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# FINGER VEIN DETECTION USING CNN

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## ABSTRACT

Finger vein verification has received more attention recently due to its unique advantages. However, most existing algorithms rely on handcrafted features, making them less robust to finger rotation and offsets. To alleviate these problems, a method to extract more discriminative features from finger vein images. First, facing the issue of insufficient training data, they adopt a heavy image augmentation strategy and develop a pretrained- weights based convolutional neural network (CNN). Second, focusing on the characteristics of finger vein verification, they construct a Siamese structure combining with a modified contrastive loss function for training the above CNN, which effectively improves the network's performance.

Finally, considering the feasibility of deploying the above CNN on embedded devices, they construct a lightweight CNN with depth wise separable convolution and adopt a knowledge distillation method to learn the knowledge from the pretrained-weights based CNN, which makes it small but effective.

## I.INTRODUCTION

In recent years, biometric authentication systems have gained significant importance due to the growing need for secure and reliable identity verification methods. Among various biometric traits, finger vein patterns have emerged as a promising modality due to their uniqueness, difficulty to forge, and stability over time. Finger vein detection, which involves capturing and analyzing the vein patterns beneath the skin of a finger, offers a high level of security and is less intrusive compared to other biometric techniques such as fingerprint or facial recognition.

Convolutional Neural Networks (CNNs), a type of deep learning model, have proven highly effective in image processing tasks, making them well-suited for the complex task of finger vein pattern recognition. CNNs can automatically learn hierarchical features from raw image data, enabling them to effectively capture the unique characteristics of finger vein patterns. This project

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focuses on developing a robust finger vein detection system using CNNs, aiming to enhance the accuracy and reliability of biometric authentication systems.

The integration of CNNs in finger vein detection not only improves the precision of vein pattern recognition but also streamlines the process of feature extraction, which traditionally required manual intervention. By leveraging CNNs, the system can achieve a high level of automation, making it more scalable and adaptable to various application scenarios, such as access control, financial transactions, and personal identification. This project explores the design and implementation of a CNN-based finger vein detection system, addressing challenges such as data acquisition, model training, and performance optimization to deliver a state-of-the-art solution in biometric authentication.

## II.EXISTING SYSTEM:

There are many biometrics in use today and a range of biometrics that are still in the early stages of development. Some of them are Fingerprint, Face recognition, Palmprint, Iris scan recognition, Speaker/Voice etc. Fingerprint based recognition method because of its relatively outstanding features of universality, permanence, uniqueness, accuracy and low cost has made it most popular and a reliable technique. Face recognition for its easy use and non-intrusion has made it one of the popular biometric.

**drawbacks**

- Accuracy is not as high as finger vein detection system.
- Less Efficient than the finger vein detection system.
- Fingerprints can be faked without too much difficult as they are anexternal feature.
- Physical contact with the scanner is required for fingerprint authenticationwhere finger vein can be contactless.
- Fingerprint detection requires more maintenance.

## III.PROPOSED SYSTEM:

Finger vein authentication system (FVAS) is more secure than other forms of authentication, such as signatures and fingerprint authentication. This is because of thefact that veins are present beneath the human skin, which makes them nearly impossible to replicate. The Finger Vein is a Promising biometric pattern for personal identification in terms of its security and convenience. The Finger-vein pattern can onlybe taken from a live body. Therefore, it is a natural and convincing proof that the subjectwhose finger-vein is successfully captured is alive. Through the use of image augmentation along with the method of building a CNN basedon pretrained weights, we alleviated the issues of lacking training samples for deep learning. By means of the Siamese structure with the MC loss(Modified Contrastive) function, the discriminative power of the deep features is greatly improved. Firstly developed trained a pretrained-weights based CNN, whose knowledge was then transferred to a newly built lightweight CNN by a knowledge distillation method, whichmade the final finger vein detection

CNN model small but effective.

## IV.LITERATURE SURVEY:

### BIOMETRICS:

Biometrics refers to identifying a person based on his or her physiological or behavioral characteristics; it has the capability to reliably distinguish between an authorized person and an imposter. A biometrics system is a recognition system which operates by acquiring biometric data from an individual, extracting feature sets and comparing it with the template set in the database. Depending upon the application context, the identity of a person can be resolved in two ways: verification and identification.

Biometrics are categorized as:

1.Unimodal biometric system (biometric system using single biometric feature)

2. Multimodal biometric system (a biometric system using more than one biometric feature)

Biometric identifiers (such as fingerprints, faces and iris patterns) are characterized by their uniqueness and stability, making biometric recognition technology more important in the identity authentication field. Unlike most biometric identifiers presenton the body's surface, the finger veins are beneath the human skin, which makes them difficult to steal or be worn. Most importantly, finger vein verification has the unique characteristic of live-body detection, which ensures the advantages of finger vein technology and attracts more attentions into this area.

### FINGER VEIN AUTHENTICATION SYSTEM(FVAS)

In view of the shortcomings within existing traditional finger vein verification algorithms based on handcrafted features and the CNN-based finger vein verification methods, we propose a novel method based on the Siamese CNN to better meet the requirements of finger vein verification.

Its contributions are summarized as follows:

1.through the use of image augmentation along with the method of building a CNN based on petrained weights, we alleviated the issues of lacking training samples for deep learning.

2. On the basis of the pretrained-weights based CNN, the Siamese structure was constructed for metric learning, and we proposed a new modified contrastive loss (MC loss) function for training,

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which further improved its discriminative power for features.

3. Considering a deployment in embedded devices with limited hardware resources, we first developed and trained a pretrained weights-based CNN, whose knowledge was then transferred to a newly built lightweight CNN by a knowledge distillation method, which made the final finger vein verification CNN model small but effective.

**Pretrained weights-based CNN**

In this section, we elaborate on our approach. We first introduce our solution to address the issue of insufficient data, which includes the use of the pretrained CNN weights and the heavy data augmentation strategy. Then, we describe the structure of our pretrained-weights based CNN, as well as the Siamese structure with our proposedMC loss function. By means of the Siamese structure with the MC loss function, the discriminative power of the deep features is greatly improved.

To acquire more representative characteristics, deeper CNNs are usually adopted which require a very large number of parameters, as well as a large training dataset for optimizing them. As far as we know, the single public dataset only contains a few thousand finger vein images, not to mention that the dataset needs to be split intoa training set, validation set and test set. To alleviate the issue of insufficient training data, we go with pretrained weight-based CNN.

**CNN Structure**

we introduce the shallow layers of the pretrained models to our CNN model. Specifically, the shallow layers of ResNet-50 are used, and some more custom designed layers are added to construct the extended network. the layers below layer 11 are base layers, and they are initialized with the weights of the pretrained ResNet-50 model; meanwhile, the layers above layer 11 are extended layers, which are randomly initialized. And trained the ResNet model through BN Batch Normalization.

**ARCHITECTURE:**

A Convolutional Neural Network or CNN is a type of artificial neural network, which is widely used for image/object recognition and classification. CNNs are playing a major role in diverse tasks/functions like image processing problems, Siamese

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Networks are a class of neural networks capable of one-shot learning. A class of neuralnetwork architectures that contain two *identical* subnetworks. '*identical*' here means, they have the same configuration with the same parameters and weights. Parameter updating is mirrored across both sub-networks. It is used to find the similarity of the inputs by comparing its feature vectors, so these networks are used in many applications.

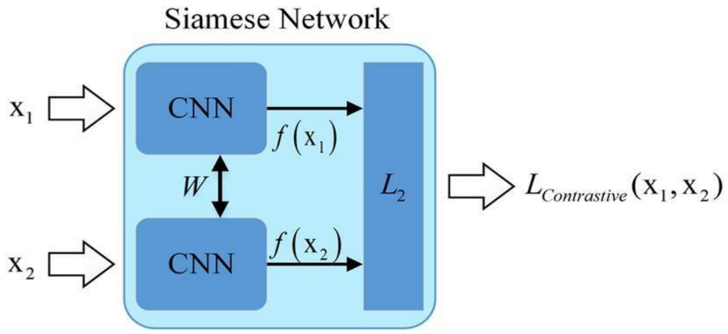


***Figure1. Siamese Structure***

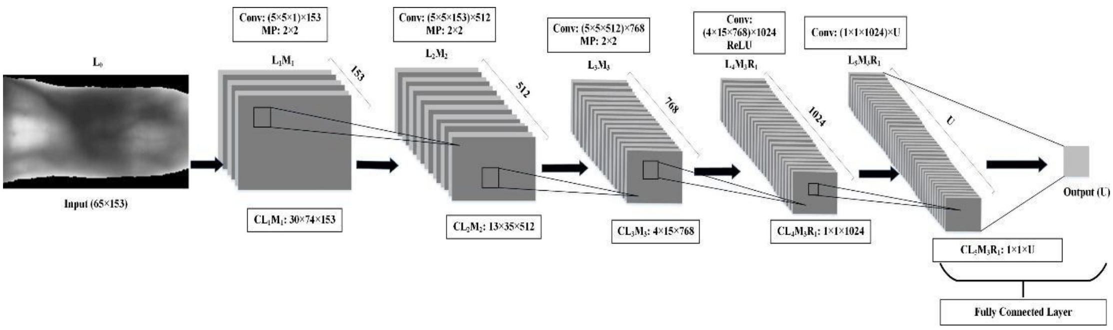

***Figure 2. CNN Architecture***

**V.MODULES:**

The proposed system has 4 modules:

- Image Acquisition
- Image Processing
- Feature Extraction
- Image Matching / Recognition

The Following are four modules involved, they are,

**1.Image Acquisition:**

It is the action of retrieving an image from a source, usually hardware systems like cameras, sensors, etc.

**2. Image Processing:**

Image processing is a method to perform some operations on an image, in order to getan enhanced image or to extract some useful information from it.

**3. Feature Extraction:**

Feature extraction is a process of dimensionality reduction by which an initial set ofraw data is reduced to more manageable groups for processing.

**4.Image Matching / Recognition:**

Image recognition is the process of identifying an object or a feature in an image or video.

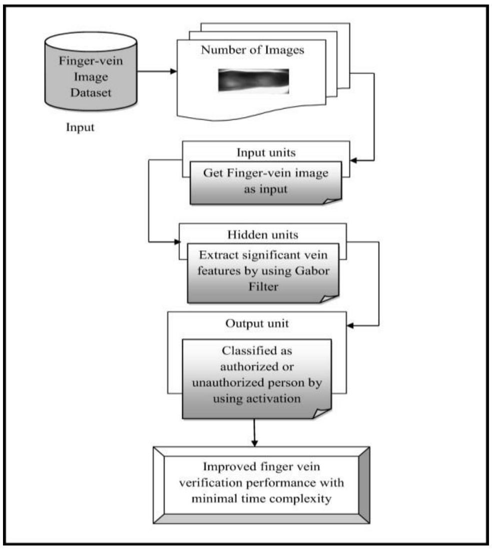


***Figure 3. Entity flow diagram***

**ADVANTAGES:**

- Since it is based on the vein patterns under the skin surface, it is said to be moreaccurate than a fingerprint, which have been faked in the past. Also, since it's the veins, this authentication process provides proof that the individual whose identity is being verified is a live person.
- The Vein is hidden inside the body and is mostly invisible to human eyes, so it is difficult to forge or steal.
- The non-invasive and contactless capture of finger-veins ensures both convenience and hygiene for the user, and is thus more acceptable.
- Finger vein patterns are relatively stable and clearly captured, enabling the use of low-resolution cameras to take vein images for small-size, simple data imageprocessing.

## VI.CONCLUSION

A new method of a finger-vein biometric identification system was developed using a CNN. A four-layered CNN with fusion of convolution and subsampling layers was proposed through the 5-13-50 model. An enhanced stochastic diagonal Levenberg–Marquardt algorithm was applied to ensure faster convergence. This work applies the winner-takes-all rule as the recognition method. This method replaces the similarity metric matching method that is normally applied in common biometric approaches. Theadvantage of this method is that a true match is assigned to each subject during the training and the identity of an unknown subject is directly known in the test phase. Ona 2.5 GHz Intel i5-3210M quad core processor, 8 GB RAM computer, the recognition time is less than 0.1574 s (including the preprocessing stage). The response time sufficiently satisfied the requirements for user convenience.

Handcrafted features have been widely used in previous finger vein verificationalgorithms but they are not robust when addressing large variations in images, and their related preprocessing processes are commonly complex. In this paper, we propose a lightweight CNN along with its training strategy. The lightweight CNN is used to extract more compact and discriminative features from finger vein images. In addition, the preprocessing procedure is highly simplified, we only need to extract the ROI of the original finger vein image instead of many image enhancements. Training with ourproposed MC loss function can highly enhance the discriminative power of features.

Experimental work has shown that optimum accuracy is achieved with the proposed CNN-based solution that implements preprocessing without the costly segmentation (local dynamic thresholding) process. The combination of Z-score and uniform weight was identified as the most appropriate normalization and weight initialization method. The input image of 55 × 67 was selected as the most optimum size. These selections led to a 100.00% and 99.38% recognition rate tested on samplesfrom 50 and 81 subjects, respectively.

A benefit of the proposed training framework is that lightweight CNN's performance is nearly the same as the pretrained-weights based CNN while the number of resources required drops significantly. All experiments were conducted using the same training procedure and hyperparameters, without any specific adjustments for a dataset and our proposed CNN still achieves the state-of-the-art performances in all datasets, which fully verifies the advantages of our algorithm.

In addition, the algorithm proposed in this paper can also be applied in other domains that have the problem of insufficient training data such as palmar veins and palm prints. The algorithm in this paper is mainly designed with a focus on the loss function without considering the ROI extraction. In the future, we will attempt to use the deep learning method to directly locate the venous ROI, to avoid the errors causedby the tedious manual design of ROI extraction methods. Furthermore, we can try to build new deep learning modules aimed at some special deformations of finger veins.

## VII.FUTURE ENHANCEMENTS

Finger-vein biometric identification using convolutional neural networks (CNNs) is an emerging technology that has shown promising results in recent years. There are severalpotential enhancements that could be implemented in the future to improve the accuracyand efficiency of this technology.

**1.Dataset size:** The size and diversity of the dataset used for training a CNN are crucial factors that determine the accuracy of the model. A larger dataset can provide more examples of different variations of finger-vein images, which can help the CNN to learn more robust and accurate features. Moreover, collecting data from individuals with different ethnicities, ages, and genders could increasethe diversity of the dataset, which is important for reducing bias in the model.

**2.Transfer learning:** Transfer learning is a technique that involves using pre- trained CNN models to initialize the weights of a new model or to fine-tune an existing model. By using pre-trained models that have already learned meaningful features from large datasets, finger-vein biometric identification systems could achieve higher accuracy with smaller training datasets. Transfer learning can also reduce the training time and computational resources requiredto train a new model from scratch.

**3.Multi-modal biometrics:** Multi-modal biometrics involve combining two or more biometric modalities to improve the accuracy and security of the identification system. For example, combining finger-vein biometrics with facial recognition or fingerprint recognition could reduce the risk of false positives or false negatives, especially in scenarios where the quality of the finger-vein images is poor. Multi-modal biometrics can also increase the difficulty ofspoofing attacks by requiring an attacker to spoof multiple modalities.

**4.Privacy-preserving techniques:** Finger-vein biometric identification systems store sensitive information about individuals, which raises privacy and security concerns. To address these concerns, privacy-preserving techniques such as homomorphic encryption, differential privacy, and secure multiparty computation could be used to protect the biometric data during storage and transmission. Homomorphic encryption, in particular, allows computation to beperformed on encrypted data without revealing the plaintext, which could provide strong privacy guarantees for finger-vein biometric identification systems.

**5. Real-time processing:** In applications such as access control systems or bordersecurity, real-time processing is crucial for efficient and effective operation. To achieve real-time processing, more efficient algorithms and hardware architectures could be developed that are optimized for finger-vein biometric identification. For example, hardware accelerators such as field-programmable gate arrays (FPGAs) or graphics processing units (GPUs) could be used to speed up the computation of the CNN.

In conclusion, these potential enhancements for finger-vein biometric identification using convolutional neural networks have the potential to improve the accuracy,efficiency, and security of the technology. As the technology continues to advance, it is likely that we will see further improvements in this area in the coming years.

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