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Finger Vein Authentication using Neural Network

Madhusudhan M V , Bushra , B S Nisarga , Meghana Sreeraj , Shipashree , Yeshashwini N

Abstract— **In today's rapidly evolving world, security has become a paramount concern. Biometric-based methods have emerged as a reliable and accurate means of authentication, with hand-based biometric traits being easily accessible for data collection. In this paper, we present a novel approach for authentication utilizing finger-vein images, addressing the challenges of collecting and processing biometric trait images for large organizations. However, the collection, storage, and processing of biometric trait images for a large number of employees pose significant challenges. To overcome these challenges, our proposed approach leverages deep learning techniques to authenticate individuals based on finger-vein images. The rise in technological advancements has brought about an elevated risk to both personal data and national security. Existing methods designed to safeguard crucial information from external threats were found to be insufficient. There emerged a necessity to implement more advanced technologies that could ensure a higher level of efficiency in protecting our data from unauthorized access. In this proposed method we use Sobel filter , open cv and gaussian blur for image pre-processing, sequential model with transfer learning for feature extraction and finally, Adam optimizer for decision making. The proposed model has shown 98% accuracy in authenticating finger veins.**

Keywords: **Sobel Filter, Open CV, Sequential Model, Transfer Learning, Adam Optimiser.**

I. INTRODUCTION

The security of vein recognition technology is heightened because the authentication data is contained within the body, making forgery extremely challenging. Notably accurate, this technology finds applications in diverse fields such as banking, healthcare, government offices, and passport issuance. The implementation of these solutions is poised to drive business growth by minimizing the size of the finger vein sensor and reducing authentication time. The objectives include extracting and restoring vein features with limited prior knowledge.

This involves automatically discarding ambiguous regions and categorizing pixels in the clear region as either foreground or background. Additionally, the aim is to recover missing finger-vein patterns in the segmented image. As modern society advances and expands, the identification of individuals and the safeguarding of their information security become critical social challenges in the current era of information technology. Traditionally, there are two methods for human identification: content-based (passwords, secret codes, etc.) and processing-based (certificates, credentials, smart cards, keys, etc.).

The identification of various components or the extraction and analysis of different features from an image play a vital role in computer vision, offering diverse applications.

This functionality is instrumental in fields such as baggage scanning at airports, the diagnosis of diseases like cancer or diabetes in medical science, and the segregation of materials in industries. Image classification, a versatile tool, is a subject of extensive research, as demonstrated in this paper, where real-time image processing and neural networks are employed for object classification.

The central focus of our study revolves around the classification of finger vein images, an advanced biometric technique. Biometrics, derived from the Greek words bio and metric (meaning life and measure), involves the identification or authentication of individuals based on unique physical or behavioural patterns. Various biometric methods include iris recognition, fingerprint recognition, face recognition, voice recognition, vein recognition, typing recognition, and others.

In the domain of finger vein recognition, the vein pattern of an individual is a key consideration.

The finger vein exhibits a complex pattern, is devoid of hair, and is less susceptible to color changes, making it an ideal identifier. This uniqueness extends even to identical twins, presenting a challenge for alteration or imitation. Finger vein recognition is also resilient against epidermal issues, enhancing its reliability in human recognition. When compared to dorsal vein recognition systems, finger vein recognition systems showcase superior accuracy and robustness.

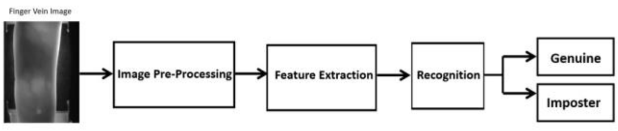

Fig 1 Steps for biometric authentication

The intricate and distinctive patterns of finger veins significantly contribute to the overall accuracy of the recognition system.

II.RELATED WORK

Khalil Hani Implemented artificial intelligence on Raspberry Pi with an IR Camera module, image classification is a fundamental component of computer vision. This process, involving tasks like image pre-processing, ROI detection, feature extraction, and neural network usage, has practical applications in enhancing security through baggage scanning and providing secure biometric identification with palm vein recognition. Our experimental results highlight the adaptability of this approach, indicating potential applications in diverse fields.

Mona A Ahmed proposed Palm vein authentication boasts remarkable accuracy as it is internal, unchanging, and secure against theft. This paper analyses recent advancements in palm vein pattern recognition, covering key processes like ROI detection, pattern segmentation, feature extraction, and matching. Notably, the absence of a benchmark database for palm vein recognition is highlighted, and various machine learning techniques exhibit consistently high accuracy across these processes.

Madhusudhan M V introduced a finger-vein authentication system employing deep learning, specifically emphasizing CNNs and transfer learning. The approach achieves notable accuracy, leveraging ResNet-50 for transfer learning and demonstrating resistance to forgery, especially applicable in large organizations. However, challenges include reliance on a limited dataset, substantial complexity/resource requirements, interpretability issues, and difficulties related to image acquisition.

Wenjie Liu et al introduced a finger vein recognition system leveraging deep learning techniques. To capture the region of interest, they extracted the width and length of the finger vein using the compass operator. Their CNN Model architecture incorporated five convolutional layers and two fully connected layers. They emphasized the importance of verifying accuracy by testing on a substantial amount of data from a public database.

Huafeng Qin et al employed a deep learning model for finger vein verification. They conducted vein pixel segmentation from the background pixels and reconstructed missing vein patterns by predicting the likelihood of a pixel belonging to a vein pattern. This involved utilizing extensive statistics on nonlinear pixel correlations through a hierarchical feature representation using a deep neural network. Additionally, they implemented a CNN-based approach to automatically learn features from the delicate pixels to enable finger vein verification. However, the trained CNN model might struggle to identify vein pixels under conditions of poor illumination.

K S Itqan et al introduced a user identification system utilizing finger vein technology with the assistance of a convolutional neural network. Their focus lies heavily on the preprocessing steps and the design of the CNN.

Madhusudhan M V proposed a method for robust finger-vein authentication system utilizing infrared technology, Gabor wavelet transform, and histogram-based correlation coefficients. Key strengths include the distinctiveness and permanence of finger vein patterns, non-invasive image capture, high overall accuracy, and a secure database implementation. Challenges encompass reliance on image quality, sensitivity to environmental conditions, potential implementation obstacles, and the need for meticulous threshold sensitivity.

Yang et al utilized 2D2 PCA for finger vein feature extraction and employed metric learning for recognition purposes. They utilized the k-nearest neighbour (KNN) classifier for each individual. Additionally, they incorporated the synthetic minority oversampling technique (SMOTE) to address class-imbalance issues.

Liu et al introduced two block selection methods based on estimating the data quantity in each block and considering block position involvement. They achieved this by observing the detection rate of each block position to reduce feature extraction and matching times. This approach aims to identify specific local finger vein (FV) regions with lower quality and noise, which would not be suitable for feature description. They employed the LBP model to extract the FV pattern feature.

Song et al researched a method that's more resilient to noise and leverages an entire network. They employed a combined image composed of two finger vein (FV) images as the input for a DenseNet model.

Madhusudhan M V proposed secure authentication process relies on statistical methods, including Harris corner detection, for finger-vein recognition, achieving high overall performance. Notable strengths include the distinctiveness and permanence of finger-vein patterns, contactless image capture, and strong overall authentication performance. Challenges involve dependence on image quality, resource-intensive database maintenance, potential sensor dependency, and the need to address spoofing challenges for comprehensive security.

Tao et al introduced a deep neural network using bidirectional feature extraction and transfer learning (TL) to enhance the efficiency of finger vein recognition (FVR). They developed a new FV database mirroring the location data of the original one and applied TL to adapt the network to the entire detection system. The feature extractor was modified by adjusting the database variables unidirectionally, capturing vein characteristics from top to bottom, among other methods. They combined these two features to generate bidirectional features for the FVs, which were classified and trained using support vector machine (SVM) for identification purposes.

Matsuda et al devised a method to extract characteristics from vein patterns and identify robust feature points that account for vein distortion and uneven shading. This technique leverages the curvature of image intensity profiles for extracting feature points, emphasizing their strength in accommodating irregular shading. To augment the number of feature points, these points are extracted from additional areas when the vein shape exhibits nonlinearity. Additionally, they introduced nonrigid registration techniques and finger shape methodologies.

Iram Malik et al employ repeated line tracking and Gabor filter methods to identify humans through finger vein patterns. By merging these two techniques, they enhance effectiveness and reliability. Combining finger vein biometrics with other methods can significantly boost accuracy, crucial for security in sensitive areas.

Hyung Gil Hong and colleagues introduced a finger vein recognition system employing convolutional neural networks. The region of interest (ROI) is determined by detecting the upper and lower boundaries of the finger. Recognition of the finger vein relies on a pre-trained CNN model. However, this approach necessitates substantial preprocessing as it acquires the finger vein image using only six 850 nm near-infrared LEDs.

Biometric Trait	Major Advantage	Major Disadvantage	Level of Security	Ease of use
Finger print	Wide application	Skin peeling, Sweating	Good	High
Knuckle print	Highly accurate	Rich in lines and creases	High	Medium
Palm vein	Highly accurate	Skin peeling, sweating	Very good	High
Finger vein	Highly accurate	Cost of implementation	Very good	High

Table 1. Pros and Cons of various biometric systems characteristics

III. METHODOLOGY

In the realm of finger-vein authentication and/or identification through neural networks, the predominant focus among researchers has been on employing conventional CNN models. Essentially, the utilization of a CNN model necessitates a substantial dataset to facilitate effective learning from the training data.

Transfer learning is a methodology in which a model undergoes pre-training on an extensive database of images, and the knowledge acquired by the model from that dataset is subsequently applied to train on another set of images.

A. HARDWARE SETUP

The hardware configuration plays a crucial role in the development of a palm vein recognition system, particularly with regard to achieving optimal lighting for accurate image capture. In our setup, we employ an infrared (IR) night vision surveillance camera to capture real-time images. This camera is connected to a Raspberry Pi. To create an IR environment conducive to vein recognition, a box is arranged with IR LEDs. The camera is positioned inside this box to capture real-time images, and this arrangement is specifically designed to minimize unwanted ambient light. The use of an IR environment is essential because the hand's tissues can introduce interference in the vein image extraction process. As we aim to isolate vein features, these tissues act as noise, necessitating their removal from the captured images.

The equation describing the imaging characteristics of palm veins is expressed as $W = \varepsilon * \sigma * T^4$, where W represents radiance, ε denotes radiation frequency, σ is a constant, and T represents temperature. The radiation frequency parameter (ε) for human skin typically falls within the range of 0.98 to 0.99.

B. IMAGE PRE-PROCESSING

The Sobel filter is widely employed for edge detection in image processing, relying on gradient-based techniques to emphasize areas in an image where notable intensity changes occur, typically corresponding to edges. Consisting of two 3x3 convolution masks, one for detecting alterations in the horizontal (x-direction) and the other for changes in the vertical (y-direction), the Sobel operator serves to highlight regions with substantial intensity variations. This output proves valuable in numerous computer vision applications, including object recognition and image segmentation. The Sobel filter belongs to a larger category of edge detection algorithms frequently utilized in image processing.

Grayscale images consist of a single channel, with each pixel representing the intensity of light on a scale from black to white. In the case of a color image, like an RGB image of a lion, the process of converting it to grayscale entails consolidating the color information into a singular intensity value. A Gaussian filter, on the other hand, is a convolution operation that employs a Gaussian-shaped kernel (matrix), sliding it across the image. The primary objective of this filter is to introduce a blur or smoothness to the image, effectively diminishing high-frequency noise while accentuating more significant, smoother structures.

OpenCV is utilized for its capacity to handle image input, interactive Region of Interest (ROI) selection, and the subsequent presentation of the cropped area. This enables a user-friendly method for selecting specific regions in image processing applications.

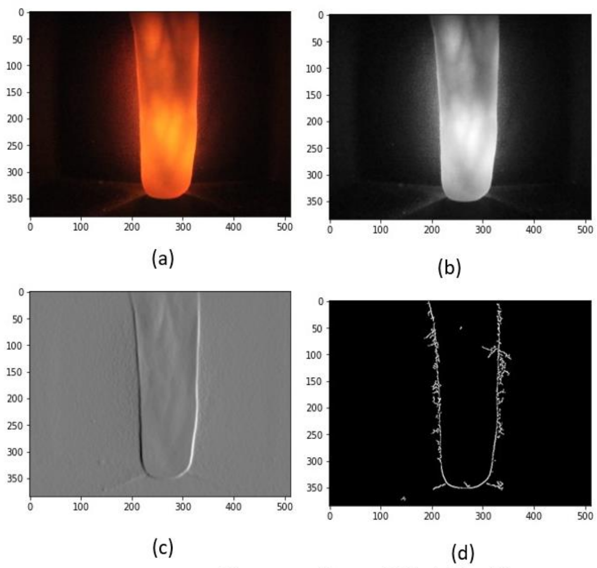

Figure 2: Preprocessing (a)Input image (b) Gray scale (c) Sobel filter (d) open CV

B. FEATURE EXTRACTION

In the domain of biometric finger vein authentication, the application of a Sequential Feedforward Neural Network (FNN) as a classifier for feature extraction is instrumental. The process commences with the collection of finger vein images, which undergo preprocessing steps to enhance quality and eliminate noise. Serving as a feature extractor, the Sequential FNN employs its hidden layers to autonomously learn and extract pertinent features from the pre-processed images, with each neuron contributing to the capture of distinct aspects of the vein patterns. The FNN is then trained using a labelled dataset, where it learns to map the extracted features to corresponding class labels through optimization algorithms like stochastic gradient descent or Adam. Validation ensures the model generalizes well, and testing involves predicting identities based on unseen finger vein patterns. During the authentication phase, a new finger vein image is processed by the trained FNN, extracting features and predicting the individual's identity, subsequently compared to the stored identity for authentication.

A decision threshold may be set to determine the confidence level required for successful authentication. The strength of this approach lies in the FNN's adaptability to the intricate and unique characteristics of finger vein images, offering a robust method for reliable biometric identity verification.

Transfer learning in finger vein biometric authentication involves leveraging a pre-trained deep learning model initially trained on a diverse dataset for generic tasks like image classification. This pre-trained model captures general features and representations from the data. To tailor the model for the specific task of finger vein authentication, it undergoes task-specific adaptation. Instead of starting from scratch with a small finger vein dataset, the model's parameters are fine-tuned to learn features specific to this biometric modality. Finger vein images possess unique patterns crucial for authentication.

The pre-trained model, proficient in recognizing generic image features, aids in extracting relevant information from these images. The benefits of transfer learning in this context include overcoming limited finger vein datasets by tapping into knowledge from larger datasets, facilitating feature learning for intricate patterns, and reducing computational costs and training time compared to training from scratch. In essence, transfer learning significantly enhances the performance of models for finger vein biometric authentication by capitalizing on pre-trained knowledge, adapting it to the task at hand, and improving the model's capacity to extract pertinent features from finger vein images.

C. RECOGNITION

In this system, a deep learning (DL) model has been trained to extract and learn distinctive features from images of veins. When an individual enters their name and submits a picture of their veins, the system retrieves the features from the input image using the pre-trained DL model. These features are then compared with the features stored in the database under the person's name. The database contains a collection of previously captured vein images, each associated with a specific individual. The verification process involves measuring the similarity between the features extracted from the submitted image and those stored in the database. If the match is sufficiently close, the system confirms the identity of the individual, providing a secure and efficient means of vein-based authentication.

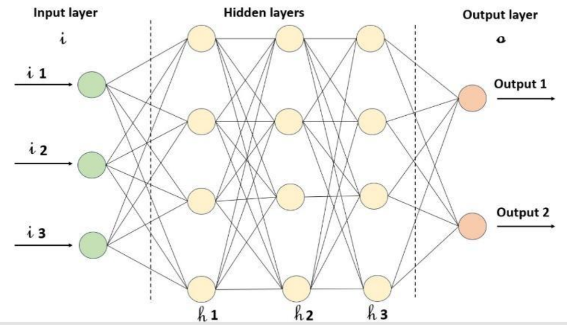

Figure 3 : Architecture of Sequential Model (FNN)

IV. CONCLUSION

The proposed system aims to create an affordable finger vein recognition system using a Raspberry Pi and an IR camera setup. The finger vein method is particularly effective for verification as it is intrinsic to the skin, making it resistant to being forgotten or stolen. The captured image undergoes pre-processing, and regions of interest (ROIs) and features are extracted.

A neural network is then employed for person identification. With an achieved accuracy of 98% in person authentication, it can be concluded that the designed sequential model (FNN) and transfer learning approach are notably effective. This system holds potential for various applications in biometric authentication, such as in passport offices, ATMs, and building access control.

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