# CHAPTER 2

# LITERATURE REVIEW

This chapter provides a comprehensive review of the methodologies employed in finger vein recognition, with a particular focus on addressing the challenges of motion tolerance—a critical factor in ensuring the accuracy and robustness of recognition systems in dynamic scenarios. Motion tolerance is essential in practical applications, as slight finger movements during image acquisition can lead to distortions and errors in recognition.

The literature on finger vein recognition is broadly categorized into three primary areas:

- **Image Processing Based Methods:** These approaches focus on traditional image enhancement and feature extraction techniques, such as filtering, edge detection, and pattern analysis, to highlight the vein patterns for further processing.

- **Machine Learning Based Methods:** These methods rely on classical machine learning techniques, including Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and decision trees, to classify and match vein patterns based on manually extracted features.

- **Deep Learning Based Methods:** Leveraging the power of deep neural networks, these methods automate the feature extraction process, providing state-of-the-art performance in recognition accuracy and adaptability to variations in data.

## 2.1 IMAGE PROCESSING BASED METHODS

Lee et al. (2009) introduced a method for finger vein recognition that uses minutiae-based alignment and Local Binary Pattern (LBP) based feature extraction. Minutiae-based alignment focused on aligning key points in vein patterns, while LBP is used to extract textural features from these patterns. An Equal Error Rate (EER) of 0.081% was achieved, with a total computational time of 118.6 milliseconds. Although this approach showed good results, it is susceptible to noise and variations in vein structure, which affect the accuracy of minutiae extraction and hence recognition performance.

Huang et al. (2010) tackled the challenges of low image quality and finger pose distortions in finger-vein authentication and proposed a wide line detector, which improved feature extraction from degraded images and resulted in an EER of 0.87%. Additionally, they proposed a novel pattern normalization model based on the hypothesis that finger cross-sections are approximately elliptical and that veins are close to the finger surface, effectively reducing pose-induced distortions. However, the method still struggled with handling extreme variations in environmental conditions and finger poses.

Rosdi B. A. et al. (2011) developed a finger vein recognition method utilizing the Local Line Binary Pattern (LLBP) approach. This method involves creating binary patterns based on the lines detected in the vein images. An EER of 3.28% for the 204 images captured from their prototype device was achieved. Although the modified LLBP approach effectively captured vein patterns, it is computationally intensive and sensitive to noise, which limits its practicality for real-time applications.

Wang K.Q. et al. (2012) proposed an approach to finger vein recognition that utilized Local Binary Pattern Variance (LBPV) in conjunction with a global matching strategy. The method used LBP variance to capture detailed local variations in finger vein images and offered a more robust representation than standard LBP. A global matching technique was used to compare the overall vein structure, leading to better performance than traditional LBP and other conventional methods. The results suggested that finger-vein authentication performs best with the index finger and progressively worsens with the ring, middle, and little fingers, as reflected by the increasing EER values from 5.6% to 11.9%. The method is limited by sensitivity to image quality, lack of robustness to finger pose variations, potential computational complexity, and limited generalization across diverse populations and conditions.

Meng X. et al. (2012) presented an innovative method for finger vein recognition that utilized Local Directional Code (LDC) for feature extraction. This method captured the intrinsic line-like structures of finger veins more effectively than traditional texture descriptors. LDC provided a robust representation of vein patterns that are less sensitive to noise and illumination changes, as it focused on the directional variations. In verification mode, the LDC-00 and LDC-45 variants achieved equal error rates (EER) of 1.16% and 1.02%, respectively, compared to 2.25% for LLBP. The effectiveness of LDC is influenced by the choice of parameters, such as the size of the local neighbourhood and the thresholds used for gradient analysis.

Liu Z. & Song S. (2012) introduced a novel finger-vein recognition system designed for real-time operation on a DSP platform. The system incorporated an algorithm based on blanket dimension and lacunarity features, which significantly improved authentication performance. The proposed method excelled in both speed and low computational complexity. It achieves an equal error rate (EER) of 0.07% on a database of 100 subjects. The DSP-based finger vein recognition system is limited by hardware constraints and environmental variability, potentially affecting accuracy and scalability for more complex applications

Lu Y, et al. (2014) proposed a method that enhances finger vein recognition by utilizing Generalized Local Line Binary Pattern (GLLBP) for feature extraction. GLLBP captured both local texture and line-based features, providing a comprehensive representation of vein patterns that improves recognition accuracy and robustness. The approach involves extracting GLLBP features from vein images and matching them against stored templates. Evaluations on the MMCBNU_6000 dataset demonstrated that GLLBP achieved the lowest Equal Error Rate (EER) of 6.1%. Despite its improved performance, the method has drawbacks, including high computational complexity, sensitivity to parameter selection, dependence on image quality, and increased storage and matching requirements. These factors may affect its practicality for real-time and resource-constrained applications.

Liu F. et al. (2014) presented a novel approach that utilized Singular Value Decomposition (SVD) for matching minutiae points in finger vein patterns. This method applied SVD to decompose the vein feature matrices, which helped efficiently represent and compare minutiae points despite variations in image quality and acquisition conditions. The primary advantage was the improved accuracy and robustness in matching vein minutiae by leveraging the mathematical properties of SVD to handle noise and distortions. The method achieved an ERR rate of 5.01% for the PolyU database and 2.46%

for the MLA database. However, a potential drawback was that it heavily relied on the accurate extraction of minutiae points, which could be affected by image quality, noise, and improper segmentation. Additionally, SVD computations introduced higher computational overhead, making real-time processing more challenging for resource-constrained systems.

Xi X. et al. (2014) introduced a method that used hyper information features (HIF) to enhance the accuracy of finger vein recognition systems. This approach focused on extracting and utilizing additional informative data beyond traditional vein patterns, potentially incorporating advanced statistical or machine learning techniques to capture intricate details of vein structures. The HIF achieved an EER of 3.2% and a feature extraction average time of 27.1ms. The increased complexity in feature extraction and data processing necessitated more sophisticated algorithms and greater computational resources.

Kauba C. et al. (2016) explored various techniques in feature-level fusion to enhance finger vein recognition accuracy and evaluated performance metrics and challenges associated with these fusion techniques, including computational complexity, the need for large datasets, and the balance between feature complementarity and redundancy. It highlights how advanced feature-level fusion improved the robustness and accuracy of finger vein recognition systems. It used the SVM fusion rule on the UTFVP database and achieved a genuine acceptance rate (GAR) of up to 87. 15% with an equal error rate (EER) of 2.63% for the ring finger. The increased computational complexity and reliance on large, diverse datasets would hinder real-time performance and scalability.

Liu B. C. et al. (2016) proposed an approach for finger vein recognition by utilizing a rotation-invariant Local Binary Pattern (LBP) descriptor that is optimized through optimal partitioning. This method enhanced the accuracy and robustness of vein pattern recognition and showed tolerance to rotation variations. Uniform LBP feature outperformed other algorithms with a recognition rate of 99.43% and EER of 1.34%. The computational complexity associated with the optimal partitioning process impacted real-time performance and increased the resource requirements for practical implementations.

Khusnuliawati H. et al. (2017) explored a combined approach that integrates Scale-Invariant Feature Transform (SIFT) and Local Enhanced Binary Pattern (LEBP) techniques to enhance finger vein recognition. SIFT is used to extract robust key points and descriptors that are invariant to scale and rotation, while LEBP captures detailed local texture information. The method fused two features for a comprehensive representation of vein patterns from both global and local perspectives. The accuracy of finger vein recognition with SIFT-LEBP at the optimum condition reached 97.50% for the HKPU dataset with images of 50 individuals. However, the increased computational complexity associated with processing and combining two different types of features affected the speed and efficiency of the recognition system.

Zeng J. et al. (2019) proposed a novel finger-vein recognition based on quality assessment and multi-scale histogram of oriented gradients feature for finger-vein recognition, integrating quality assessment with multi-scale HOG features and resulting in a significant improvement in recognition performance. The multiscale HOG achieved an EER of 1.22% for MMCBNU_6000. The system performance was significantly affected by low-quality or noisy images, as the quality assessment module misclassified such images.

Ismail B. & Mohammed O. Z. (2019) addressed the issue of low finger vein image quality due to tissue variations and uneven illumination. The method applied Histogram Equalization and Gabor filtering to highlight and enhance vein patterns, followed by fusing these enhanced images using Discrete Cosine Transform (DCT). The enhanced images are evaluated using three criteria—mean gray values, image entropy, and image contrast—demonstrating significant improvements over baseline methods. The fusion method improved image quality in the FV-USM dataset with an average gray value of 0.5338, contrast of 0.0447, and entropy of 7.0874; and in the SDUMLA dataset with an average gray value of 0.3698, contrast of 0.0575, and entropy of 7.5373, and outperformed original images and other enhancement methods like MCGF and CLAHE. However, as the approach relied on parameter choices, such as filter orientations and mask size, careful optimization to achieve optimal results was necessary.

Dahea W. & Fadewar H. S. (2020) enhanced finger vein recognition accuracy by combining Gabor filters and Local Binary Pattern (LBP) techniques in Finger Vein

Recognition System Based on Multi-Algorithm Fusion of Gabor Filter and Local Binary Pattern. Gabor filters captured multi-scale and multi-orientation features, and effectively extracted global texture information, while LBP encoded local texture details. This multi-algorithm fusion approach achieved a recognition accuracy of 94.94%, and outperformed the individual methods, Gabor filters at 94.13% and LBP at 94.06%. A notable limitation was its increased computational complexity due to the fusion of multiple algorithms.

Tahir A. A. & Mustafa A. A. (2022) introduced a novel method to enhance finger vein recognition accuracy and utilized local histogram concatenation of image descriptors. This technique aggregated histograms from different regions of the finger vein images to capture more comprehensive and detailed vein patterns, which improved the overall recognition performance. The experimental results demonstrated that their approach achieved a recognition accuracy of 98.5%, with a False Acceptance Rate (FAR) of 0.5% and a False Rejection Rate (FRR) of 1.0%. They lacked generalization across diverse datasets, as it is dependent on accurate ROI extraction.

Krishnan A. & Thomas T. (2023) proposed a feature representation based on six anatomical vein patterns—Fork, Eye, Bridge, and Arch (FEBA), along with two additional variations. This anatomically based 6×6 feature matrix improved recognition performance, enhanced template security and showed invariance to scaling, translation, and rotation. This approach achieved an average recognition accuracy of 98% and an Equal Error Rate (EER) of approximately 2.0% across two public datasets and an in-house dataset. The method was limited by its reliance on manually defined anatomical vein patterns, and its performance is affected by poor image quality or non-ideal imaging conditions.

## 2.2 MACHINE LEARNING BASED METHODS

Liu Z. et al. (2010) addressed challenges in finger vein biometric systems by introducing a novel approach that combined manifold learning with point manifold distance concepts. The method employed Optimal Neighbourhood Preserving Projections (ONPP) and tackled issues such as noise and pose variations for manifold learning, and used a point-to-manifold distance function for classification. The system achieved robustness against noise and deformation and has achieved a recognition rate of 97.8% with the identification model and an EER of 0.8% with the verification model. However, the system performance was affected by residual information in infrared images, such as shading caused by varying thicknesses of finger muscles, bones, and surrounding tissue networks. Additionally, variations in finger pose during image capture led to recognition failures.

Park K. R. (2011) proposed the use of Local Binary Convolution (LBC) to extract multi-directional features from finger vein images, which used prior knowledge of vein patterns to improve feature representation and matching accuracy. The LBC technique effectively captured fine-grain, directionally diverse features. The system achieved an EER of 1.1% with a total processing time of 98.2ms. The system's accuracy was compromised by inaccurate vein pattern extraction due to variations in finger positioning or image quality.

Khellat-Kihel S et al. (2014) proposed a method that combines Gabor filters and Support Vector Machines (SVM) to improve the accuracy of finger vein recognition. Gabor filters are employed to extract texture features from the finger vein images, as they are effective in capturing vein patterns at various orientations and scales. These features are then fed into an SVM, for classification and recognition of the vein patterns. They achieved a recognition rate of 98.75%. The computational expense associated with applying Gabor filters and training the SVM, leads to longer processing times and higher resource consumption. Also, blurred images or irregular shadows in finger vein images compromise the accuracy of vein pattern extraction.

T. Thilagavathy and K. Siruba (2014) proposed a method using Support Vector Machines (SVM). The approach involved capturing finger vein images, extracting relevant features from these images, and then using SVM for classification and verification. The SVM was trained to distinguish between individuals based on the unique patterns of their finger veins. The EER obtained for 100 images of 10 fingers was 0.01%. It faced challenges with scalability for large datasets, intricate parameter tuning, and the critical selection of an appropriate kernel function.

Prabu A. J. & Bai S. C. (2017) proposed a method aimed at enhancing the security of private information through biometric identification, which included a novel quality estimation algorithm and multi-scale matched filtering for image enhancement. For vein extraction, it combined information from the enhanced image and vein quality using an

SVM classifier. This approach effectively addressed challenges such as hair, skin texture, and varying vein widths, although it depended on high-quality vein images, which could be challenging to obtain in suboptimal conditions, potentially affecting its accuracy and reliability. This method achieved a recognition accuracy of 98.7%, with a False Acceptance Rate (FAR) of 0.2% and a False Rejection Rate (FRR) of 1.1%. The method's performance was affected by variations in finger positioning, image quality, and the presence of noise or artifacts.

Xi X. et al. (2017) presented a novel method for generating Discriminative Binary Codes (DBC) to improve finger vein recognition. The approach used a subject relation graph to capture the correlations between different individuals and was used to transform binary templates that represented vein characteristics, optimizing the templates to maximize the distance between different subjects' codes and ensuring they contained maximum subject information. Support Vector Machines (SVMs) were used to train the binary codes, which were found to be more discriminative and compact compared to traditional methods. Experimental results proved the method's effectiveness and efficiency in comparison to binary coding techniques for finger vein recognition. This method achieved an Equal Error Rate (EER) of 2.57% when trained on the SDUMLA-HMT database and 5.08% for the HKPolyU database. The method's performance could degrade when applied to heterogeneous datasets with significant variations in image quality, lighting conditions, or sensor characteristics, as it was primarily evaluated on small, homogeneous datasets.

Roza W. A. et al. (2019) developed a novel feature extraction method called Straight Line Approximator (SLA) to enhance the feature space of vein patterns using the SDUMLA-HMT dataset. They used ensemble learning with Extreme Learning Machine (ELM) and Support Vector Machine (SVM) classifiers employing different kernels and applied combination rules to optimize performance. The proposed method achieved an identification accuracy of 98.50% on the SDUMLA-HMT dataset. It faced limitations in handling variability in vein patterns across different populations and imaging conditions.

Shazeeda S. & Rosdi B. A. (2019) addressed the limitations of traditional Sparse Representation Classification (SRC) in biometric systems, where classification was based on the class with the minimum reconstruction error. Recognizing based solely on reconstruction error was not ideal due to the sparsity of images, so the authors proposed an improved methodology called Mutual SRC (MSRC). This approach enhanced the recognition rate by introducing a decision rule that not only considered the nearest sparse neighbour but also identified the training sample that regarded the test sample as its nearest neighbour. Across four finger vein databases, FV–USM, SDUMLA-HMT, HKPU, and THUFVDT, the MSRC method improved accuracy from 91.06% to 95.73%, 57.49% to 68.08%, 49.29% to 76.11%, and 96.07% to 99.51%, respectively, which increased the average computation time per image due to more iterations. Despite its effectiveness, the MSRC method entailed computational complexity, particularly in solving sparse representation problems, which could limit its applicability in real-time systems.

Zhang X. & Wang W. (2020) addressed the challenges of finger vein recognition by proposing an algorithm that enhanced image quality using Contrast Limited Histogram Equalization (CLHE) and adaptive median filtering, and improved feature extraction through Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and Principal Component Analysis (PCA) for dimensionality reduction. Support Vector Machine (SVM) was then utilized for classification. The proposed method achieved an accuracy of 98.2% on the SDUMLA-HMT dataset. This approach demonstrated significant improvements in recognition accuracy, speed, stability, and robustness, although it relied on high-quality image preprocessing and was computationally intensive.

Kapoor K. et al. (2021) introduced a finger vein recognition framework that combined Local Phase Quantization (LPQ) and Local Directional Pattern (LDP) for robust feature extraction, addressing challenges such as motion blur, noise, and lighting variations. The framework employed Grey Wolf Optimization-based SVM (GWO-SVM) to optimize SVM parameters for better classification accuracy. The proposed LPQ-LDP feature extraction method, coupled with GWO-optimized SVM, achieved a recognition accuracy of 98% and an Equal Error Rate (EER) as low as 0.1020%. The increased complexity of integrating multiple feature extraction techniques and the added computational overhead of using GWO for parameter optimization made it resource-intensive for large-scale implementations.

Rosdi B. A. et al. (2021) introduced an adaptive K-Nearest Centroid Neighbour (akNCN) classifier to improve the efficiency of the traditional kNCN classifier, which suffered from slow classification times due to the need to evaluate all training samples. The akNCN classifier adaptively adjusted the neighbourhood size based on two new rules: adjusting the size if the centroid distance of the $j^{th}$ nearest neighbour exceeded a boundary and halting the search once the maximum number of same-class samples was found. Their findings demonstrated the akNCN's ability to effectively determine neighbourhood size, enhancing both speed and accuracy. The proposed akNCN classifier achieved an accuracy of 98.5% and an Equal Error Rate (EER) of 0.02% on the FV-USM dataset. The complexity introduced by adaptively selecting the neighbourhood size made the method harder to tune for different datasets.

Shakil S. et al. (2023) utilized Principal Component Analysis (PCA) for vein pattern extraction and Support Vector Machine (SVM) for classification. It focused on optimizing performance based on varying vein pattern qualities. The recognition rates achieved progressive improvement across datasets, reaching up to 98.87% for THU-FVFDT2, 98.52% for SDUMLA-HMT, and 90.67% for FV-USM. However, the reliance on the quality of the vein patterns, which was affected by factors like image noise or poor illumination, and the relatively small dataset size, limited generalizability and scalability.

## 2.3 DEEP LEARNING BASED METHODS.

Radzi S. A. et al. (2016) proposed a robust approach for finger vein biometric identification using Convolutional Neural Networks (CNN) combined with the stochastic diagonal Levenberg–Marquardt algorithm. This method addressed common issues in biometric systems, as CNNs were particularly effective in handling noise and minor misalignments in the acquired images, thereby enhancing the reliability and accuracy of the identification process. The system achieved 99.38% accuracy when tested on an in-house dataset with 81 subjects. While CNNs were effective at handling noise and minor misalignments, they still required substantial computational resources and large, well-annotated datasets to achieve optimal performance, which could be a challenge in real-world applications with limited resources or varying image quality. Also, the model's performance was evaluated solely on a proprietary dataset, which may have limited its generalizability to public or more diverse datasets with varying acquisition conditions.

Qin H. et al. (2017) proposed CNNs for robust finger-vein segmentation and Fully Connected Networks (FCN) for recovering missing vein patterns, significantly improving verification accuracy. It achieved EER reductions of 2.7% on the HKPU-FV database and 1.42% on the FV-USM database. However, it faced challenges with over-segmented images and imbalanced illumination, which affected the system's performance in accurately identifying vein patterns under varying lighting conditions.

Hong H. G. et al. (2017) investigated the use of CNNs for finger-vein recognition. This approach incorporated data augmentation to enhance the training process, specifically using only translation for augmentation. The CNN model achieved an EER of 3.906% for SDU-DB and 1.275% for PolyU-DB. While the use of CNNs with data augmentation improved the system's robustness and performance, the limitation of using only translation for augmentation did not address other variations such as rotation, scaling, or changes in illumination, potentially affecting the generalization capability of the model.

Meng G. et al. (2017) addressed the complexities and inefficiencies in traditional finger vein recognition systems, which often required extensive image pre-processing and used non-representative feature vectors. They proposed a method that directly inputs image samples into a CNN model to extract feature vectors and authenticate based on the Euclidean distance between these vectors. Utilizing the Deep Learning Framework Caffe, the proposed system demonstrated robust performance under varying illumination and rotation conditions, showing promise for practical applications. This method achieved 99.4% accuracy and 0.21% EER for a small dataset. However, challenges in maintaining high performance across real-world scenarios highlight the need for a larger dataset to train a more effective network.

Chen C. et al. (2017) proposed a method that combined Feature Block Fusion and Deep Belief Network (FBF-DBN) with CNN, enhancing recognition stability and robustness compared to traditional template matching methods. By incorporating feature points from vein images into the deep network input, the algorithm reduced learning and detection time, making it suitable for embedded systems. This method achieved recognition accuracies of 98.88% on the FV-USM dataset and 98.58% on the SDUMLA-HMT dataset. However, the algorithm's performance and efficiency improvements were limited by its dependency on feature block fusion and deep belief networks, which did not fully address variations in vein image quality or environmental conditions.

Huang H. et al. (2017) used deep CNN to enhance biometric verification by exploiting the feature extraction capabilities of deep learning models. The DeepVein approach achieved a recognition accuracy of 97.12% on the FV-USM dataset and 98.45% on the PolyU-DB dataset. The influence of training data volume on the accuracy of the model emphasized the importance of data quality and quantity in achieving optimal performance.

Xie C. et al. (2017) proposed an approach for finger vein authentication that integrated CNN with supervised discrete hashing. The study systematically evaluated several popular CNN architectures, including Light CNN, VGG-16, Siamese, and a CNN with Bayesian inference-based matching, to determine their performance in vein identification. The results indicated that the combination of supervised discrete hashing with a CNN trained using a triplet-based loss function achieved the lowest EER of 0.1223% and significantly reduced the template size to 2000 bits, outperforming other methods. However, the study acknowledged limitations such as the relatively small size of the publicly available database used.

Jalilian E. & Uhl A. (2018) proposed a novel finger-vein recognition model based on fully convolutional deep neural networks (FCNs), which directly segments the actual finger-vein patterns from input images and utilizes these segmented patterns as binary features for the recognition process. They emphasized the importance of training data quality by comparing manually annotated data with automatically generated labels. The study found that incorporating automatically generated labels enhanced the network's performance, leading to higher recognition accuracy. The model achieved an EER of 2.17% on the SDUMLA-HMT dataset. However, the recognition performance was limited by the quantity and quality of training data, especially in training deep segmentation networks to generalize well across datasets.

Fang Y. et al. (2018) introduced a finger vein verification method that utilized a two-stream convolutional network learning. This approach aimed to enhance verification accuracy by simultaneously processing two streams of input data. The two-channel network achieved an EER of 0.94% on the SDUMLA database and 0.2% on the MMCBNU database. However, it lacked sufficient training data and an end-to-end testing framework, which limited its invariance to rotation and displacement, especially affecting performance on the SDUMLA database. Additionally, the preprocessing steps did not adequately address issues related to the rotation and displacement of finger veins.

Kim W. et al. (2018) explored the integration of finger-vein and finger shape biometrics using a deep CNN and an NIR light camera sensor. This multimodal approach aimed to improve biometric recognition accuracy by utilizing complementary information from both finger-vein and finger shape features. The method achieved an EER of 3.3653% on the SDU-DB dataset and 1.0779% on the PolyU-DB dataset. However, the study identified that most false rejection cases were caused by misalignment between finger-vein images due to changes in finger position between the enrolment and recognition phases, highlighting the challenge of maintaining consistent image capture conditions.

Song J. M. et al. (2019) investigated the use of DenseNet, a deep learning architecture, for finger-vein recognition. Their approach utilized composite images to enhance feature extraction and recognition, achieving an Equal Error Rate (EER) of 0.33% on the PolyU dataset and 2.35% on the SDUMLA dataset. However, the method required significant computational resources, limiting its practical application in environments with constrained processing capabilities. To address this, they suggested improving processing speed while maintaining recognition accuracy by reducing the number of layers and transition layers in DenseNet.

Lu Yu et al. (2019) proposed a CNN-based local descriptor called CNN Competitive Order (CNN-CO) to address the challenge of limited training data availability. CNN-CO enhanced the feature extraction process by selecting features based on the appearance and response of CNN filters. This method improved recognition accuracy by leveraging the competitive nature of the filters, enabling the system to effectively identify and utilize the most relevant features from finger vein images despite limited training data. The method achieved EER values of 0.74% and 2.37% on the MMCBNU_6000 and SDUMLA-HMT datasets, respectively. However, a limitation of the CNN-CO approach was that the CNN filters were manually selected based on their appearance and responses, potentially limiting scalability and adaptability to other CNN architectures.

Yang W. et al. (2019) addressed challenges in finger vein verification by proposing FV-GAN, a framework that utilized Generative Adversarial Networks (GANs) to enhance robustness against outliers and vessel breaks, along with fully convolutional networks to reduce computational load and input size constraints. Experimental results demonstrated significant improvements in verification accuracy and equal error rate, achieving EER 1.72% on the THUFV-F1 dataset. Future work aimed to expand databases, stabilize GAN training, and leverage the generator to enhance and enlarge finger vein datasets. However, the main limitation of FV-GAN was its reliance on high-quality training data, as variations such as noise and illumination changes could adversely affect the accuracy of the generated vein patterns.

Gumusbas D. et al. (2019) introduced a Capsule Network-based approach for finger-vein biometric identification to address challenges faced by traditional CNN algorithms, such as limited sample sizes in benchmark finger-vein databases and increasing spoofing attacks that hinder optimal vein representation. The capsule network effectively utilized convolutional operations with a limited number of samples, enhancing feature extraction without relying on pre-trained weights. This approach, applied to 32x32 image resolutions, achieved an average accuracy of 95.5% across four benchmark sub-databases. However, the reliance on relatively low-resolution images limited the method’s ability to capture finer details and complexities of finger-vein patterns.

Jalilian E. & Uhl. A. (2019) presented a novel finger-vein recognition method using semantic segmentation CNNs for vein pattern extraction. The model combined automatically generated labels with manually annotated ones to enhance recognition accuracy, reduce manual annotation effort, and improve training efficiency. The approach achieved an EER of 2.21% on the UTFVP dataset, demonstrating improved performance through joint training with both label types. However, the method’s effectiveness was limited by the quality of automatically generated labels, which could introduce noise and negatively impact overall recognition accuracy.

Kuzu R. S. et al. (2020) explored an advanced method for real-time biometric recognition by integrating CNN for feature extraction with Long Short-Term Memory (LSTM) networks to capture temporal dependencies. This combination enabled on-the-fly processing, making it suitable for dynamic and immediate applications. The method achieved an accuracy of 99.13% on a challenging in-house dataset collected from 100 individuals, consisting of sequences of nine images captured from their left hand. However, the system’s performance was affected by motion blur and varying lighting conditions inherent in real-time acquisition, which impacted recognition accuracy in practical scenarios. Additionally, the approach required further optimization to address its computational demands.

Noh K. J. et al. (2020) addressed the limitations of previous methods by integrating texture and shape images through score-level fusion. The approach used a deep convolutional neural network to process both types of images: texture images for detailed feature extraction and shape images to minimize noise and mis-segmentation effects. By combining these images, the method enhanced recognition performance and reduced sensitivity to illumination changes and noise. The EER rate obtained for the HKPolyU database was 0.05%, and for the SDUMLA database was 1.65%. The system faced challenges related to increased processing time due to the use of two image types and the complexity of the preprocessing algorithm.

Huang Z. & Guo C. (2021) integrated ResNet for deep feature extraction and UNET for spatial attention and bias field correction. This method improved accuracy by focusing on significant features and correcting image variations and achieved an EER of 0.48% on the FV-USM database. The model's performance was constrained by the limited availability of labelled training samples and the absence of pixel-level vein texture annotations in public finger vein databases.

Krishnan H. & Khare S. (2022) presented a transfer learning-based model that was trained using vein images with varying levels of quality, including original, blurred, and noisy images, to improve recognition performance under suboptimal conditions. The approach’s effectiveness was attributed to its use of data augmentation and transfer learning. The model achieved an accuracy of 94.56%. However, its performance heavily depended on the availability of large and diverse datasets, which restricted its generalization to different imaging conditions.

Li J et al. (2022) investigated finger vein verification using deep learning and the triplet loss function across multiple datasets, achieving high accuracy and ROC AUC values, which indicated strong model performance. The use of cross-validation with completely unrelated training and validation sets enhanced the model's generalizability. The accuracies of the ResNet18 and VGGNet16 models varied between 92% and 98% for various configurations, and the ROC AUC values were above 0.98. However, the approach faced limitations in handling datasets with significantly different characteristics or extreme variations in vein image quality.

Zhang Z. & Wang M. (2022) proposed an algorithm that simplified the recognition process by generating a feature code from finger vein images without requiring segmentation, utilizing block-based averaging and centrosymmetric coding. The method measured similarity through Hamming distance ratios and demonstrated effectiveness through extensive experiments on two public databases. This method achieved an EER of 2.86% for the HKPU database and 1.16% for the USM database. However, this method had reduced accuracy compared to advanced techniques, potential sensitivity to image quality, a lack of large-scale public databases for comprehensive evaluation, and limited generalization across diverse datasets.

Liu W. et al. (2023) introduced a model that used a multiscale and multistage residual attention network to enhance feature extraction from low-resolution, grayscale vein images. The model integrated a Fusion Residual Attention Block (FRAB) with distinct subpaths—Main Vein Path (MVP) and Guided Attention Path (GAP)—and a Multistage Residual Attention Connection (MRAC) to effectively capture and combine various vein features. This architecture improved recognition accuracy to 98.1% even with a large number of parameters.

Zhang Z. et al. (2023) addressed issues of low accuracy and high computational demand in finger vein recognition by integrating ResNet with a self-attention mechanism. The model combined the global focus capabilities of self-attention with the local feature extraction strengths of CNNs. This integration was achieved through the Convolution and Self-Attention (CASA) block, which used shared linear projections to reduce parameter count and computational complexity while avoiding gradient issues. The use of cosine annealing for the learning rate further enhanced training stability. Experimental results showed an accuracy of 99.9% for the FV-USM dataset, while maintaining lower parameter count and computational requirements compared to existing models. However, it still required further research to achieve even greater model simplification without sacrificing recognition accuracy.

Devkota N. & Kim B. W. (2024) introduced a novel approach to finger vein recognition by employing a DenseNet enhanced with a channel attention mechanism and hybrid pooling techniques. The Squeeze-and-Excitation-DenseNet model integrated channel attention to refine feature representations and hybrid pooling to effectively capture and consolidate spatial information, aiming to improve recognition accuracy and robustness. The method achieved recognition accuracies of up to 99.35% and 93.28% from good-quality vein patterns for the FV-USM and HKPU datasets, respectively, and attained EERs of 0.03%, 1.81%, 0.43%, and 1.80% for the FV-USM, HKPU, UTFVP, and MMCBNU_6000 datasets, respectively. This method necessitated data augmentation to handle variations in image quality and features.

## 2.4 SUMMARY

This chapter provides a detailed survey of the previous research on finger vein recognition methods. This survey highlights the progression from image processing techniques to sophisticated machine learning and deep learning approaches. Deep learning methods emerged as the most effective solution for enhancing the performance and robustness of finger vein recognition systems.