A Comprehensive Study on Integration of Segmentation and Enhancement Approaches for Robust Finger Vein Recognition

V. Vathsala
Research Scholar (Registration Number: 23113152282008), Department of Computer Science and Research Centre, S.T. Hindu College, Nagercoil- 629002, Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli- 627012, TamilNadu, India

K. Pazhanikumar, PhD
Head and Assistant Professor, Department of Computer Science and Research Centre, S.T.Hindu College, Nagercoil- 629002, Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli- 627012, TamilNadu, India

ABSTRACT
Finger vein reputation's extremely good safety, internal feature forte, and forgery resistance have made it a capability biometric identity method. But a hit vein pattern segmentation and augmentation are essential for obtaining reliable and correct detection. The segmentation and augmentation techniques currently utilized in finger vein recognition structures are thoroughly reviewed in these paintings. traditional photograph processing techniques, device studying algorithms, and new deep gaining knowledge of-primarily based models that decorate vein visibility, assessment, and boundary localization are all methodically tested on these paintings. to emphasize their have an impact on reputation performance, some of pre-processing strategies also are covered, which includes vicinity of interest (ROI) extraction, illumination correction, and noise reduction. Furthermore, the paper examines the benefits and boundaries of various strategies, specializing in their integration to enhance feature pleasant and recognition robustness. The mixing of segmentation and development strategies to growth the accuracy and resilience of finger vein recognition systems is the main aim of this thorough assessment. For precise vein sample extraction, a spread of segmentation strategies is investigated, which includes thresholding, vicinity-based totally, and deep getting to know-based models. Moreover, included are improving strategies like deep getting to know-based photograph augmentation, Gabor filtering, and evaluation-constrained adaptive histogram equalization. This analysis emphasizes the want of integrating segmentation and enhancement algorithms to provide remarkable reputation overall performance below a diffusion of imaging conditions with the aid of examining recent tendencies and limitations. Sooner or later, they have a look at discusses present day problems, which includes unpredictability in imaging occasions, dataset limits, and computational complexity, and shows new research avenues for constructing adaptive, hybrid, and actual-time finger vein detection frameworks.

Keywords
Finger Vein Recognition, Vein Enhancement, Vascular Biometrics, Finger Vein Identification and segmentation.

1. INTRODUCTION
Finger vein popularity's intrinsic, awesome, and impenetrable traits have made it a secure and reliable biometric identification method. Finger vein patterns are amassed the use of near-infrared (NIR) imaging, which guarantees greater privacy and resistance to imitation compared to exterior capabilities like fingerprints or facial images. However, reaching excessive recognition accuracy is often severely hampered by way of differences in illumination, finger posture, and photograph exceptional [1].Finger vein identity has drawn a variety of hobby these days as a truthful biometric verification technique due to its high protection, individuality, and spoofing resistance. Finger vein patterns are internal, imperceptible to the unaided eye, and consistent over the course of a person's life, in evaluation to outward biometric traits like fingerprints or facial capabilities. Finger vein reputation is therefore best for use in identity verification, banking, and protection get admission to manipulate systems. But, the pleasant of the photographs taken and the precision of vein sample extraction play a chief function in how properly finger vein reputation systems paintings [2]. Variations delivered on with the aid of poor comparison, movement blur, finger misalignment, and uneven illumination can substantially impair reputation overall performance. Segmentation and enhancement are vital pre-processing strategies for finger vein pix in order to conquer these difficulties. The purpose of segmentation strategies is to exactly separate the vein patterns inside the ROI from the encompassing tissues and historical past. Present day deep learning architectures like U-net and attention U-net, which offer correct and adaptive segmentation, have supplemented conventional strategies like thresholding, morphological operations, and region-primarily based segmentation [2]. But, improving strategies make vein patterns extra visible and contrasted, which increases the efficiency of feature extraction. Vein sample readability has been proven to be drastically improved via techniques like CLAHE (assessment-confined Adaptive Histogram Equalization), Gabor filtering, and deep mastering-based totally image enhancement algorithms. Inside the pre-processing segment of finger vein popularity, segmentation and augmentation are critical for resolving those issues. Even as enhancement increases image assessment and vein visibility, segmentation concentrates on exactly figuring out the area of interest (ROI) that homes the vein patterns. Combining these strategies makes vein extraction more accurate and will increase the popularity device's ordinary resilience. This thorough research examines a number of traditional and deep getting to know-based segmentation and enhancement methods, emphasizing how properly they paintings together to enhance overall performance in more than a few imaging scenarios [3]. The paper also covers present day trends, limitations, and capability paths for growing honest and powerful finger vein recognition structures.

1.1 Progress and Trends in Deep Learning Architectures
- Over the past ten years, deep learning research has rapidly expanded, changing how machines understand and comprehend data. Delivering state-of-the-art

performance in a variety of applications, such as image recognition, audio processing, medical diagnostics, and natural language comprehension, has been made possible by the development of innovative architectures [4].

- Convolutional Neural Networks (CNNs), which transformed computer vision applications by way of integrating spatial characteristic extraction and hierarchical brand new, were the focal point modern day early research [5]. Later trends in long quick-time period reminiscence (LSTM) networks and Recurrent Neural Networks (RNNs) superior their capacity to model temporal and sequential input, main to gains in text and voice interpretation (7).
- As the field advanced, scientists checked out state-of-the-art elaborate deep modern day strategies to get across the difficulties that include analyzing clinical pics:
- Ensemble modern day: a few research used ensemble brand new strategies to combination predictions from numerous CNN models that allows you to enhance predictive power and robustness [4 & 5]
- This method lowers the possibility modern day over fitting and increases overall accuracy by means of utilising the form of various fashions. [8].
- Latest research traits spotlight the superiority present day Transformer-based totally architectures, which use self-attention techniques to address long-variety dependencies extra effectively than RNNs [6].
- Fashions like BERT, GPT, and vision Transformers (ViT) have upped the bar for each language and vision issues by way of emphasizing scalability and generalization.
- Researchers are also looking into neural structure search (NAS) as a way to automate version design and decrease the need for manual correction. There's also ultra-modern attention on lightweight and electricity-green models, such as cellular net and green internet, to enable deep modern day on facet devices. Recent research trends highlight the prevalence of Transformer-based architectures, which use self-attention techniques to handle long-range dependencies more successfully than RNNs [6].
- Models like BERT, GPT, and Vision Transformers (ViT) have upped the bar for both language and vision problems by emphasizing scalability and generalization.
- Researchers are also looking into Neural Architecture Search (NAS) as a way to automate model design and reduce the need for manual correction. There is also a lot of focus on lightweight and energy-efficient models, including Mobile Net and Efficient Net, to enable deep learning on edge devices.
- When considered collectively, these trends demonstrate how deep learning architectures are developing toward more interpretable, flexible, and resource-efficient models that satisfy the growing demands of real-world AI applications.
- Recent research has concentrated on efficient and lightweight designs like Mobile Net, Shuffle Net, and Efficient Net to enable deep learning on devices with limited resources. Because it can automate the design process and identify the optimal network topologies, Neural Architecture Search (NAS) has also attracted attention.
- The development of Graph Neural Networks (GNNs) and Vision Transformers (ViTs) has significantly improved deep learning's ability to handle complex data structures and multi-modal tasks. Explainable AI (XAI), energy-efficient computing, and federated learning are also becoming increasingly relevant in order to promote sustainability, privacy, and transparency. All things considered, recent advancements in deep learning architecture design indicate a shift toward more accountable, perceptive, and flexible AI systems that can deal with real-world issues.
- When combined, these methodological and architectural advancements allow deep learning to advance by providing dependable and flexible solutions to a range of practical problems.
- Healthcare: From prediction models to image-based disease diagnostics, deep learning is providing individualized and private healthcare solutions.

1.2 Reducing the Drawbacks of Finger Vein Identification using Cutting-Edge Deep Learning Techniques

Finger vein recognition, which uses the unique vascular patterns beneath the skin, is a potential biometric method for safe personal identification. However, the system has some shortcomings, including poor image quality caused by variations in blood flow, skin thickness, finger position, and lighting.

Conventional image processing and machine learning techniques often struggle to extract reliable features under these challenging conditions. To solve these issues, sophisticated deep learning methods have been created, enabling improved vein pattern augmentation, noise reduction, and automatic feature extraction. Deep architectures that effectively capture intricate vein structures and enhance image clarity, leading to more dependable recognition performance, include Convolutional Neural Networks (CNNs), U-Net, and attention-based models. Additionally, Siamese networks and transfer learning approaches improve the system's ability to generalize across different users and imaging settings. By integrating segmentation, augmentation, and classification into a single framework, deep learning-based solutions significantly lessen the shortcomings of traditional approaches. Finger vein detection systems become more accurate, adaptable, and reliable as a result.

Finger vein recognition is very safe and difficult to develop, but its reliability and effectiveness are compromised by several technological problems. One of the primary challenges is poor image quality, which is often caused by variations in blood flow, finger thickness, and illumination during image acquisition. When there is little distinction between the veins and the surrounding tissues, it might be difficult to distinguish unique vein patterns.

Finger rotation and misalignment during scanning might also result in inconsistent data. Noise, blurring, and occlusion caused by skin conditions or sensor limits further diminish image clarity.

These problems cannot be sufficiently resolved by traditional image processing methods. On the other hand, deep learning models have proven to be useful in overcoming these challenges. Deep learning uses advanced designs such as Convolutional Neural Networks (CNNs), Attention U-Nets, and Siamese networks to provide automatic feature extraction, dependable segmentation, and adaptable learning in a range of contexts.

By enhancing image quality, reducing noise, and raising matching accuracy, these models address many of the technical problems that have long impeded accurate finger vein detection performance.

2. SEGMENTATION OF FINGER VEIN IMAGES THROUGH ACTIVE CONTOUR MODELS

Accurately segmenting vein patterns from gathered images is crucial for finger vein detection. However, segmentation of finger vein pictures is sometimes challenging due to poor contrast, noise, uneven illumination, and variations in finger posture [9]. By developing a curve to match the edges of vein patterns in an image, active contour models (ACMs), sometimes referred to as snake models, provide a dependable solution. The model can handle complex vein morphologies and local variations since it iteratively modifies the contour based on image gradients and energy minimization concepts.

When it comes to finger vein segmentation, ACMs excel at identifying small and curved vein characteristics that conventional thresholding or edge detection methods could miss. By integrating both local and global image data, variations such gradient-based snakes, region-based snakes, and level set techniques increase segmentation accuracy [10]. Because active contour-based segmentation accurately defines venous structures, it improves the effectiveness of subsequent processes including feature extraction, matching, and biometric verification. All things considered, ACMs provide a versatile and reliable solution to the problems associated with finger vein image segmentation.

2.1 An Overview of Active Contour Models for Robust Finger Vein Segmentation

A safe and reliable biometric method is finger vein recognition, which entails accurately extracting vascular patterns from finger photos. However, segmentation is often complicated by issues like low contrast, noise, uneven illumination, and finger misalignment. Because they can adapt to complex and curved venous systems, Active Contour Models (ACMs), also referred to as snakes, are commonly used to overcome these difficulties [11].

In order to minimize an energy function that incorporates both external (pushing the contour toward picture characteristics like vein boundaries) and internal (ensuring the contour's smoothness and continuity) pressures, ACMs iteratively construct a contour. Gradient-based snakes, region-based snakes, and level set approaches are variations that enhance resilience by fusing global region features with local edge information.

Following segmentation, vein patterns are often altered using post-processing methods including skeletonization and morphological operations to get them ready for feature extraction and matching.

All things considered, active contour-based segmentation improves the performance and dependability of biometric systems by providing a flexible, adaptive, and accurate solution to robust finger vein recognition.

2.2 Function of Active Contour Models in Finger Vein Segmentation

The main objective of using Active Contour Models (ACMs) in finger vein segmentation is to reliably and accurately extract vascular patterns from finger images, which function as distinctive biometric characteristics for identification and authentication. Low contrast, noise, uneven illumination, finger misalignment, and skin flaws are common problems with finger vein images that make standard segmentation techniques ineffective. In order to solve these problems, ACMs provide a versatile framework that can take into account the intricate, curved forms of vein patterns.

2.2.1 Key purposes

Accurate Vein Boundary Detection: By gathering the minute details needed for identification, ACMs develop a contour to accurately outline vein structures. Noise and Artefacts Handling: ACMs can improve segmentation quality by limiting the impact of noise and irrelevant features by concentrating on energy saving. Adaptability to Variations: ACMs provide consistent segmentation across images by reacting dynamically to variations in finger position, orientation, and illumination. Assistance with Complicated Vein Patterns: The model can handle branching, splitting, and merging veins more effectively thanks to advanced versions like level set techniques. Enhanced Recognition Accuracy [12]: ACMs improve the performance of subsequent stages in biometric systems, like feature extraction and matching, by producing distinct, continuous vein maps.

3. WORKFLOW OF FINGER VEIN SEGMENTATION PROCESSING

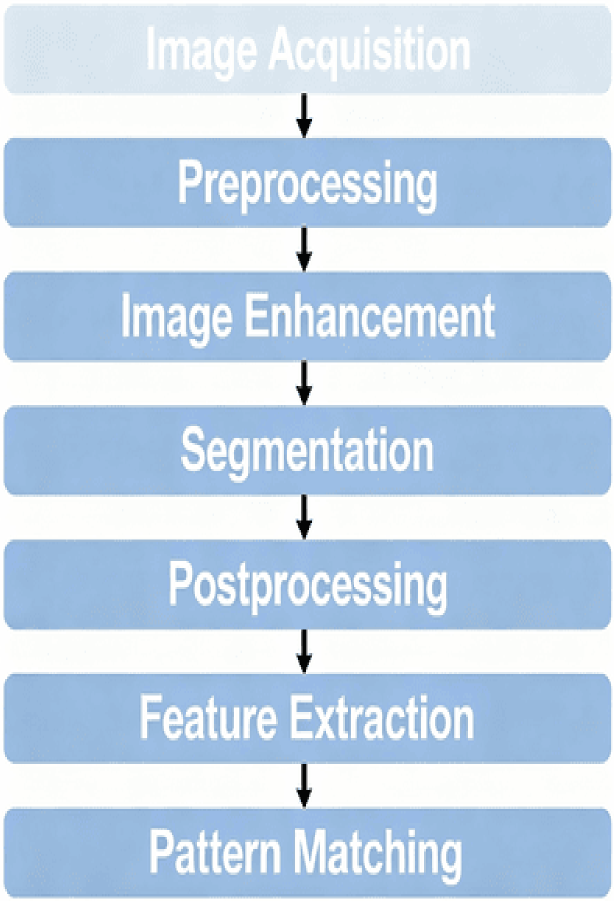


Figure 1. Finger Vein Image Processing Stages

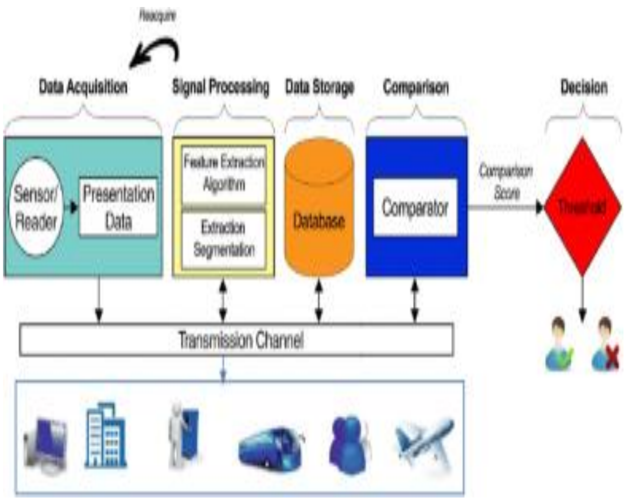


Figure 2. Illustrates the overall process and working stages of a finger vein authentication system

The procedure starts with a special sensor that has a finger guidance device and an infrared light source. Infrared light passes through the device when the user touches it with their finger. The vein structure appears dark because the hemoglobin in the blood vessels absorbs light. This gives the appearance of finger veins [13].

The sample image shows a person putting their finger on the sensor for scanning, while the cross-sectional figure illustrates how transmitted infrared light interacts with veins.

Images of finger veins are captured and sent to the authentication system for computer processing.

Pattern Extraction: To create a distinct, binary vein map, the system extracts and improves the vein pattern from the gathered image.

Database Storage: Following user registration, the extracted vein pattern is stored as a reference in a finger vein database.

Matching: The system checks the new image's pattern to the previously saved pattern in the database when a user tries to authenticate.

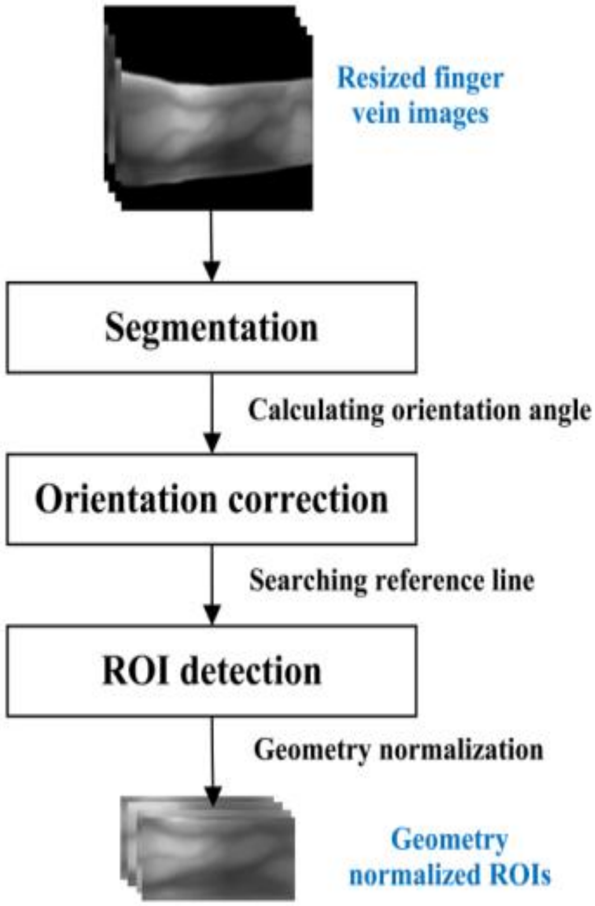


Figure 3. Illustrates the preprocessing workflow of finger vein images

Resized Finger Vein photos: The captured photos are downsized to a common size for uniformity.

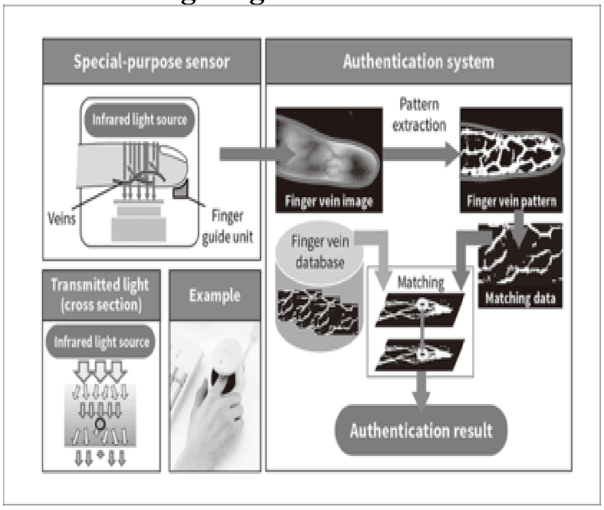
Segmentation: The finger region is divided from the backdrop in order to isolate the area of interest.

Orientation Correction: To ensure that the finger is positioned appropriately, the system finds a reference line, calculates the orientation angle, and adjusts the image alignment.

Finding the Region of Interest (ROI) that has the crucial vein features is known as ROI detection.

Geometry Normalization: The retrieved ROIs go through geometric normalization to guarantee uniform size and shape over all samples. This produces ROIs that have been geometry-normalized and are ready for feature extraction and matching.

3.1 Block Diagram of Finger Vein Authentication systems operation Processing Stages



Its two main parts are a special-purpose sensor and an authentication system.

The special-purpose sensor uses an infrared light source that passes through the finger.

Because the haemoglobin in the veins absorbs infrared light, the vein pattern may be seen in the picture. A finger guide unit ensures proper placement.

The finger vein image is subsequently sent to the authentication system, which uses pattern extraction to generate a finger vein pattern.

This extracted pattern is matched to information stored in the finger vein database using a matching procedure.

Database Storage: The extracted vein patterns are stored in a finger vein database during enrolment for later comparison.

Matching and Verification: During the authentication process, a newly recorded pattern is compared to templates that have already been stored. The system matches to determine the degree of similarity.

Authentication Result: Based on the matching score, the system provides the authentication result, which confirms whether or not the identity has been verified.

Finally, based on the matching result, the system outputs an authentication result (either validated or rejected).

3.2 Structural Overview of a Finger Vein Authentication System: Imaging and Image Processing Units

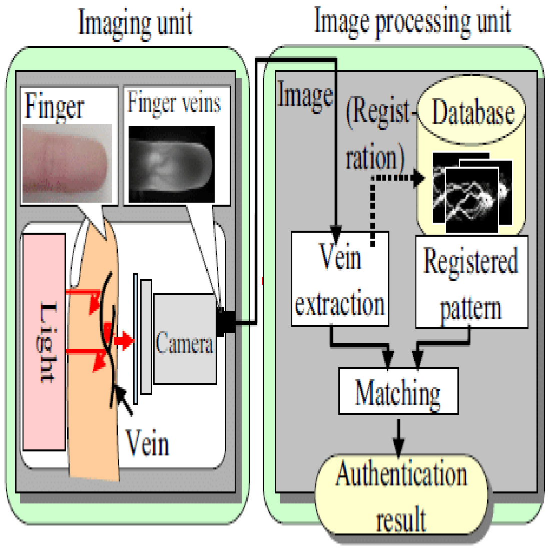


Figure 4: Illustrates a finger vein authentication system, divided into two main parts: the Imaging Unit and the Image Processing Unit.

Finger vein pictures are obtained by the Imaging Unit. It uses a camera or sensor in conjunction with near-infrared (NIR) light sources. The vein patterns are visible when a finger is placed on the device because NIR light penetrates the skin and is absorbed by haemoglobin in the blood [14]. The camera then captures the image of the veins inside without being affected by the colour or texture of the skin outside. For the aim of authentication, the Image Processing Unit enhances and examines gathered photos. Pre-processing (noise reduction and contrast enhancement),

Segmentation (vein pattern isolation), feature extraction (identifying of distinctive vein characteristics), and matching (compared with database templates) are all part of this.

Together, these tools allow precise, safe, and contactless identification by utilizing each person's finger's own vascular patterns.

When it comes to finger vein segmentation, ACMs excel at identifying small and curved vein characteristics that conventional thresholding or edge detection methods could miss. By integrating both local and global image data, variations such gradient-based snakes, region-based snakes, and level set techniques increase segmentation accuracy [10].

Because active contour-based segmentation accurately defines venous structures, it improves the effectiveness of subsequent processes including feature extraction, matching, and biometric verification. All things considered, ACMs provide a versatile and reliable solution to the problems associated with finger vein image segmentation.

The initial image of a finger vein was taken using near-infrared light by the imaging apparatus. It often displays a grayscale image of a finger with faint veins.

Pre-processed image: Following normalization, contrast enhancement, or noise reduction [13 & 14]. There is less background disruption and the veins are more noticeable.

Segmented image: Using a segmentation technique like Active Contour, Thresholding, or U-Net, the vein region is separated from the background. Binary/Mask Representation: A black-and-white binary image where the backdrop is represented by black pixels and veins by white pixels.

Overlay Output: To demonstrate the precision of the extraction, the segmented veins are superimposed on the original image.

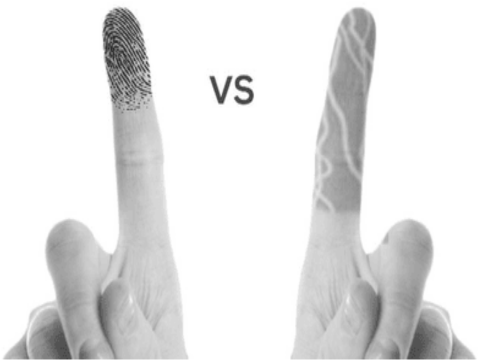


Figure 5. Output Signature of Isolated Resultant Pattern

3.3 Finger Vein Pattern Enhancement Approaches

An essential pre-processing technique that enhances the visibility and clarity of vein structures prior to segmentation and recognition is finger vein pattern enhancement. Because finger vein photos often have low contrast, uneven lighting, and background noise, boosting techniques are employed to sufficiently highlight the vascular patterns [15]. Typical techniques include filtering-based techniques like Gabor and matched filters, which emphasize vein-like line structures; histogram-based techniques like Histogram Equalization and CLAHE, which enhance global and local contrast; and Retinex-based techniques, which improve brightness consistency and correct illumination variations.

Narrow vein lines are also highlighted using morphological methods such as top-hat and bottom-hat transformations. Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), two deep learning-based methods, have been developed recently to automatically create the best improvement maps. Additionally, some systems employ fusion-based techniques, which combine multiple improving strategies to yield more reliable results. All things considered, these augmentation techniques improve image quality and guarantee accurate finger vein characteristic extraction, leading to successful biometric authentication.

3.4 Feature Extraction

Feature extraction is an essential step in image processing and pattern recognition that simplifies an object or pattern by removing relevant information from unprocessed data. Instead of using the entire image, which may contain extraneous or unneeded features, feature extraction focuses on obtaining the most important characteristics, such as shape, texture, boundaries, color, or essential locations [7 & 8]. For example, unique vein morphologies, ridge orientations, or line patterns that distinguish one individual from another may be characteristics of biometric systems such as vein or fingerprint recognition [7]. One technique used in computer vision and deep learning that automatically extracts characteristics like edges in the first layers and increasingly complex patterns in the deeper levels is convolutional neural networks (CNNs). Classification and recognition accuracy are increased through feature extraction.

4. INTEGRATION OF FINGER VEIN SEGMENTATION AND ENHANCEMENT PROCESS

For biometric recognition systems to be more accurate and dependable, finger vein segmentation and enhancement techniques must be integrated. Even under challenging imaging settings, this integrated technique produces high-quality vein extraction by combining segmentation and enhancement to work in tandem [16]. Using methods like histogram equalization, Gabor filtering, or Retinex-based correction, the improvement process starts by enhancing image contrast, eliminating noise, and emphasizing vein structures. As a result, the image is sharper and has more distinct vein patterns. Then, utilizing methods like active contour models, thresholding, and deep learning networks, the segmentation process precisely isolates these enhanced vein regions from the background. By combining the two procedures, the technique guarantees that the segmentation is carried out on a rectified image, improving vein pattern extraction and lowering mistakes brought on by dim lighting or low contrast. The accuracy and dependability of finger vein authentication systems are increased by this combo technique.

Metrics Used

A range of quantitative metrics that take into account both image quality and segmentation accuracy are used to evaluate the performance of finger vein segmentation and enhancement algorithms. The clarity, contrast increase, and visual quality of enhanced images are often evaluated using metrics like Contrast-to-Noise Ratio (CNR), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The richness of features and brightness uniformity after improvement are also evaluated using entropy and intensity statistics (mean and standard deviation). Vein segment retrieval performance is assessed using accuracy-based criteria in segmentation techniques. These measures, which evaluate the overlap and accuracy of segmented vein sections to the ground truth, include Accuracy, Precision, Recall (Sensitivity), F1-Score, Dice Similarity Coefficient (DSC), and Jacquard Index (IoU). The False Acceptance Rate (FAR) and False Rejection Rate (FRR) are also used to assess recognition reliability in certain biometric evaluations. When combined, these standards guarantee that the segmentation and enhancement processes produce reliable, accurate, and high-quality venous pattern extraction for robust finger vein authentication [17].

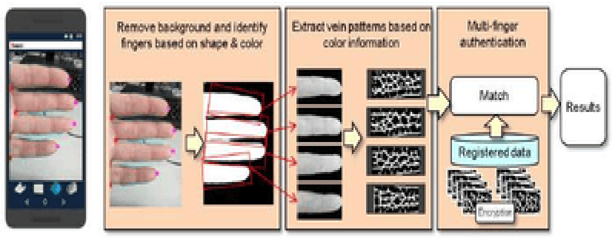


Figure 6. Finger Vein Authentication Framework

Compared to other biometric techniques like fingerprint, facial recognition, or voiceprint, finger vein authentication offers the advantage of employing in-vivo features for biometric identification, making it more difficult to counterfeit or spoof. However, up until now, finger vein patterns that are hardly noticeable to the unaided eye had to be captured using a particular photo sensor that uses infrared light. The method now in use allows for extremely accurate finger vein authentication utilizing smartphones' built-in cameras without the need for a specialized image sensor. More precisely, the system can accurately extract vein pattern information and identify each finger from a colour camera image of the user's hand. The accuracy of authentication is increased by combining data from multiple fingers.

5. FUTURE DIRECTIONS AND OPPORTUNITIES

In order to improve biometric authentication systems, future finger vein segmentation and augmentation research will concentrate on improving accuracy, flexibility, and real-time performance. Intriguing opportunities exist for automatically enhancing image quality and segmenting vein patterns in a range of lighting and skin situations using advanced deep learning and hybrid models. Security and dependability can be further enhanced by using multimodal biometrics, which integrate finger veins with fingerprints or palm veins [10]. Additionally, lightweight and effective algorithms that enable real-time computation are being developed for application in portable or embedded systems. Self-supervised learning, explainable AI, and transformer-based architectures can all lead to more reliable and transparent systems. In order to address sensor and environment variations, future research may also examine cross-device interoperability and 3D vein imaging. All things considered, these developments provide many opportunities to create finger vein recognition technology that is more precise, safe, and easy to use. More precise multimodal authentication is possible when finger vein recognition is paired with other biometric modalities like fingerprint or iris recognition. There is a chance to develop adaptive augmentation and segmentation models that function well in real time thanks to the development of AI and deep learning [19].Additionally, lightweight algorithms and embedded systems enable deployment in mobile and IoT-based applications. Emerging research in 3D vein imaging, cross-sensor matching, and explainable AI broadens the scope of innovation, making finger vein recognition a promising solution for future biometric security systems. .

6. CONCLUSION

Finger vein augmentation and segmentation are critical aspects in ensuring the accuracy, dependability, and durability of finger vein recognition systems. The enhancement method improves image quality by increasing contrast, decreasing noise, and emphasizing vein patterns, while the segmentation process accurately separates these patterns from the background for later feature extraction. Together, they lay the framework for reliable and efficient biometric identification [5]. The use of current techniques such as deep learning, Retinex models, Gabor filtering, and active contour segmentation has significantly improved the performance of these approaches under a variety of lighting and imaging conditions. As research advances, the emphasis on developing adaptive, real-time, and intelligent enhancement-segmentation frameworks promises to increase recognition accuracy and allow for more widespread deployment of finger vein systems in secure authentication applications [10].Research progresses, there is a heavy emphasis on merging deep learning architectures like attention-based and lightweight networks to increase accuracy, speed, and robustness in a variety of settings. Another intriguing opportunity is multimodal biometric systems, which integrate finger vein detection with other features such as fingerprints, iris, or face identification to improve security and reduce spoofing issues. With the rise of IoT and edge computing, developing low-power, real-time vein identification systems for mobile and wearable devices will provide new opportunities for healthcare monitoring, financial transactions, and smart access management [16]. Furthermore, research into anti-spoofing techniques and privacy-preserving biometric frameworks will be critical in addressing security and ethical concerns.

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