FINGER VIEN VERIFICATION USING A SIAMESE 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.

INTRODUCTION

To solve the problem's of data losing by unauthorized users or access. Present finger print verification and face detection and passwords are in usage. But these are easily tampered or make unauthorized access, so here protect user's data in secure manner. Here proposed a new system i.e., FINGER VEIN DETECTION USING CNN.

For all this, we need a knowledge distillation method for our optimisation framework for transferring the knowledge of the pretrained-weights based CNN into our lightweight CNN. Consider a deployment in embedded devices with limited hardware resources, Firstly develop and train a pretrained weights-based CNN, whose knowledge will then be transferred to a newly built lightweight CNN by a knowledge distillation method, which will give the final finger vein detection CNN model small but effective. Which Performs a sufficient open-set experiment on self-built dataset, which will verify that our method achieved a state-of-the-art performance. The following are the objectives to be achieved:

1. To achieve smart recognition of human identity for security and control, which is a global issue of concern in our world today.
2. To minimize financial losses due to identity theft can be severe, and the integrity of security systems which are compromised.
3. Most importantly, finger vein detection has the unique characteristic of live-body detection, which ensures the advantages of finger vein technology and attracts more attentions into this area.

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.

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 the fact 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 only be taken from a live body. Therefore, it is a natural and convincing proof that the subject whose finger-vein is successfully captured is alive. Through the use of image augmentation along with the method of building a CNN based on 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, which made the final finger vein detection CNN model small but effective.

IMPLEMENTATION

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. The advantage 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. On a 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 verification algorithms 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 our proposed 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 samples from 50 and 81 subjects, respectively.

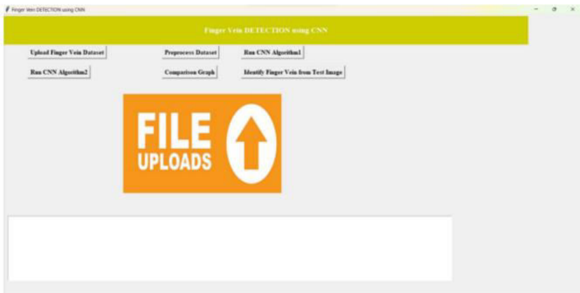

Fig.1. Home page.

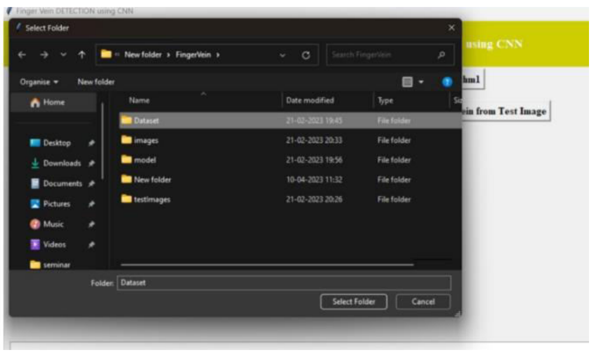

Fig.2. Upload the data set.

Fig.3. Prediction page.

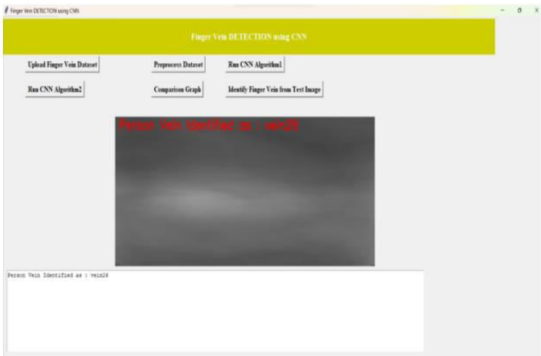

Fig.4. Finger detected data.

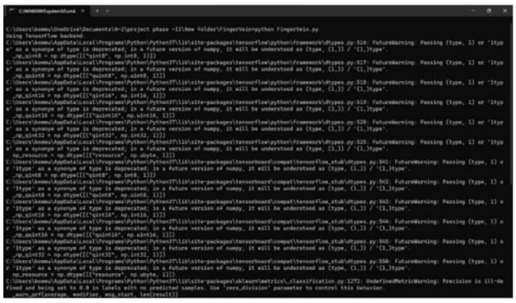

Fig.5. Back ground application.

CONCLUSION

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 caused by 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.

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