CHAPTER 1

INTRODUCTION

Biometric systems are used for verifying a person's identity by analyzing unique physical or behavioural characteristics. Biometrics offer a more secure and reliable solution when compared to methods like passwords, Personal Identity Numbers (PIN), Identity cards etc. The most common types of biometrics used for security purposes are fingerprint, face, iris etc. Nowadays, from unlocking smartphones to controlling access in high-security zones, biometrics plays an important role.

Some challenges for biometrics include privacy concerns, spoofing attacks, and performance variations due to environmental factors etc. Research in this area focuses on improving the accuracy, precision and security of biometric systems.

1.1. CATEGORIES OF BIOMETRIC SYSTEMS

Biometric systems can be classified into physiological biometrics and behavioural biometrics.

a. Physiological Biometrics

Physiological biometrics deals with the unique physical characteristics of individuals. Physiological biometrics includes fingerprints, face, iris, retina, vein patterns, hand geometry etc. These biometric traits are generally inherent to the body and remain stable over time, making them reliable for security and identity verification systems.

i. **Fingerprint Recognition:** This is one among the earliest and most used biometric techniques. The pattern of fingerprint captured from an individual is compared with a stored template for authentication. It is vulnerable to spoofing, i.e., fingerprints can be replicated using various methods, such as creating synthetic fingerprints or lifting prints from surfaces etc. User may be hesitant to use fingerprint scanners in public places due to hygiene concerns.

ii. **Facial Recognition:** This biometric method analyzes the distinctive characteristics of an individual's face. Facial recognition systems use algorithms to detect attributes such as the gap between the eyes, the position of the nose and mouth to create a facial template for identification. Facial recognition technology has privacy concerns, as it can be used for mass surveillance and tracking without the consent of individuals. Variations in lighting, facial expressions, or changes in appearance like aging, facial hair etc may affect the recognition.

iii. **Iris Recognition**: Iris recognition systems scan the patterns in the eye's iris. This method is highly accurate and often used in high-security environments. However, iris recognition systems require individuals to get close to a scanning device, which some users may find uncomfortable. Implementing iris recognition technology is costly due to the specialized hardware required for accurate scanning.

iv. **Retina Recognition:** This technology analyzes the unique blood vessel patterns at the back of the eye. It requires the person to be very close to the scanning device. Retina recognition uses a flashing light directly into the eye, which can be uncomfortable for some users and may raise health concerns.

v. **Vein Recognition**: The vein patterns found within the human body are unique and can be used for authentication purposes.

vi. **Hand Geometry Recognition:** It uses the physical features of a person's hand, like width, length of the finger, shape of the palm etc. It is sufficient for small systems, but lacks uniqueness when considering it for large-scale systems. It is also not suitable for individuals with hand disabilities.

b. Behavioural Biometrics

Behavioural biometrics uses patterns in human activities and behaviours. It uses an individual's interaction with their environment, like movements, actions, and reactions. These types of biometrics can be used for continuous authentication. Behavioural biometrics includes voice, gait, keystroke dynamics etc.

i. **Gait Recognition:** It uses a person's walking style or gait. The features such as step length, angle of arm swing, and timing of steps are used to create a gait signature. Gait varies with factors such as footwear, terrain, or physical condition. Gait recognition may not be suitable for all scenarios, as it requires capturing a person's walking pattern, which may not always be practical.

ii. **Voice Recognition:** The unique features of a person's voice, including pitch, tone, and frequency, can be used for person identification. Voice recognition systems can be used for authentication over the phone or in voice-controlled devices. However, it is susceptible to spoofing attacks, where a person mimics another person’s voice to gain unauthorized access. Background noise or changes in voice due to illness or affect the accuracy of voice recognition systems.

iii. **Keystroke dynamics:** An individual's typing patterns, such as the speed, rhythm, and pressure applied to keys, are monitored. These typing patterns are unique to each person and can be used to confirm identity. Keystroke dynamics can be integrated with other authentication systems to provide continuous user verification, to ensure continuous security beyond initial login.

1.2. FINGER VEIN BIOMETRICS

Most of the biometrics, such as fingerprints, facial recognition etc rely on external features. Finger Vein (FV) biometrics (Kono, M., 2000) uses the unique patterns of blood vessels within an individual's finger. The Finger Vein Recognition (FVR) method involves capturing and analyzing the vein patterns present in the fingers, using near-infrared light. FVR systems are suitable for applications where space is limited, such as in ATMs, access control systems, and mobile devices etc. Since the finger is an easily accessible part of the body, users may find it easier and quicker to position their fingers for scanning.

FVR requires specialized infrared sensors to capture vein patterns, which increases cost and makes it harder to integrate into everyday devices like smartphones. There is also limited public awareness and minimal commercial adoption, so the technology has not gained much popularity. Additionally, the lack of publicly available datasets has slowed down research and development in this area. Finger vein systems can be sensitive to factors like finger movement, lighting, or movements, which makes them complex. Due to these reasons, despite its strong security features, it is not widely adopted.

The features of the vein patterns that make them unique include:

1. **Bifurcations and Branching**: Vein patterns consist of a complex network of branch points and unique branches. The arrangement of these bifurcations is unique to individuals.
2. **Spatial Distribution**: Each person's finger has a unique spatial arrangement. Even the small variations in the pattern of veins can provide unique identifiers.
3. **Thickness and Shape of Veins**: The diameter and shape of the veins vary from individual to individual. The shape differs in curvature and branching patterns.
4. **Vein Density**: The density and number of veins can vary between individuals.
5. **Non-linear and Irregular Paths**: FVs do not follow linear paths. Instead, they often take irregular, twisting routes with varying curvature and length, which also contribute to their uniqueness.
6. **Texture and Fine Details**: The vein structures have fine textures with smaller veins or branching off from the main veins. These fine details are unique to everyone.
7. **Orientation of Veins**: The direction in which the veins travel (e.g., horizontal, vertical, diagonal) is also unique, as the veins of each individual's finger follow a particular orientation that does not match others.

1.2.1. Advantages of Finger Vein Biometrics

The following advantages of FV biometrics makes it an effective method for biometric authentication in various applications (Hou B. et. al., 2022):

- **High Security**: FV biometrics provide a high level of security as the veins are located under the skin. Unlike surface-level biometrics such as fingerprints, which can be more easily copied or altered, the subcutaneous nature of vein patterns makes them much harder to forge. An attacker would need to replicate the exact internal vascular structure of a legitimate user, which is an extremely complex and invasive process. The near-infrared technology used to capture vein patterns requires direct interaction with the individual's finger, which enhances security by limiting accessibility through physical access points.

- **Uniqueness:** FV patterns differ for even identical twins, who share the same DNA. Hence, the likelihood of two individuals having the same vein pattern is very low. This minimizes the chances of false identifications.

- **Liveness Detection:** FV biometrics captures the vein patterns using near-infrared light, which requires blood flow in the veins. This means that only a living finger, with active blood circulation, can produce a valid vein pattern for authentication. Hence, attempts to use fake fingers are prevented.

- **Stability:** Unlike other biometrics that can change with age or injury, the internal structure of veins remains relatively constant. Hence, once a person's vein pattern is enrolled in the biometric system, it remains reliable for many years. Users need not frequently update their biometrics.

- **Hygienic**: FV authentication systems operate in a contactless manner or with minimal contact. Hence, it is more hygienic compared to systems that require full contact, such as fingerprint scanners. It reduces the risk of transmitting germs and is advantageous for situations where hygiene is very important.

- **Resistance to Environmental Factors:** FVR is less influenced by dirt, grease, moisture or surface injuries. It works properly, even if the surface of the skin is dirty or damaged, as it uses an internal vein pattern.

- **Quick and Convenient:** FV pattern capturing is a quick process. Users simply need to place their finger on or near the sensor. The system can instantly capture the vein pattern and authenticate the individual.
- **Reduced Risk of Wear and Tear:** Fingerprint sensors may wear out over time due to constant physical contact. But FV scanners are less prone to wear and tear. Hence, FV biometric systems remain functional over a longer period, reducing maintenance costs.

1.2.2. Applications of Finger Vein Biometrics

The high security, accuracy, and convenience of FV biometrics makes it well suited for authentication in different fields (Zhou L., 2023, Mohsin A. H et. al., 2020). The applications across various fields are outlined below:

- **Financial Services:** Banks can use FV technology for authentication instead of Personal Identity Numbers or cards for ATMs and mobile banking applications.
- **Healthcare:** Medical mistakes can be avoided by using FV for person identification. It also ensures that patients receive the correct treatments and medications.
- **Government and Law Enforcement:** FV biometrics can be used for national ID cards such as Aadhar card, voter verification and passport authentication. It helps in accurate citizen identification, reduces electoral fraud and enhances border security.
- **Corporate Security:** Accessibility to buildings, rooms and information systems can be granted using FV biometrics so that only authorized persons are granted entry. It also finds application in employee time and attendance tracking.
- **Education:** Student identity during exams can be verified using FV biometric. Secure access to library resources can be controlled using FVR. Hence, only authorized users can borrow books and access digital resources.
- **Personal Security:** Home security systems, and personal devices such as smartphones, laptops etc can use this biometric to ensure secure user authentication to protect them from unauthorized access.
- **Transportation:** Secure ticketing and driver verification can be ensured using FV biometrics in logistics and public transit networks.
- **Retail:** Convenient customer authentication can be achieved in retail payment systems for transactions.

- **Military and Defence**: The Military can use this biometric to restrict access to controlled areas. It can also be used to control access to weapons, ensuring that only authorized individuals can use them.

- **Airports and Aviation:** Airports use these biometrics for passenger verification during check-in, security screening, and boarding. Secure access to confined areas within airports, such as control towers and service zones, can be managed using FVR.

1.3. CAPTURING FINGER VEIN IMAGES

A Near-InfraRed (NIR) scanner is used to acquire Finger Vein (FV) images. It emits light that penetrates the skin and reaches the blood vessels beneath. When the finger is illuminated, haemoglobin in the blood absorbs the NIR light, causing the veins to appear darker than the adjacent tissue. This allows for clear visualization of vein patterns.

The light source is composed of uniformly arranged LEDs. This ensures even illumination. An infrared-sensitive camera captures the reflected patterns by detecting variations in light absorption. Since NIR light is non-harmful to humans, it is considered safe for imaging applications. The captured images undergo pre-processing to enhance vein clarity and maintain consistency for biometric analysis.

Movements and inconsistencies during the scanning process of FV biometrics can affect the quality of the captured vein patterns. Differences in how users place their fingers on the scanner can lead to variations in captured images. Misalignment can result in partial or distorted vein patterns. The angle at which the finger is placed can affect the visibility and clarity of the vein pattern. Small movements or shakes during the scanning process can blur the captured image, making it difficult to extract accurate vein patterns. Users may unintentionally move or reposition their fingers during scanning. This leads to inconsistencies between images captured at different times. Changes in lighting can affect the contrast and clarity of the images captured.

1.3.1. Components of a Finger Vein Imaging System

Major components of the imaging system are:

- **Near Infrared Emitter:** It is an NIR illumination source with a 760-850 nm wavelength. This is used to illuminate the finger. This wavelength range of NIR light penetrates the skin and is absorbed by the haemoglobin in the blood.

- **Image Sensor**: A camera or a sensor sensitive to NIR light is used to capture the vein structure. It is made up of Charge-Coupled Device (CCD) or Complementary Metal-Oxide-Semiconductor (CMOS) sensors.
- **Optical Components**: Lenses and filters are used to focus the infrared light on the finger and to filter out other light wavelengths. This ensures the capture of clear and sharp images of the vein patterns.
- **Finger Placement Guide**: A guide bar is used to position the finger correctly under the sensor and light source.

1.3.2. Capturing Process of Finger Vein Images

1. Finger Placement

When the individual positions their finger on or within the imaging device, proper placement is important to capture the vein patterns correctly. The device contains markers to help users align their fingers properly. This reduces the errors caused by variations in position or orientation.

2. Illumination

Once the finger is in place, a NIR light source illuminates the finger. Infrared light traverses through the skin and reaches the blood vessels. Haemoglobin absorbs the infrared light, making the veins appear darker compared to the surrounding tissue. This contrast is the basis for visualizing the vein patterns.

3. Image Capture

The illuminated finger image is then taken by a camera which is responsive to NIR light. It records the dark vein patterns against the lighter background of the surrounding tissue. This captured image serves as the initial input for further processing. The quality of the imaging device ensures that even minute details of the vein patterns are visible.

4. Image Pre-processing

The raw image is pre-processed to enhance its quality and make the vein patterns more visible. Some of the techniques for preprocessing include:

- Region of Interest (ROI) extraction: Crop the finger area from the image, to eliminate unwanted regions of the captured image.
- Noise Reduction: To remove unwanted artifacts and ensure a clearer image.
- Contrast Enhancement: To highlight the variations in the vein patterns and the surrounding tissue.
- Binarization: To convert the image into a binary format, making the vein patterns easier to analyze.

5. Feature Extraction

The unique vein characteristics from the pre-processed image are extracted. These characteristics may include vein bifurcations, intersections, and the overall structure of the vein network. A biometric template is created using the extracted features. This template serves as a unique representation of an individual's vein pattern.

6. Matching and Authentication

The newly collected vein pattern is compared with stored templates during the authentication phase. Matching algorithms finds the similarity between the patterns to authenticate the individual. If the captured pattern matches an existing template, access is granted otherwise, the individual is denied access.

1.3.3. Methods of Capturing Finger Vein Images

There are two methods for capturing FV images: the transmission method and the reflection method. Both methods work on the absorption property of haemoglobin to differentiate veins from other tissues.

a. Transmission Method: In this method, the NIR light source is positioned on one side, while the camera is positioned on the opposite side. The NIR light traverses through the finger and illuminates the veins. This method captures clear and distinct vein patterns. Because when the light passes through the finger, it creates a high contrast between the veins and the surrounding tissues. Figure 1.1 depicts FV scanning using light transmission method.

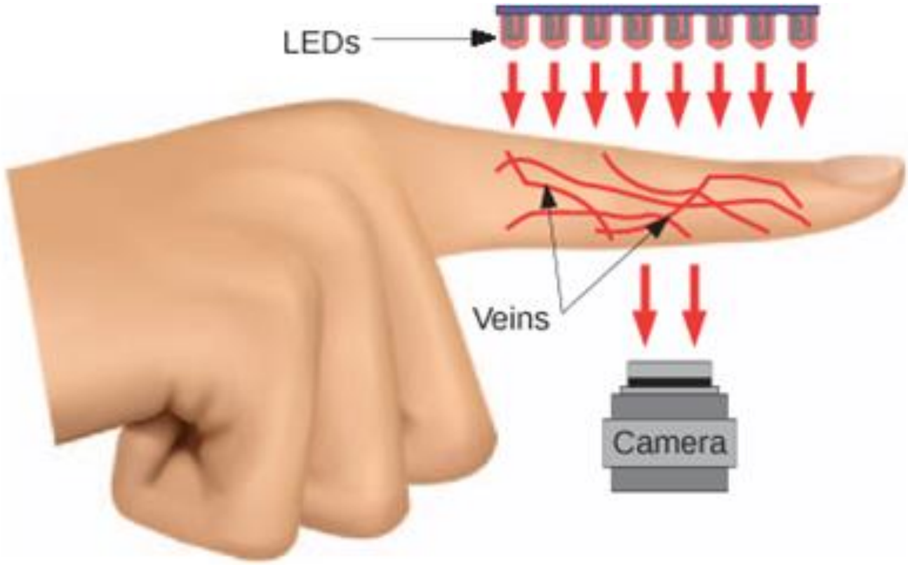

Figure 1.1 Light Transmission Method

b. Reflection Method: Here, both the near-infrared light and the camera are positioned on the same side. When the NIR light illuminates the finger, the reflection is captured by the camera. This method is more practical for compact and portable devices, as it is simpler to set up this configuration compared to the transmission method. Figure 1.2 depicts FV scanning using the light reflection method.

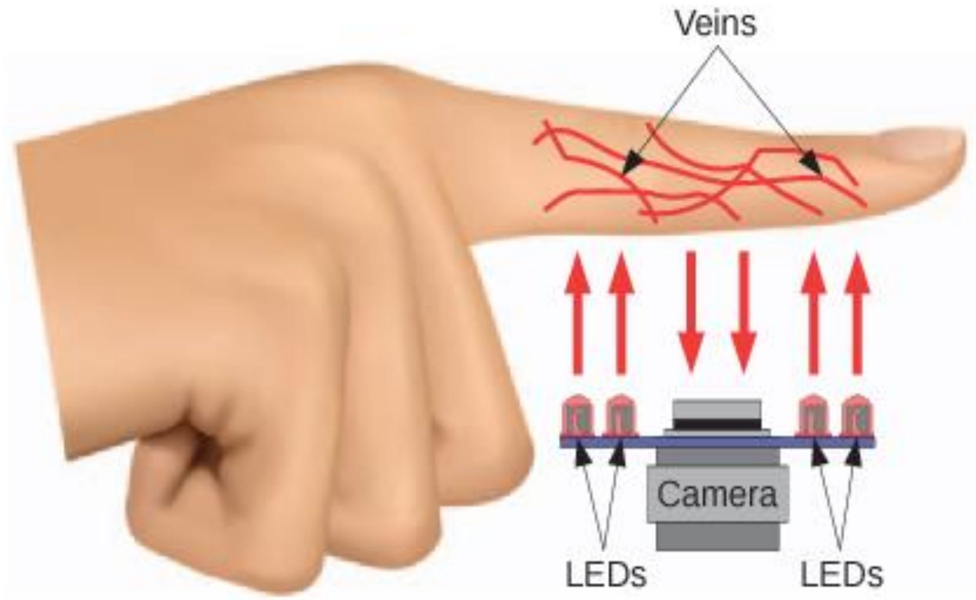

Figure 1.2 Light Reflection Method

1.4. FINGER VEIN IMAGE LABELLING

FV images in the dataset are labelled to extract relevant information from the raw vein images before it is used for training. After the basic preprocessing steps, each pixel in the vein image is annotated to indicate whether it belongs to a vein or the background. This is often done manually or using an algorithm to distinguish veins from the surrounding tissue based on intensity differences. Every pixel is classified as either part of the vein structure or the surrounding area.

Vein pixels appear as darker pixels in the infrared images. Background pixels are the lighter pixels surrounding the vein patterns. These images provide detailed ground truth data to the Deep Learning (DL) model, which enables it to learn characteristics of veins more accurately when compared to the background. With pixel-wise labels, the model gathers specific characteristics that are unique to veins, such as their shape, texture and intensity differences from the surrounding tissue. This will improve the capability of the model to detect and segment veins in the new, unseen images.

Labelling provides context-aware outputs when compared to binarization. Binarization uses hard thresholds, resulting in the loss of thin gradient information. Labelling can capture fine-grained information, adapting to intensity variations.

Labelling can be done either manually or through an automated process. Manual labelling is done by human annotators. They identify and label the pixels associated with vein structures using software tools. This method is labour-intensive and time-consuming, making it challenging to annotate large datasets accurately. Human errors can occur in manual labelling.

Automated labelling uses some predefined rules or algorithms to annotate the image. This method is more effective and time-consuming when handling large volumes of data. This method is not only cost-effective but also ensures uniformity in labelling, as the algorithms consistently apply the same rules across the dataset. Automated labelling is a preferred choice in many large-scale biometric projects.

1.5. DATASET AUGMENTATION

FV datasets usually contain less number of images as it is difficult to obtain high-quality vein images under controlled conditions. Augmentation serves to address this limitation by increasing the dataset size and diversity. Through augmentation, an image with variations can be created. These variations mimic different real-world conditions, such as changes in illumination, finger orientation, scale, and noise. Hence model learns to recognize vein patterns even when the input conditions differ from those in the training data. Dataset augmentation will help in improving the performance of the model and reducing overfitting. Some commonly used augmentation techniques are:

a. Geometric Transformations

Geometric transformations introduce variations in the spatial properties of images.

- **Rotation** replicates scenarios where the finger is slightly tilted during imaging, enabling the model to handle angular variations.
- **Translation** shifts the image horizontally or vertically, mimicking cases where the finger is not perfectly aligned within the imaging frame.
- **Scaling** adjusts the size of the image to compensate for the gap between the finger and the camera.
- **Flipping** mirrors the image, providing additional perspectives and helping the model learn invariant features across orientations.
- **Shifting** Slight variations in the finger position while capturing the image can be handled using shifted images.
- **Brightness variations** help the system to adjust to a changing lighting environment.
- **Contrast Adjustment**: Changing the contrast to highlight vein patterns under various lighting scenarios.

b. Illumination Adjustments

Variations in lighting can affect the clarity and quality of FV images. These variations can be simulated using the following techniques:

- **Brightness adjustment** helps the model to handle images captured under varying light intensities.
- **Contrast enhancement** modifies the difference between light and dark areas in the images. It helps the model to learn from images having low contrast.

c. Generative Networks

Generative Adversarial Networks (GANs) is an advanced technique to augment image dataset. GANs generate high-quality, realistic FV images that expand the dataset while introducing controlled variations.

1.6. TRADITIONAL METHODS FOR FINGER VEIN RECOGNITION

Traditional methods rely on feature extraction and matching techniques. The steps involved in this recognition process are given below (Rosdi B. A. et. al., 2011):

1. Image Capture: FV images are typically captured using near-infrared lighting, which penetrates the skin and highlights the vein patterns. NIR imaging devices are designed to capture clear and distinct vein patterns.

2. Preprocessing: During the preprocessing, the captured images are standardized to a consistent size and orientation. Then various filtering techniques like Gaussian, median filters etc. are applied to reduce noise and enhance the vein patterns. Techniques like histogram equalization and contrast enhancement are used to improve the clarity of the veins.

3. Feature Extraction: The unique features from the pre-processed vein images are extracted during the process. Some commonly used methods for feature extraction include:

a. Vein Pattern Extraction

- Repeated Line Tracking: It tracks the vein lines by iteratively following the paths of the veins based on pixel intensity. But it can be sensitive to noise.
- Maximum Curvature: The curvature of the image intensity is analyzed to detect the veins. Areas with maximum curvature are identified as veins.
- Mean Curvature: It is similar to maximum curvature but uses mean curvature to enhance the vein patterns. This makes it less sensitive to noise when compared to repeated line tracking.

b. Statistical and Transform-Based Methods

- Principal Component Analysis (PCA): The dimension of the vein images can be reduced using PCA. It can also retrieve the principal components, which will contain the important features that are relevant to the veins.
- Wavelet Transform: This transforms the image into various frequency components, where the vein patterns can be processed at multiple scales.

c. Texture-Based Methods

- Local Binary Patterns (LBP): The Texture of the vein images is captured by LBP. This is to label the pixels of an image into objects and background, by thresholding the neighbourhood of each pixel.
- Gabor Filters: It can capture the patterns of veins at different scales and orientations, providing a robust representation of the vein texture.

4. Matching

The features derived from a captured image are matched to previously stored templates to verify a person. This is measured through a comparison of the features on the captured image and the templates to yield accurate and reliable recognition. There are different methods that can be used for matching, from more traditional methods to more complex machine learning classifiers, each with its advantages and disadvantages.

a. Template Matching

The features extracted from the FV image are compared directly with templates stored using distance metrics. It is a simple method for matching with good computational efficiency. The distance metrics that can be used are:

- **Hausdorff distance**: It finds the maximum distance between the closest points from both images. It is a measure of how far apart the two images are from each other.
- **Modified Hausdorff Distance (MHD)**: It finds the forward and reverse Hausdorff distances between two images and returns the minimum of the two.

Template matching is a simple and effective method for small or controlled datasets. However, its performance can degrade under varying imaging conditions.

b. Statistical Matching

Statistical methods use correlation and regression analysis to assess the matching between features extracted from a biometric sample and stored templates.

- **Correlation Analysis**: Measures the correlation of the vein patterns from the image acquired to the vein patterns in the templates.
- **Regression Models**: Provide an estimation of the likelihood of a match based on the extracted feature sets.

The statistical methods help identify patterns that have relatively consistent statistical relationships but will struggle with variable data.

c. Traditional Machine Learning Classifiers

Traditional Machine Learning classifiers can also be used for matching vein patterns, which can handle diverse data distributions.

- **Support Vector Machines (SVM):** Separate feature spaces into distinct classes by identifying the optimal hyperplane. SVMs are good for small datasets, but they require careful parameter tuning.
- **k-Nearest Neighbours (k-NN):** Classifies data points based on the average of the k closest neighbours in the training set. k-NN is computationally expensive for large datasets.
- **Decision Trees:** Splits data into branches based on feature values and classifies by making decisions from root to leaf nodes. It is prone to overfitting without proper pruning.

d. Matching Approaches in Deep Learning

i. Distance-Based Matching with Deep Features

Distance metrics are used to evaluate the similarity of the feature vectors of the input images.

- **Cosine Similarity**: Calculates the similarity between feature vectors, regardless of their magnitude.

- **Euclidean Distance**: Computes the straight-line distance between two feature vectors in a space.

- **Mahalanobis Distance**: A measure of the distance between a point and a distribution which interprets the correlations between variables. It can be used when there are complex feature distributions.

ii. Siamese Network

Siamese Network is a DL architecture used for matching tasks consisting of two identical sub-networks that process a pair of input images and generate feature vectors. The similarity between the two vectors is then calculated using a distance metric such as Euclidean distance or cosine similarity. The triplet loss function is used during training to bring matching pairs of samples together and non-matching pairs apart. This method is highly effective when limited training data is available.

iii. Metric Learning

DL models can also learn a custom similarity function through metric learning.

- **Triplet Networks:** This is an extended Siamese Network which considers triplets of inputs: a reference image, a positive match, and a negative match. The network learns to bring the positives closer to the reference while pushing the negatives farther away.

- **Learnable Distance Metrics:** Neural networks are trained to directly predict the likelihood of a match, bypassing predefined metrics like Euclidean distance.

iv. End-to-End Matching

In end-to-end matching systems, the entire pipeline, from raw image input to similarity prediction, is handled by a single DL model. The network outputs a similarity score, eliminating the need for separate feature extraction and matching. Softmax or binary classifications are used in the output layer.

v. Attention Mechanisms

Attention Mechanisms give attention to the most important elements of the vein patterns. Self-attention layers allow the network to weigh different regions of the feature map according to their importance. This method is effective when the contains noise or occlusions.

vi. Deep Generative Models for Matching

Variational Autoencoders (VAEs) or Generative Adversarial Networks (GANs) can be used for matching by learning latent feature representations. They map visual input into a structured latent space where similarity corresponds to spatial proximity.

1.7. DEEP LEARNING ALGORITHMS FOR FINGER VEIN RECOGNITION

DL models eliminate the necessity for extracting the features manually and can learn from data. Researchers have explored different DL techniques for authenticating FV patterns. The Convolutional Neural Networks (CNNs) are the most effective among the different DL algorithms. They can effectively model spatial hierarchies in the data. CNN uses a large dataset for training. This allows the network to learn complicated and unique patterns of individual vein structures. CNNs enhance recognition accuracy and make the system more robust to changes in imaging conditions and finger placement (Hong H. et al., 2017).

Different CNN architectures are used for FV authentication, each offering unique strengths. LeNet (Gumbaz D. et al., 2019) are suitable for basic tasks because of its simple and efficient design. AlexNet (Fanjiang Y. Y. et al., 2021) enhances feature extraction with deeper layers and Rectified Linear Unit (ReLU) activations. VGGNet (Bilal A. et al., 2021) captures finer details using small convolutional filters. GoogLeNet's (Sharma S. & Lohchab, 2021) inception modules allow multi-scale feature extraction efficiently. ResNet (Wang Y. et al., 2022) uses residual learning for very deep networks to overcome vanishing gradient problem. DenseNet (Song J. et al., 2019) maximizes information flow with dense connections. MobileNet (Sun Q. & Luo X., 2022) provides better computational efficiency and EfficientNet (Ma X. & Luo X., 2023) gives high accuracy. MobileNet and EfficientNet are ideal for resource-constrained environments. SqueezeNet (Boucetta A. & Boussaad L.,

2022) offers high accuracy with fewer parameters, suitable for memory-limited applications. When combined with data augmentation and transfer learning, these architectures improve recognition systems' performance.

Long Short-Term Memory (LSTM) networks are known for their ability to handle sequential data. They can learn the temporal dependencies in vein patterns when sequences of vein images are considered (Kuzu R. et al., 2020). Autoencoders are used for unsupervised feature learning. They encode vein patterns into a reduced-dimensional latent space. (Hou B. & Yan R., 2019). Synthetic FV images can be generated using GANs to enhance dataset diversity (Zhang J. et al., 2019). Graph Neural Networks (GNNs) can model the relational structure of vein patterns by treating the vein network as a graph. This helps in capturing complex vein relationships (Chang J. et al., 2023). Transfer learning can also be used to reduce computational overhead and to improve model performance. (Tao Z. et al., 2021). DL approaches provide better accuracy, reduced computation time, and improved adaptability over traditional techniques.

1.8. MOTIVATION FOR THE RESEARCH

Existing verification system using fingerprint, face, and iris etc are more vulnerable to spoofing and fraudulent input. These biometrics are externa to human body and can be replicated using various techniques like printing, moulding, or even high-resolution images. A facial recognition system can be fooled using a high-quality photograph. Artificial fingerprints made from materials like silicone can fool fingerprint scanners. As a result, these security systems may be compromised.

Finger veins are hidden beneath the surface of the skin. This makes them highly resistant to forgery and duplication. The uniqueness and hidden nature of these patterns ensure more security and integrity in biometric authentication. The difficulty in capturing vein patterns without the individual's cooperation adds a layer of security. Moreover, vein images can be captured only from fingers with blood flow.

DL algorithms are well-suited for automatically learning and extracting complex and discriminative characteristics from FV images This helps in eliminating the requirement for feature selection by human. Slight variations in finger positioning or illumination variations can be handles by augmenting the dataset. Motion-tolerant solutions ensure that these systems are not only accurate but also practical.

1.9. RESEARCH GAP

Deep learning methods have shown better performance in FV recognition when compared to traditional methods. However, the complexity of vein patterns increases the training time of the DL models. Most of the FV datasets available contain limited number of images, for each individual, to train the DL models. Existing data augmentation techniques address only a few of the variations in the images. Hence, more effective augmentation methods are required to avoid overfitting of the model and to ensure more reliable recognition. Present models cannot handle motion artifacts, which are common in contactless FV scanning. These limitations of the existing FV recognition systems lead to reduced performance during authentication.

1.10. PROBLEM STATEMENT

Finger vein recognition systems need to be improved to enhance the precision and reliability of this biometric technology. One major issue is data scarcity, as obtaining a large and diverse set of finger vein images can be difficult. Optimizing training time in deep learning models is important to make the models practical and scalable. It is also crucial to integrate techniques that handle the movement of fingers during image capture, as slight movements or variations in finger positioning can influence the consistency and accuracy of vein pattern recognition. These challenges impose the need for a more robust system for authenticating individuals using contactless finger vein acquisition devices.

1.11. OBJECTIVES OF THE RESEARCH

The primary objective of this research is to develop a motion-tolerant and efficient deep learning model for finger vein recognition that enhances performance in contactless acquisition scenarios.

The secondary objectives are:

- To identify and implement an effective finger vein labelling method for extracting baseline vein patterns from raw images, thereby reducing training time for deep learning models.
- To augment the finger vein dataset with diverse samples to improve accuracy, increase robustness, and prevent overfitting.

- To develop an efficient deep learning algorithm that accurately recognizes finger vein patterns.

1.12. CONTRIBUTIONS OF THE RESEARCH

The major contributions which bring novelty to this research are listed below:

1. The research explores the adaptation of UNET, originally designed for medical image segmentation. A modified UNET is designed to adapt it for classification. The performance of the modified UNET is compared with the VGG16 architecture. The findings indicate that VGG16 is more effective FV image recognition.

2. The research introduces a hybrid labelling algorithm to achieve faster convergence and reduced training times. This method efficiently identifies and labels baseline patterns in raw images. This helps in more faster training of the DL models, allowing them to learn only from relevant information.

3. FV datasets are augmented using conventional image transformation techniques and conditional Generative Adversarial Networks (GANs) to improve the diversity and amount of training data.

4. The research introduces a Motion Tolerant Model that combines the VGG16 architecture with LSTM networks to handle the temporal behaviour and motion of fingers during image capture. This model enhances the performance and reliability of FVR in contactless acquisition devices, ensuring consistent results despite variations in finger positioning and movement.

1.13. ORGANIZATION OF THE THESIS

The structure of the thesis is as follows:

Chapter 1 provides overview, motivation, problem statement, research objectives and contributions of the research.

Chapter 2 studies and analyzes the literature related to this research work.

Chapter 3 details the implementation and performance of the modified UNET and VGG16 model.

Chapter 4 introduces a hybrid algorithm for FV image labelling to achieve faster convergence and reduced training times by identifying baseline patterns in raw images.

Chapter 5 discusses the use of conventional image transformation techniques and the implementation of conditional Generative Adversarial Networks (GANs) for dataset augmentation.

Chapter 6 focuses on the design of a finger vein recognition model that combines the VGG16 architecture with LSTM networks. The model is designed to handle the temporal behaviour of fingers during image capture, making it motion tolerant.

Chapter 7 summarizes the performance analysis of VGG16 and the Motion Tolerant DL model on the original dataset, labelled dataset and augmented dataset.

Chapter 8 concludes with limitations and provides the scope of future enhancement.

1.14. SUMMARY

This chapter describes the details of FV biometrics with an introduction to biometrics, its different types, advantages and applications. The process of capturing FV images, the components of a FV imaging system and various methods used for image capturing are also explained in this chapter. It also gives an introduction to image labelling and dataset augmentation. Traditional methods for FVR are explored, followed by DL algorithms. The dynamic behaviour of fingers during scanning is considered, leading to an overview of the FV authentication system. A description of the dataset used, the motivation for the research, the problem statement, the research objectives, the contributions of the research, and an outline of the thesis organization are also included.