Finger Vein Recognition Using Deep Learning

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Abstract

Recently, finger vein recognition technology has gained wide acceptance in both research as well as in commercial uses like access control and authentication. Finger vein recognition is a novel biometric technology which is challenging to spoof and has a wide array of potential applications. Many deep learning based finger vein recognition system has been proposed so far. The vein images are always prone to quality degradations due to the noise, blurring and illumination variations introduced while capturing the images using near infrared technique. However, most of the existing deep learning methods for finger vein recognition are based on ideal vein images (images with minimum image quality). Since the network is trained based on the vein images which are having a minimum image quality, the performance of recognition may get affected when the vein image quality is poor. We propose a transfer learning based model which is trained using vein images with varying image quality. From a unique vein image, four different quality images (original image quality, blurred image, noisy image1, and noisy image2) will be generated and used for training the model. To the best of our knowledge, this is the first work based on transfer learning model that relies upon varying qualities of vein images in order to improve the overall recognition performance. We have utilized SDUMLA vein image dataset for experiments. The experimental results shows that the proposed approach can perform better than the existing deep learning based methods.

Keywords: finger vein recognition, biometric technology, deep learning approaches, transfer learning

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I. INTRODUCTION

In the current era, biometric technologies is one of the prominent in the security system to help government agencies and private companies to authenticate personal identity and to limit access for various resources like computer networks, offices etc. Intelligent biometric applications use biological characteristics like finger vein, finger print, facial and hand features, and iris patterns to identify a person. Behavioral characteristics which are learnt or acquired over a period of time are also being considered for identification purpose. [1]

Finger vein recognition is a biometric technique that can be used to consider human finger vein and analyze them to perform biometric and authentication applications [2]. Finger vein, being an intrinsic feature is less prone to spoofing and since finger vein biometrics is contactless, it can be considered the safest biometric system. By scanning a database for a match based on the finger vein, a finger vein identification system authenticates a person from the entire population. Secure financial transaction, data protection, application login, health and insurance system, law enforcement system, attendance tracking, ATMs and physical access control systems can be benefited from the finger vein authentication [3].

Various deep learning methods have been developed and implemented for finger vein recognition. Algorithms like neural network, convolution neural network (CNN), transfer learning models like VGG Net, Alex Net, and Inception are used. But most of the existing methods for finger vein recognition using deep learning utilizes ideal vein images, which includes minimum quality images. The recognition performance maybe hampered if the image quality is inadequate. In our work, we propose a transfer learning based model, trained on finger vein images from SDUMLA dataset and with varying image quality.

Different transfer learning models like VGG-16, VGG-19, Alex Net and Inception V3 are used and compared. The training dataset with varying image quality is generated from the original vein image dataset itself. The vein image is blurred to generate the blurry image, added gaussian noise to generate noisy image1 and salt and pepper noise to generate noisy image2. Training and testing split is done on 80:20 ratio and the recognition accuracy was found to be 99.99% and is better than the existing deep learning methods.

Rest of the paper is organized as follows: The related work in the area of finger vein recognition using deep learning algorithms is discussed in section II. Section III explains the proposed methodology in detail, while section IV describes the experimental results before concluding and outlining future work in section V.

II. RELATED WORK

In recent years, different works were carried out using machine learning and deep learning approaches for recognizing humans finger vein patterns. CNN model was mostly used in finger

The work of Ahmad Radzi et al. proposed the use of reduced complexity 4 layer CNN for finger vein recognition. CNN with fused convolution subsampling architecture is used. Normalization is performed on the images and the training is boosted by using special custom made stochastic algorithm, which resulted in faster convergence rate. Identification accuracy of 100% is achieved [6].

All the deep learning works used open vein image datasets like SDUMLA and other custom made datasets. Most of the works focused on image datasets with minimum image quality. It can be challenging if the dataset quality is very poor and can be a potential drawback for existing deep learning solutions provided. Also, minimum amount of preprocessing is performed in most of the works which can never guarantee a workable model in every condition. Our proposed approach uses the transfer learning approach for training image dataset with varying image quality. Image quality is varied by applying blurring and noise addition techniques. Proper image analysis is performed on the images and augmented data is also given for training so as to incorporate transformed version of images into the training dataset.

TABLE.1 DEEP LEARNING BASED RELTED WORK RESULTS

Algorithm	Accuracy
CNN	99.53% [4]
CNN	> 95% [5]
CNN	100% [6]

vein recognition. Transfer learning approache like Alex Net, VGG16, VGG19, and Inception

V3 were also used for recognizing finger vein. This section discusses and compares some of theimportant deep learning based literatures on the related works.

The work of Wenjie Liu et al. put forward finger vein recognition based on CNN. The proposed system consists of roi vein image region extraction followed by recognition using CNN with 2 fully-connected and 5 convolution layers. Comparison is then made with traditional finger vein recognition methods like Gabor, LBP, and HOG. CNN outperformed in the finger vein recognition by achieving 99.53% accuracy [4]. Rig Das et al. proposed approach for identifying finger vein using deep learning with the focus on getting high accuracy considering different environmental conditions. There are 5 convolution layers, 3 max pooling layers, 1 ReLU layer and a softmax layer. Using the design, authors were able to obtain accuracy of over 95% for different datasets. [5]

Table 1 shows the accuracy obtained from the literature papers using different deep learning based solutions.

III. PROPOSED METHODOLOGY

A. Dataset Generation

SDUMLA finger vein database taken from Shandong University of China has been used for the proposed work. It includes images of finger-vein of 106 subjects or classes. The index, middle and ring finger were selected and six grey level bmp format with 320 x 240 pixels resolution, were taken from theleft and right hands for each of these fingers.

Total of 3816 vein images were present in the original dataset. 80:20 ratio split is done for train and test. Training dataset included 3000 images from original dataset along with augmented data and varied quality image data. Testing is done on the rest 816 images from the original dataset.

Vein image quality is varied by performing different techniques to the original images from the SDUMLA dataset.

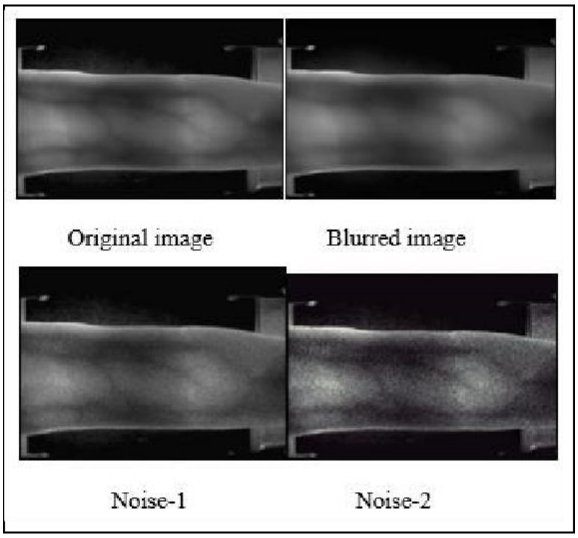

Fig. 1 Creation of different quality image

Fig. 1 shows the different quality images created by using various image processing techniques. Original image is the real vein imagetaken as such from the database. The image degradation is then performed. Initially, gaussian blur is added to the original vein image to getthe blurred image. This technique utilizes gaussian distribution to process the images, especially to smoothen it.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

I_d(x,y) = Blur_filter(I(x,y) G(x,y))

where I_d(x,y) is the initial degraded image using gaussian blur, I(x,y) the ordinal image and G(x,y) the gaussian blur filter. Guassian blur is used for smoothening an image based on Gaussiandistribution, where sigma represents the standard deviation.Quality is further varied by adding noise to the images. Noise-1 introduced Gaussian noise tothe images.

Noise-2 type of image degradation is performed by adding salt and pepper type of noise to the original vein image. Here both black and white noise is added to the image. Salt and pepper noise model only two values a and b for salt and pepper whose intensity value corresponds to 0 and 255.

$$PDF_{salt\&pepper} = \begin{cases} A & for\ g = a\ ("\ pepper\ ") \\ B & for\ g = b\ ("\ salt\ ") \end{cases}$$

B. Transfer Learning

Transfer learning is a deep learning approach, which uses the feature extraction and trained weights from the pre-trained models for training and validating new models with less training time. It can perform very well for the generalized data points. This algorithm is very much useful when you have less samples in the training dataset. For the image processing application, there are various best performance Off-the-shelf Pre-trained models are available like Inception V2, V3, V4, Rest ;.Net, VGG 16,

19. We mainly use VGG16,19, Inception V3 and Alexnet models for recognition as all the these models showed significant results for finger veinrecognition.

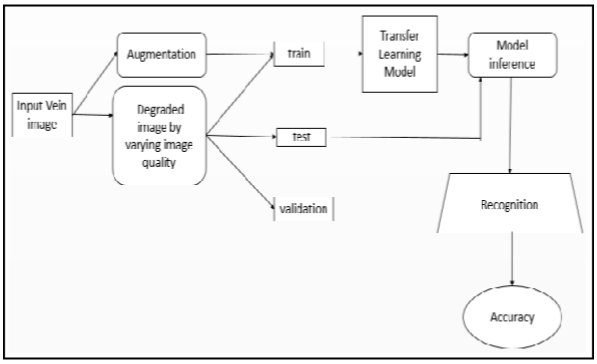

Fig. 2 Design

Fig 2. has got a train and test dataset. Input vein image is degraded by adding different noises. Training and testing split is done on 80:20 ratio and training receives vein images both from augmentation and degradation. Testing is done on rest 20% degraded images and then transfer learning models are used for vein recognitionand accuracy is checked.

Image Augmentation

Image Augmentation is one of the major methodologies for creating artificial images by transmuting the original image dataset. Image datagenerator class has important features to serialize and optimize data augmentation for training and testing the deep learning model. This class is used for producing artificial images for training and validation dataset with practical dataaugmentation.

B. Algorithm

Algorithm 1: Finger Vein Recognition

Input: input finger vein image f(x, y)

Output: output recognition class R(f)

1: Vary image quality from input imagef(x, y) as f1(x,y) f2(x,y) and f3(x,y);

2: Perform Image analysis on the input images and obtain analyzed images fp(x,y), fp1(x,y), fp2(x,y), fp3(x,y);

3: Give the analyzed images fp,fp1,fp2,fp3 as input to the transfer learning models to perform the recognition and to get the class R(f);

4: Return the output

Algirthm1 describes step by step implementation of finger vein recognition. Finger image f(x,y) is provided as the input to recognition system. Image quality is varied using different degradation techniques in step 1. Image analysis techniques like basic processing are performed in step2. The next step involves the use of analyzed images likefp,fp1,fp2,fp3 are given as the input to the transfer learning model for recognitionpurpose.

RESULTS

After the successful training process, the history object contains training metrics as dictionary. Our finger vein model trained with validation dataset has important information like accuracy, loss and execution time.

TABLE.2 ACCURACY COMPARISON

Algorithm	Accuracy
CNN	99.53% [4]
CNN	> 95% [5]
CNN	100% [6]
Transfer Learning Model	99.99%

Table 2 shows the accuracy obtained for the proposed transfer learning model and the other CNN models as discussed in the related work section. The transfer learning model is able to achieve higher accuracy of 99.99%.

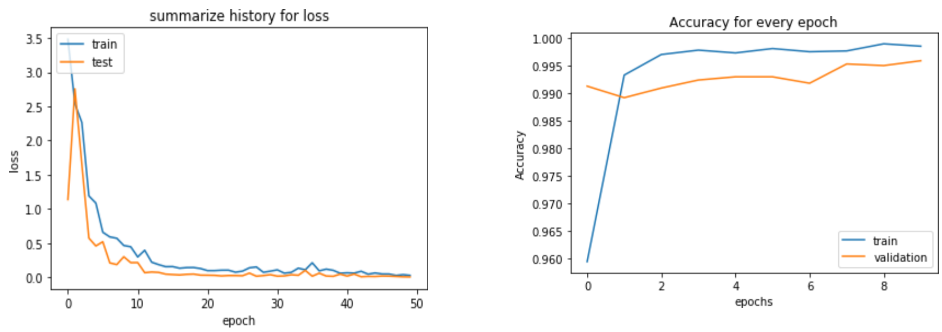

Fig 3. Accuracy and Loss graph

Fig. 3 shows the graphs of accuracy and loss for the model trained. From Fig. 3, it is clearly understood that the model is well trained on both train subset and validation subset with less no of epochs.

TABLE.3 ACCURACY COMPARISON OF TRANSFER LEARNING MODELS

Model	**Accuracy**
Alexnet	93%
VGG16	99.99%
VGG19	98%
Inception V3	96%

Table 3 shows the accuracy obtained by different transfer learning models mainly VGG16, VGG19, Alexnet and Inception V3. VGG16 performed well by achieving highest accuracy of 99.99% followed by VGG19, Inception V3 and Alexnet.

IV. CONCLUSION

The performance results shows that our novel methodology is very efficient in finger vein recognition for varied quality images using the exclusive transfer learning approach. Also this is quite dynamic due to data augmentation and transfer learning approach. It can reach to the highest performance by giving maximum accuracy of 99.99% and least loss even though our dataset has less no of samples. Due to transfer learning it can outperforms most of the ANN algorithms. In our proposed application we have used the image size of (320,240). Therefore, it can produce a better accuracy compared to any research which has the image small sizes like 32 * 32, 64 * 64 etc. Hence, this approach can become integral part of any mission critical authentication application by introducing a workable efficient model for finger vein recognition.

As a future extension, database can be improved with the help of synthetic fingers. Additionally, focus can be given to develop customized algorithms for effective finger vein recognition.

Also the same approach can be tried on different datasets for finger vein recognition purposes whichcan actually help many useful application usingfinger vein.

REFERENCES:

1. Kashif Shaheed, Hangang Liu , Gongping Yang , Imran Qureshi , Jie Gou and Yilong Yin
2. ,"A Systematic Review of Finger Vein RecognitionTechniques", MDPI, 2018.
3. Lu Yang, Gongping Yang, Yilong Yin, and Xiaoming Xi, "Finger Vein Recognition with Anatomy Structure Analysis", IEEE, 2017.
4. M. Rajalakshmi,R. Rengaraj , Mukund Bharadwaj , Akshay Kumar, N. Naren Raju and Mohammed Haris, "An Ensemble Based Hand Vein Pattern Authentication System", CMES, 2018.
5. Wenjie Liu, Weijun Li, Linjun Sun, Liping Zhang, Peng Chen," Finger Vein Recognition Based on Deep Learning" ,IEEE Explore 2017.
6. Rig Das, Emanuela Piciucco, Emanuele Maiorana, and Patrizio Campisi, "Convolutional Neural Network for Finger-Vein-based Biometric Identification",IEEE Transaction for Information Forensics and Security,2019.
7. Syafeeza Ahmad Radzi1, Mohamed Khalil-Hani, Rabia Bakhteri, "Finger-vein biometric identification using convolutional neural network", Turkish Journal of Electrical Engineering & Computer Sciences, Turk J ElecEng & Comp Sci (2016) 24: 1863 – 1878.
8. Amitha Mathew, Amudha Arul, "A Review on Finger Vein Recognition Using Deep Learning Techniques", ResearchGate, 2020.
9. Shivam Shendre, Dr. Shubhangi Sapkal, "A hybrid approach for deep learning based finger vein biometrics template security", International journal of advance scientific research and engineering trends,2020.
10. Samer Chantaf, Alaa Hilal, and Rola Elsaleh," Palm Vein Biometric Authentication Using Convolutional Neural Networks", SEITI, Springer, 2020
11. Rama Vasantha Adiraju , Kranthi Kumar Masanipalli , Tamalampudi Deepak Reddy , Rohini Pedapalli, Sindhu Chundru, Asisa Kumar Panigrahy, "An extensive survey on finger and palm vein recognition system",Materials Today: Proceedings, Elseiver, 2020.
12. N.Lalithamani, R.Balaji , M.Ramya, S.Sruthi, A. Aiswarya, "Finger Knuckle Biometric Authentication using Convolution Neural Network", International Journal of Pure and Applied Mathematics Volume 117 No. 10 2017, 31-35.
13. G. Radhika ,S.Vidhya, S. Divya Bharathi, "Survey process model on palm print and palm vein using biometric system", International Journal of Pure and Applied Mathematics Volume 118 No. 18 2018, 1557- 1563.
14. N. Lalithamani, Dr.M. Sabrigiriraj," Embedding of Iris Data to Hand Vein Images Using Watermarking Technology to Improve Template Protection in Biometric Recognition", IEE, 2015.
15. A. P. R., Nair, M. D., Mohan, S., P., D., and S. K. Sreenivasan Nair, "Design of Portable Biometric Authenticator – Finger Vein Pattern Recognition", in Annual Photonics, Workshop 2014.H. M. Priya and N. Lalithamani, "A Survey for Securing Online Payment

Transaction using Biometrics Authentication”, Advances in Intelligent Systems and Computing, vol. 517, pp. 81-91, 2017.
16. S. Vuppala, Varier, N. S. and Sangita Khare, “Diabetes Prediction Using Machine Learning Techniques”, in Sixth International Symposium on Intelligent Systems Technologies and Applications (ISTA'20), 2020.
17. Arya Krishnan, Tony Thomas, Gayathri R Nayar, Sarath Sasilekha Mohan,”Liveness detection in finger vein imaging device using plethysmographic signals”, International Conference on Intelligent Human Computer Interaction, 2018.
18. Arya Krishnan, Tony Thomas, “A survey of mathematical techniques in finger vein biometrics”, J Theoret Comput Math, 2015.
19. Arya Krishnan, Gayathri R Nayar, Tony Thomas, N Ake Nystrom, “FEBA-An Anatomy Based Finger Vein Classification” , IEEE International Joint Conference on Biometrics , 2020.S Marcel, M X Nixon and S Z li, “Handbook of Biometric Anti Spoofing”, Springer 201