Near Infrared Hand Dorsal Vein Biometric Pattern Classification based on Deep Learning

Abstract: This paper proposes a novel method, deep Learning classification strategy by Convolutional Neural Network (CNN) method to identify and recognize hand vein patterns using Near Infrared (NIR) images. This NIR hand vein images have different temperature conditions, and provide a better quality and advance security with its vein pattern uniqueness. Initially, vein input images are taken to pre-processed for high quality hand vein images and which provides suitable images for dorsal hand vein extraction. Then, Fuzzy C-Mean (FCM) segmentation method is used to segment vein from hand dorsal background to support the future extraction stage. For the vein recognition phases, Convolutional Neural Network is trained Region of Interest (ROI) classified to preformed recognition. Furthermore, CNN approach significantly improves the accuracy and helps us to solve to our problem hand vein recognition performance. In this paper, it is also illustrated that the increased level of model has deeply affected to report the accuracy. Finally, the analysis of our represented model results is presented with simple visualization techniques. Experimental result show that our model achieved 94.5% accuracy.

1. Introduction

Biometric technology is used for the human identification and verification of human body physiological or behavioural characters (Hossain and Chetty 2011). Examples of biometric physiological characters include facial, fingerprint, Palmprint, Iris, ear, and vein recognition (Huang et al. 2016) etc. On the other hand, biometric human behavioural characters includes gate, signature, and handwriting recognition (Huang et al. 2016) etc. During the last decade, vein pattern recognition has attracted researchers in pattern recognition field, and was the research focus for some, which include finger vein pattern, hand vein pattern, face vein pattern, palm vein pattern, head vein pattern, heart vein pattern, food vein pattern and iris vein pattern (Mishra, Mishra, and Agrawal 2016) etc. The most prominent vein patterns recognition are hand vein pattern recognition, finger vein patterns recognition, this study focuses on hand vein pattern on back of the hand area.

Recently, due to its stability, uniqueness, and universal personal attributes, hand vein recognition technology the process of the vein identification and the template for hand images of vein curve, have been significantly considered in the biometric recognition system, However, generally there is lack of a comprehensive method to perform hand vein recognition, even though the hand vein template is widely used,. Moreover, hand vein recognition system often takes in a large amount of data in training before testing. It is similar to the other biometric recognition systems, hand vein pattern in recognition system whereby the quality of the images will affect the environmental illumination, ambient temperature, physiological change, light scattering, user behaviour, and inaccurate parameter estimation during the image pre-processing stages (Arik et al. 2015).

Despite of the challenges faced by hand vein recognition system mentioned above, the increased quality of the hand vein image and usage of novel classify technology may help to increase the accuracy of the vein recognition. In previous studies, Convolutional Neural Network (CNN) achieved a great success in biometric pattern classification. Specially, the application of the convolution neural network method on biometric pattern recognition has shown high accuracy and improved over state-of-the-art recognition approaches. CNN is a multi-layered neural network whose perceptions are involved in multiple, overlapping receptive fields that resembles biological visual mechanisms of the visual cortex in most organisms (Kim and Brunner 2017).

In this research, we focus on three different fundamental problems: first, designed and established special methods to recover the quality of vein images and vein performance. Second, applied the Region of Interest (ROI) localization-based algorithm to determine the position of the ROI of hand vein images and by using CNN to predict vein from hand images. Third, compared and analysis three methods, namely Principle Component Analysis (PCA), Support Vector Machine (SVM) and CNN, in hand vein pattern recognition system.

2. Related Works

2.1 Convolutional Neural Network for Image and Pattern Recognition

Science 2000, various high recognition rates has been proposed in deep learning. For the next decade, one of the major challenges of computer vision, machine learning, and artificial Intelligent (AI) will be to devise methods that can automatically learn good features of hierarchies from unlabeled and labeled data using an integrated fashion (LeCun, Kavukcuoglu, and Farabet 2010). There are some literatures, which applied Convolutional Neural Network (CNN) on image and pattern recognition with high recognition rates.

Handwrite character recognition and text detection (Ren et al. 2016) are one of the challenging pattern recognitions in image vision area. In handwritten recognition, the researches attempt to activate application of CNN classify techniques on Latin handwritten digits (Cun et al. 1990), Chinese handwritten digit (Chen n.d.), and Arabic handwritten digit (El-Sawy, EL-Bakry, and Loey 2017). In deep learning to handwritten character recognition, and explored the Convolutional Neural Network, which preformed 99.28% best accuracy for recognize Latin handwritten digit dataset (Meiyin Wu and Li Chen 2015).

In biometric recognition studies, CNN has been successfully applied on face recognition (Xiaojun Lu, Yang Wang, Weilin Zhang 2016) , fingerprint recognition (Nogueira, de Alencar Lotufo, and Campos Machado 2016), gate recognition (Alotaibi and Mahmood 2015), Irish and eye recognition(Gangwar and Joshi 2016), and finger vein pattern recognition (Itqan et al. 2016) problems as it has number of various advantages compared to other image and pattern recognition techniques. Face pattern is most challenging applications in image recognition tasks and the application of CNN to face pattern has attracted researchers in face recognition. Particularly, CNN represented on face detection (Fan et al. 2014), face feature extraction(Sun, Wang, and Tang 2013) , face recognition (Afaq Ali Shah, Bennamoun, and Boussaid 2016), and many other parts. The aim of our research is to apply LaNet-5 common architecture (Syafeeza et al. 2014) CNN to solve non-linear effects such as illumination variances and poses for face recognition. They applied LaNet-5 CNN architecture on different two-face datasets and achieved 99.5% and 85.7% recognition accuracy rates, respectfully.

Convolutional networks and other deep models have achieved best accuracy in vision tasks such as logo recognition (Arivazhagan n.d.), image spam recognition (Shang and Zhang 2016), traffic sign recognition, food recognition (Lu 2016), plant identification (Zhao et al. 2015)(Grinblat et al. 2016), automatic book detection (Beibei Zhu et al. 2016), and extreme weather detection(Liu et al. 2016) etc. Among others, studies that applied CNN on vision recognition experiments have resulted in outstanding performances with the comparison to other machine learning studies.

2.2 Convolutional Neural Network for Vein Pattern Recognition

Some studies have focused on addressing the problems related to image and pattern recognition such as vein pattern recognition, mainly the experiments conducted on finger vein recognition dataset. There are some research propose to apply finger vein automatic recognition using advanced technology CNN to explore the performance of the different CNN architectures.

Itqa and his colleagues (2016) have introduced CNN with Graphical User Interface (GUI) as the user input approach applied finger vein recognition system. CNN architecture proposed in this research has used four layers to retrain network for new input train finger vein subjects, the convolution and subsampling layers have been fused, and classification has been processed through two fully connected single nodes. The final performance of finger vein recognition gives average 96% accuracy rate by increasing train subject numbers from 1 to 10 with in less than 10 second.

In a study, researchers demonstrated four layers fused convolutional layer and subsampling layer without including input layer of CNN architectore for applying the finger vein recognition system. This proposed CNN architectore is implying 5, 13, and 50 feature maps in first three layers. The last layer represents the output layer which fixed with 50 neurons as perform 50 subjects target classify with 10 finger samples for each finger. An interesting performance derail in this research, implimint indentificate result with tasted from 50 to 81 finger vein subjects, accuracy rates achived 100% and 99.38%(AHMAD RADZI, KHALIL-HANI, and BAKHTERI 2016).

Kashihara (2016) has utilized deep convolutional neural network (DCNN) as a super-resolution in order to improve the quality of downgraded images with a low level abnormal vein image. In this research, DCNN was designed with five covolutional deep layers and the size of the filter kernel has beed fixed to 3×3 and exited for more suitable optimal number of feature maps. Moreover, maximum pooling layer operation has exited by each convolutional layer. At the same time, last convolutional layer was not performed with any pooling layer, which connected with the final image output process. In the current research, the final result is consistent with the other techniques and DCNN is able to enhance the accuracy of complicated vein shapes by modifying filter kernels, although the estimated quality of the vein image with DCNN optimal structures and parameters.

There are other vein pattern recognitions have been proposed based on dorsal hand vein recognition system, and received strong attention from researchers and security manufactures. CNN methods take a different approach and achieve high accuracy by applying on hand vein recognition. In another study, researchers have investigated deep learning based methods on dorsal hand vein recognition and have done a comparative study of popular CNN architectures (i.e., AlexNet, VGG Net and GoogLeNet) for such an issue(Li, Huang, and Wang 2016). To the best of our knowledge, this study will be the first attempt that applies deep models to dorsal hand vein recognition. The evaluation is conducted on the NCUT database, and state-of-the-art accuracies are reached. Meanwhile, the experimental results have also demonstrated that the advantage of deep features to the shallow ones is to differentiate dorsal hand venous network and have confirmed the necessity of the fine-tuning phase.

3. Experiment of Pre-Processing Analysis

Since 2006 deep learning methods start to apply on Machine Learning and Artificial Intelligences areas. Deep learning strategies promise to leverage very large data sets for finding hidden structure and also make accurate prediction (Angermueller et al. 2016). A class of machine learning techniques that exploit many layers of non-linear information processing for supervised or unsupervised feature extraction and transformation, and for pattern analysis and classification (Deng and Yu 2013). In this section we discuss and summarize the experiential of pre-processing analysis deep learning approach Convectional Neural Network techniques classify hand dorsal vein recognition, which provide best accuracy.

The preprocessing of Hand vein recognition divided in four stages shown in **Fig. 1**. The process start with using Dataset for free of charge from the head of Brain Diseases Analysis Laboratory (BDALab) at the BRNO University of Technology. This image processed will flowing stages:

i. Hand preprocessing: in this stage is preprocessing the original NIR hand dorsal vein side image, which procedure after system receiving the raw data (Fayyaz et al. 2016). First, image banalization from RGB image, crop hand region, image rotate, and image resize process. The output applied median filter (Zhu and Huang 2012) to reduce image noise. Median filtering is a nonlinear method used to remove noise from images, which is widely used as it is effective at removing “salt and pepper” type noise.

ii. Hand segmentation: a segmentation process done with Fuzzy C-mean algorithm, which converts a gray scale images in to binarization images with black and white pixels. The segmentation techniques used in this paper to segregate the hand finger from hand image to acquired hand dorsal part and it also, filter some noise parts from hand dorsal site to gets successfully process area.

iii. Hand vein feature extraction: The Region of Interest Algorithm is represented in this system, as ROI is referred to an area, which can represented the characteristics of a hand vein in image. Extracting the ROI from hand vein images is a main procedure of the hand vein acquisition system (Zhu et al. 2015).

iv. Classification: Three different Machine learning methods were tested: Convolutional Neural Network (CNN), Principle Component Analysis (PCA) Algorithm combine with Minimum Distance Classifier (MDC) and PCA combine with Support Victor Machine (SVM) classifier. Those methods trained by previous stages proposed the feature obtains.

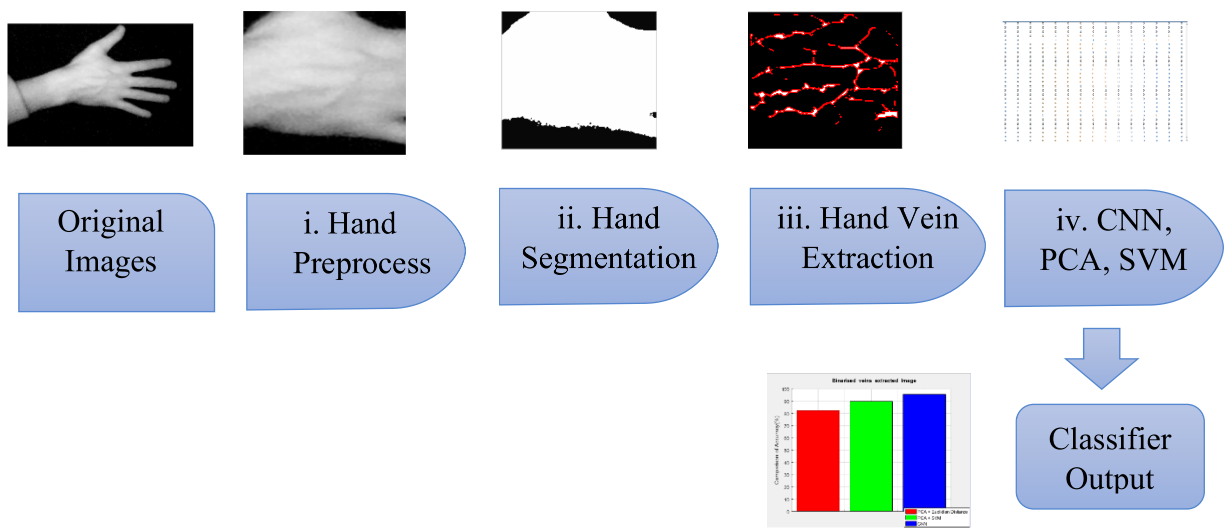


Fig. 1. Thermal Hand Vein classification processing

4. Propose Methods

In this paper, we propose novel approaches algorithm like convolution neural network, PCA (Principle component Analysis) based MDC (Minimum Distance Classification) and PCA based SVM (Support Vector Machine) classifier to recognize hand dorsal vein that allows us to perform the best accuracy.

A. CNN classify Model

The CNN is one of the most notable deep learning approaches, which is consider a convolutional layer and a pooling layer (Deng and Yu 2013). It has been found highly effective and become the most commonly used method in diverse computer vision applications. CNN is extended from artificial neural network, the convolutional layer shared many weights, and the pooling layer subsample the output of convolutional layer also reduced the data from previous layer. First, deep learning mainly applied for character recognition tasks such as reading zip codes and digit (Le Cun et al. 1989)(LeCun et al. 1989)(Cun et al. 1990). At the time, this deep learning subject used CNN method, which was first CNN design used architecture named LeNet by Yann LeCun. The pipeline of the general CNN applied computer vision architecture is shown in Fig. 2. Generally, a CNN consists of three main neural layers, which are convolutional layers, pooling layers, and fully connected layers. Different kinds of layers play different roles.

The CNN basic architecture design by us for hand vein recognition is shown in **Fig. 2**. The main operation for vein recognition is done with five stages:

- Input images layer: CNN required a fixed input image size and we proposed input images that consist of 3 feature maps (an RGB color image) with size 640×480.
- Convolution: each convolution operation uses same kernel size 5×5 for each feature map in convolutional layer C1 and C2. First convolutional layer C1 with 6 feature maps and second convolutional layer C2 with 12 feature maps.
- Pooling or subsampling: most popular pooling layer includes max-pooling and average pooling. In our system, we designed using the max-pooling layer. Pooling layers are usually apply convolutional layer, which simplify the source in the output from the convolutional layer. In the proposed system architecture includes two subsampling layers, namely S1 and S2. S1 layer contains 6 feature maps and a 2×2 kernel for all feature maps. For the S2 layer consists of 12 feature maps and a 2×2 kernel for all feature maps.
- Classification (Fully connected layer): this is the final layer, which is connected to all network and also connected to every neuron from the max-pooled layer to every output neuron. Fully connected layer is used to finalize the network after feature extraction. The process was done by convolutional and pooling layers.
- Output result (non-linear or softmax): output result will represent non-linear function of sigmoid or softmax transfer functions.

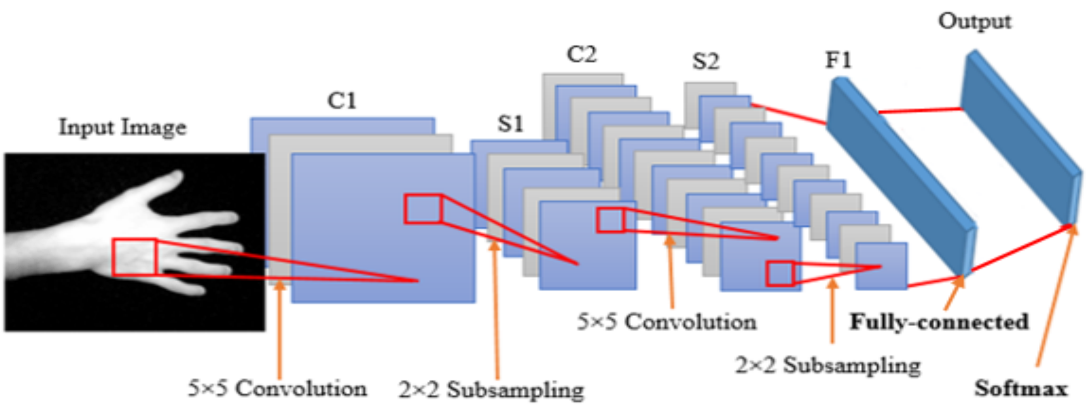


Fig. 2. Convolutional Neural Networks LeNet-5 Architecture

B. PCA combine with MDC and SVM classify Model

This studies proposed a method, which is developed by combining principle component analysis (PCA) for feature extraction and minimum distance classifier (MDC) for classification. In PCA is a powerful tool for analyzing data, identifying patterns and expressing the data to highlight their differences (Wu and Liu 2011), so PCA method is reducing the dimensions to provided most distinguishing features for classified.

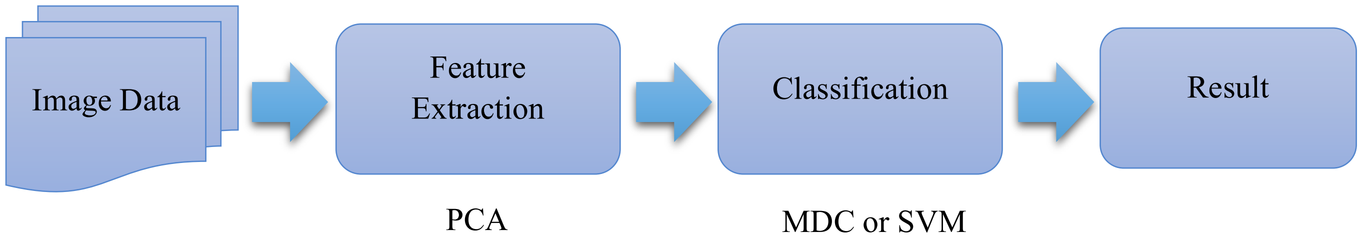


Fig. 3. Block diagram of PCA combine MDC or SVM hand dorsal vein method

Hand vein recognition system PCA combine MDC method is indicated **Fig. 3**. After input data from dataset, resize each image 50×50 to reduce the computational time, after resized images, each image will have represented one column. In this paper we train 9 samples and calculated the PCA space, eigenvalues and eigenvectors to selected principle components. After training data on the PCA spaces, each image is assessed on PCA spaces to classified. In this method, we are going to performed hand dorsal vein based on Minimum Distances Classifier (MDC) and Support Victor Machine (SVM) to classified hand dorsal vein pattern from dorsal hand image. SVM is a powerful classification in machine learning methods. It has been widely applied on pattern recognition system. image data included more classes, so we are going to use SVM to solve binary classification problems in our research. Hand vein recognition is a nonlinear classification model, so we used kernel function (references) to efficient computation of input data directly in feature spaces. Here have some kernel functions like linear, polynomial, RBF and sigmoid. And we proposed sigmoid kernel function in this article also 10 fold cross-validation applied to calculate misclassification rate.

5. Experiment Result

In this study, we applied CNN method for the recognition of hand dorsal site vein pattern. From the CNN design architecture, every convolutional layer is represented by the size and the number of the maps, and kernel size parameters. The parameter values are compared based on the CNN classification accuracy and time. The experimental results are conducted in MATLAB R2015a programming environment. Furthermore, LeNet-5 network architecture is used for implementing CNN on hand dorsal vein recognition.

5.1 Dataset

In order to design reliable hand vein recognition system, we need to use a high resolution thermal hand image database. The database in this study has been obtained from the Brain Diseases Analysis Laboratory (BDALab) at the BRNO University of Technology.

The Hand dorsal images have been collected in different environment using 10 different hands for each participants. There are 100 participants altogether, with 10 samples from each participant. Hence, there is a total of 1000 samples. In this research we used only 60 participants' data from the dataset. Fig.4. shows sample of hand dorsal images from (BDALab) dataset.

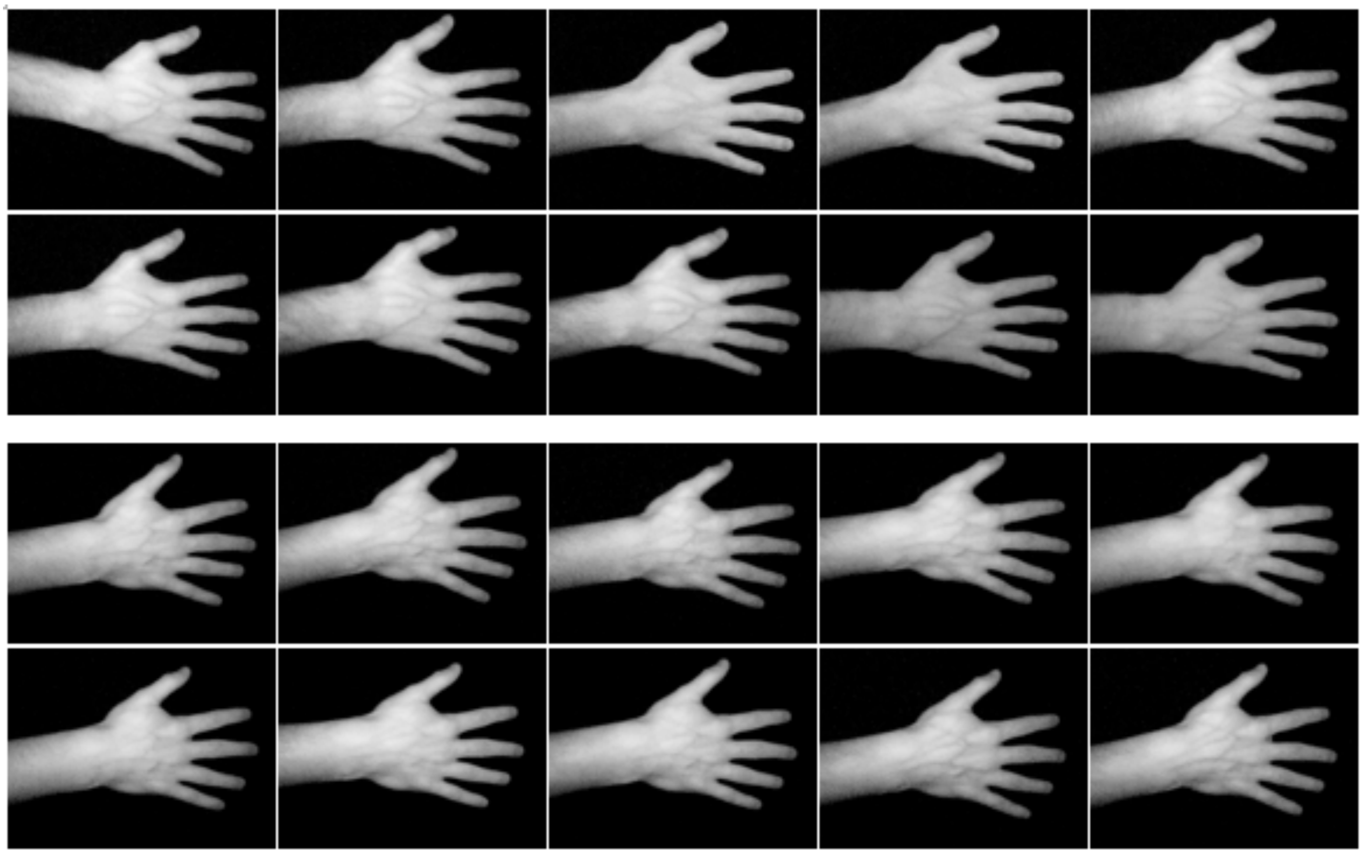


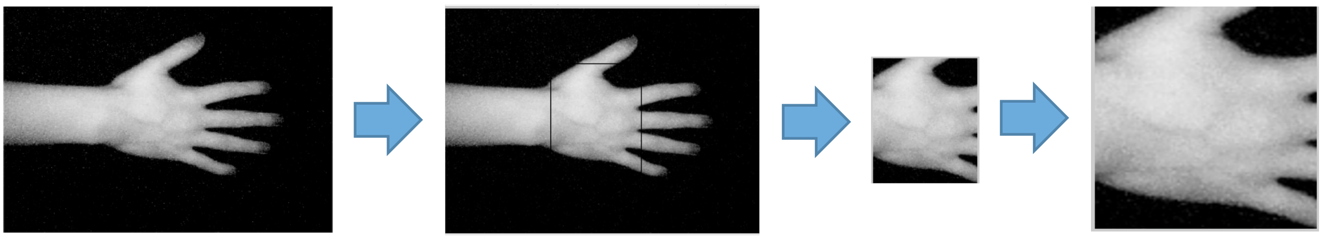
Fig.4. Sample of hand dorsal images from the BDLab Dataset

5.2 ROI feature extraction and CNN classification

To analyze hand dorsal vein recognition system, we need to first perform preprocessing step, then allocate the region of interest (ROI) feature extraction technique, and finally apply the CNN as a classification method to recognize the vein pattern on samples. **Fig.5.** depicts the main GUI design which includes all parts of the proposed method. The GUI contains several information such as the image preprocessing, FCM image segmentation, image feature extraction and image classification.

Fig.5. GUI of application after load Image

Hand image samples will be selected from the dataset through “load image” to operate preprocessing stage. The original image size in the database is 640×480 and after images are cropped, the region hand dorsal image size reduces to 250×250. **Fig.6.** illustrates image preprocess stage results.



Original Raw Image 640×480 | Region of Process | Image crop | Image resize 250×250

Fig. 6. Result of Image preprocessing for Hand Vein

When the images have been preprocessed, next step is to apply median filter to reduce image noise, and the image segmentation which is done by Fuzzy C-means clustering method. Hand dorsal part segmentation is key to enable integrated hand dorsal vein region part for vein recognition. This segmentation task will pose challenges by the fact that the hand dorsal vein region may overlaps with the cropped section. Fuzzy C-means clustering methods brings better segmentation results and improved feature extraction accuracy. **Fig. 7.** Demonstrates the procedure of segmentation with two cluster.

Median Filtering | FCM Segmentation | FCM Segmentation

Fig. 7. Result of Fuzzy C-means clustering methods represent on Hand Dorsal site

Hand dorsal vein feature extraction model follows the hand vein template (Ricardo, Neves, and Correia 2010), which will be used for classification stage, however in this study we used the convolutional neural network for classification step. Feature extraction stage has been developed using the Region of Interest (ROI) method. In this study, we have used crow search algorithm (Askarzadeh 2016) to select vein extraction area, and extracted vein from the hand dorsal site with maximum curvatures method (Miura, Nagasaka, and Miyatake 2007), which try to extract the center lines of the veins on the dorsal hand. **Fig. 8.** shows results from vein features extraction of the hand dorsal images.

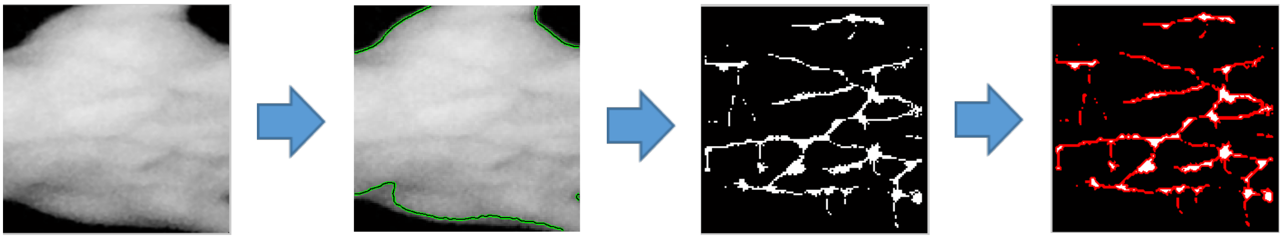


Fig. 8. Result of Region of Interest (ROI) Feature Extraction methods represent on Hand Dorsal site

Experimental result for hand vein recognition with CNN classification method is shown in **Fig. 9.**

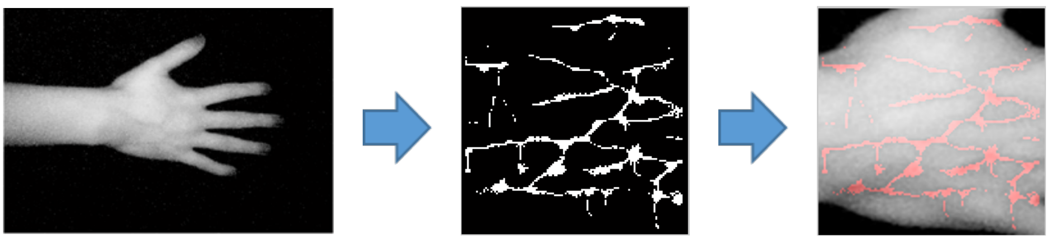


Fig. 9. CNN classification Hand Vein on Hand Dorsal site

Table 1. compares the accuracy and the time of CNN method in terms of epoch number, which clearly shows that epoch 4 outperforms in both accuracy and time measures; in our CNN design, the accuracy for epochs 4 is 94.5%.

Epochs	**Time (second)**	**Accuracy (%)**
1	17.6245	91.5
2	17.2147	90.5

3	16.8478	93.5
4	**16.8844**	**94.5**
5	17.0674	92.5
6	16.9596	91.5
7	16.9035	90.5
8	17.0705	90.5
9	17.0997	92.5
10	17.3611	90.5

Table 1. The accuracy result of epochs changes 1-10

5.3 PCA, SVM and CNN

Table 2. shows average results of expression recognition rates include PCA+MDC and PCA+SVM methods in this article compared under the same condition.

Recognition Methods	**Accuracy (%)**
PCA+MDC	87.8
PCA+SVM	90.0

Fig. 10. shows the performance of vein pattern recognition of CNN with PCA and SVM. It shows the experimental results of CNN outperformed the PCA with the accuracy 94.5%.

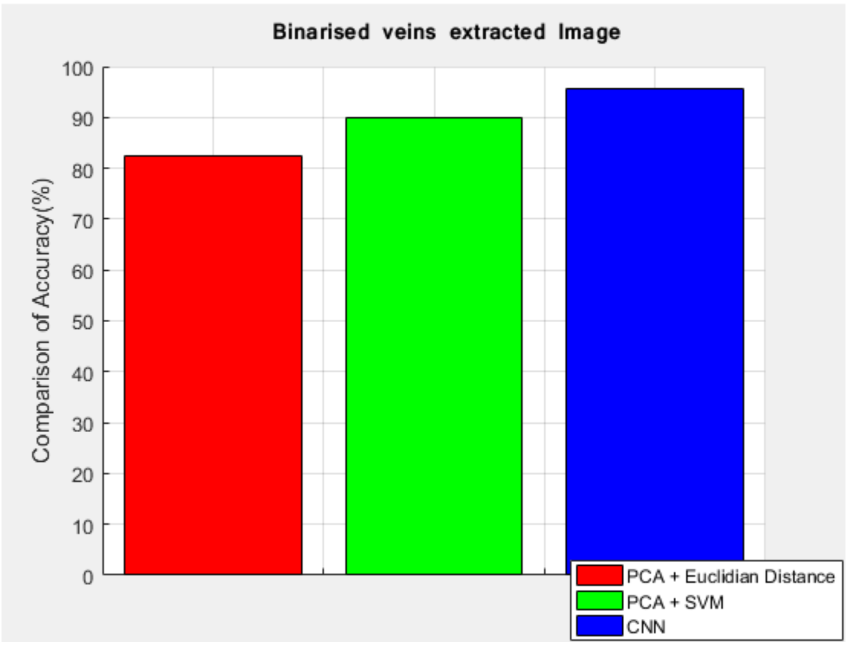


Fig. 10. Comparison of hand dorsal vein recognition performance of CNN with PCA and SVM

6 Conclusion

In this article we reported a successful application of deep learning to vein recognition in deferent temperature conduction, especially to hand dorsal side vein pattern recognition. We promoted a specifically module in a state of the art processing pipeline with a convolutional neural network. Also we proposed dorsal hand vein recognition used based on PCA, MDC and SVM methods. PCA is used for vein feature extraction and dimensional reduction. In the experimental result section, we obtained the best accuracy using a standard parameters present in the CNN model. In the propose method, it is not necessary to handcraft a specific feature extraction method. We also showed that accuracy monotonically improved than other methods on same dataset. In the future work, we will focus on hand dorsal site vein recognition for person identification.

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