporating additional preprocessing techniques to further enhance vein pattern recognition accuracy. Additionally, expanding the dataset to include a more diverse range of finger vein images could improve the model's robustness and generalization capabilities. Moreover, exploring the application of advanced template matching techniques to these refined vein patterns could address the third research question, ensuring consistent and accurate personal identification while accounting for variations in finger pressure and movement during image capture.

A. Future Directions

Several dimensions for future research emerge from the current study. Firstly, exploring the integration of advanced image enhancement techniques, such as super-resolution algorithms or deep learning-based denoising methods, could further enhance the quality of low-resolution finger vein images. By effectively reducing noise and distortions while preserving essential vein patterns, these techniques could significantly improve the reliability and accuracy of vein pattern recognition systems.

Secondly, advancements in feature extraction and refinement methods hold promise for refining vein patterns from low-quality images. Research into novel feature descriptors or the development of tailored convolutional neural network (CNN) architectures optimized for vein pattern extraction could lead to more robust and efficient biometric verification systems. Additionally, exploring multimodal approaches that combine vein pattern information with other biometric modalities, such as fingerprint or iris recognition, could further enhance the overall accuracy and reliability of biometric authentication systems.

Lastly, the application of advanced template matching techniques to refined vein patterns warrants further investigation. Research into adaptive template matching algorithms capable of accommodating variations in finger pressure and movement during image capture could improve the consistency and accuracy of personal identification. Moreover, exploring the integration of machine learning techniques, such as support vector machines or random forests, alongside template matching approaches could lead to more robust and versatile vein pattern recognition systems.

References

[1] R. Bhupal, K. L. Sanjana, N. K. Khaneja, P. Bhartiya, A. S. Bhat, and B. Sandesh, "Finger vein authentication system," in *2021 International Conference on Computer Communication and Informatics (ICCCI)*. IEEE, 2021, pp. 1–7.

[2] M. Madhusudhan, V. Udaya Rani, and C. Hegde, "Finger vein recognition model for biometric authentication using intelligent deep learning," *International Journal of Image and Graphics*, vol. 23, no. 03, p. 2240004, 2023.

[3] 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, p. 89, 2021.

[4] J. Huang, M. Tu, W. Yang, and W. Kang, "Joint attention network for finger vein authentication," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–11, 2021.

[5] K. Shaheed, A. Mao, I. Qureshi, M. Kumar, S. Hussain, and X. Zhang, "Recent advancements in finger vein recognition technology: methodology, challenges and opportunities," *Information Fusion*, vol. 79, pp. 84–109, 2022.

[6] Z. Zhang and M. Wang, "A simple and efficient method for finger vein recognition," *Sensors*, vol. 22, no. 6, p. 2234, 2022.

[7] A. Krishnan, T. Thomas, and D. Mishra, "Finger vein pulsation-based biometric recognition," *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 5034–5044, 2021.

[8] M. S. M. Asaari, S. A. Suandi, and B. A. Rosdi, "Fusion of band limited phase only correlation and width centroid contour distance for finger based biometrics," *Expert Systems with Applications*, vol. 41, no. 7, pp. 3367–3382, 2014.

[9] B. Hou, H. Zhang, and R. Yan, "Finger-vein biometric recognition: A review," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–26, 2022.

[10] S. Rastogi, S. P. Duttagupta, A. Guha, and S. Prakash, "Palm vein pattern: Extraction and authentication," in *2020 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT)*. IEEE, 2020, pp. 1–5.

[11] A. Boucetta and L. Boussaad, "Biometric authentication using finger-vein patterns with deep-learning and discriminant correlation analysis," *International Journal of Image and Graphics*, vol. 22, no. 01, p. 2250013, 2022.