ISSN: 2633-4828 Vol. 6 No.1, January, 2024

International Journal of Applied Engineering and Technology

Extreme Learning Machine and Fast Learning Machine based Finger Vein Classification

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Date of Submission: 15th November 2023 Revised: 27th December 2023 Accepted: 17th January 2024

How to Cite: **Ahmed Kawther Hussein (2024), Extreme Learning Machine and Fast Learning Machine based Finger Vein Classification. International Journal of Applied Engineering & Technology, 6(1), pp.26-30.**

***Abstract*--** **Biometrics-based identification is becoming more attractive than other technologies of identification. Among them, finger vein approaches are receiving an increasing interest due to many factors. The accuracy of classification is based on finger vein detection, feature extraction with classifier kind. In this article, the comparison between two types of classifiers extreme learning machine ELM and fast learning network FLN using different types of finger vein detection methods. We use a histogram of the gradient for feature extraction. Results, show the best-achieved accuracy was for FLN with MC detection method with an accuracy of 68% while the best-achieved accuracy of ELM was 67%.**

***Keywords*--** **pattern recognition, finger vein, identification, ELM, FLN**

INTRODUCTION

Biometrics is a technology for human identification using physiological and/or behavioral measures with meeting various conditions such as universality, distinctiveness, permanence, collectability, acceptability, circumvention, and performance (Liu et al., 2017). Various technologies were used for biometrics identifications such as ear (Dalal et al., 2005), iris, palm print (Rida et al., 2018),gait (Gadaleta et al., 2018), face(Hu et al., 2018), voice(Boles et al., 2017), ….etc.

Finger vein recognition is gaining increasing interest among researchers due to various reasons; most importantly, it is non-invasive identification technology without any concern about privacy part, also, it has a discriminative power if researchers were able to resolve its challenges. Some of the challenges are poor quality of image due to pose, deformation, change in illumination, non-completeness …etc.(Liu et al., 2016).

The idea of finger vein identification was found by researchers in Hitachi Research Laboratory at the end of the nineties. In some experiments near-infrared (NIR) light is absorbed significantly by hemoglobin transporting carbon dioxide (in veins) was found out by researchers. Furthermore, there is a recognized difference between the absorption of finger veins and the absorption behavior of surrounding tissues.

This enabled registering a patent for the finger-vein reading in 2001 (Anjos et al., 2019) and various commercial devices came out to the market for both finger vein identification and vein other parts of the body. From a technology of manufacturing perspective, there are two types of technology for vein image capturing: the first one is the right reflection method and the second one light-transmitting method. The two technologies are shown in Fig. 1.

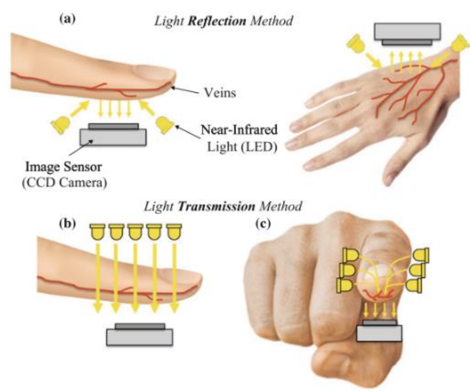

Figure 1.Technology of capturing the image for vein

The remaining of the article is prepared as the following. In section 2 we provide the related work, in section 3 we give the methodology while in section 4 we provide the experimental works and results. Finally, section 5 presents a summary and conclusion.

RELATED WORKS

The literature contains increasing work for tackling the problem of finger vein recognition. From a segmentation and feature perspective, in the work of (Yang et al., 2017) to extract and restore vein features the authors have proposed a deep learning model. the authors have identified two regions: a clear region and an ambiguous region to label the pixels of the clear region as foreground or background and to automatically discard the ambiguous region and.

The clear region has been linked with pixels on which all the segmentation techniques above assign the same segmentation label (either foreground or background), while the ambiguous region is linked to all the residual pixels. A training dataset is constructed based on the patches centered on the labeled pixels. This dataset is used to train a Convolutional Neural Network (CNN) given a patch centered on each pixel of being foreground (i.e. vein pixel) to predict the probability of it. Moreover, to restore missing finger-vein patterns in the segmented image fully Convolutional Network was created. In the work of (Yang et al., 2018), adaptive vector field estimation was used. The approach fits vein curves locally and closely using a set of spatial curve filters (SCFs).then a variable Gaussian model was used for weighting SCFs. Also, to make weighted SCFs adaptive to vein-width variations a curve length field estimation method is proposed. In the work of (Rida et al., 2018), the minutiae-based fingerprint feature set and image-based finger-vein feature set were combined to create a multi-biometric system for fingerprint and finger-vein. a feature-level fusion strategy with three fusion options was developed. the work of (Syarif et al., 2017), a combination between the Enhanced Maximum Curvature method and Histogram of Oriented Gradient descriptor for finger vein verification was used. to extract small vein delineation that is not easily visible in the extracted vein patterns Enhanced Maximum Curvature includes an improvement mechanism. Two benefits are for HOG, the first one is converting a two-dimensional vein image into a one-dimensional feature vector to make easier matching. Second, the Local spatial representation of a finger vein can be characterized in an effective way using the HOG descriptor. Observing the previous works, we see that much work has been done on the part of segmentation and feature extraction while less work was conducted on the part of the classification. In this article, our goal is to compare the performance between two famous classifiers: extreme learning machine ELM and support vector machine SVM based on training on a histogram of gradient HoG after doing one of three-finger vein segmentation approaches maximum curvature MC, wide line detector, and repeated line.

METHODOLOGY

1. Dataset

We build our methodology on The SDUMLA-HMT database (Yin et al., 2019) which includes face images from 7 view angles, 6 fingers of finger vein images, gait videos from 6 view angles, iris images from an iris sensor, and fingerprint images acquired with 5 different sensors. The database consists of real multimodal data from 106 individuals. Our concern is in the finger vein images that are provided. We consider only one of the fingers for experimental work. Figs 2a and 2b provide some pictures from the dataset.

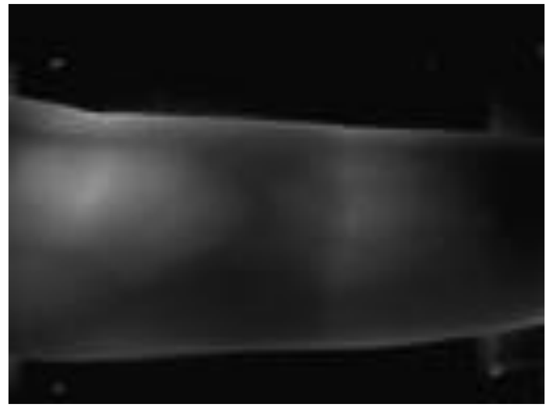

Figure 2a. An index image of the SDUMLA-HMT database

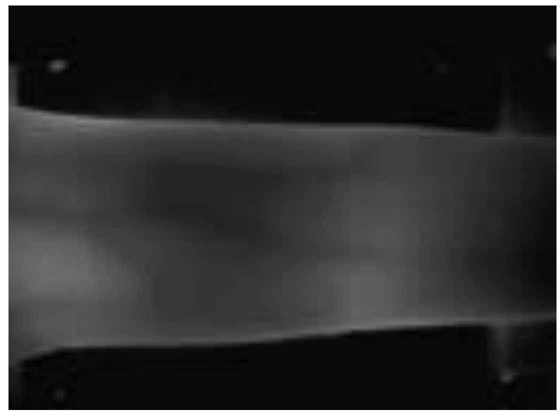

Figure 2b. An index image of the SDUMLA-HMT database

2 Pre-Processing and Region of InterestIdentification

Pre-processing is composed of resizing the image and contrast adjustment. This step is followed by identifying the region of interest identification.

The identification of the region of interest is based on the work of (Lee et al., 2009). Minutia points like bifurcation and the finger vein region ending points for image alignment are used alignment with a simple affine transform, which can be performed at fast. Finally, a unique finger vein code using a local binary pattern is used for extraction.

FINGER VEIN DETECTION

Three approaches are used: repeated line tracking (Miura et al., 2004), wide line detector (Huang et al., 2010), and maximum curvature method (Syarif et al., 2017). The algorithm of maximum curvature consists of three steps: veins extract the center position, connect the center position, and labeling the image. The algorithm of repeated line tracking: 1-Definition of the moving-direction attribute and the start point for line tracking. 2 the movement of the tracking point Detection and the dark line direction. 3-Updating the time's point number in area space has been tracked. 4-Repeated implementation of steps (1 -3) N times. 5 The finger vein pattern gaining from the area space.

To extract all the points on the vein lines in the image here, a Wide line detector is used to extract all the points on the vein lines in the image. Here, F is the finger vein image and V is the feature image. We define the values of pixels in V as the background parts as 0 and the pixels values as parts of the vein region as 255[9]. For each point (x_0, y_0) in F, consider its circular neighborhood region with the radius r:

$$N_{(x_0,y_0)} = \{(x,y) | \sqrt{(x-x_0)^2 + (y-y_0)^2} \le r\} \quad (1)$$

Using the pixels in it, we can calculate:

$$V(x_0,y_0) V(x_0,y_0) = \begin{cases} 0 & m(x_0,y_0) > g \\ 255 & otherwise \end{cases} \quad (2)$$

$$m(x_0,y_0) = \sum_{(x,y)\in N_{(x0,y0)}} s(x,y,x_0,y_0,t) \quad (3)$$

$$s(x,y,x_0,y_0,t) = \begin{cases} 0 & F(x,y) - F(x_0,y_0) > t \\ 1 & otherwise \end{cases} \quad (4)$$

g, r, t are parameters and set to $g = 70, t = 1, r = 7$. Also, Figure -3- helps to explain the equations [9]

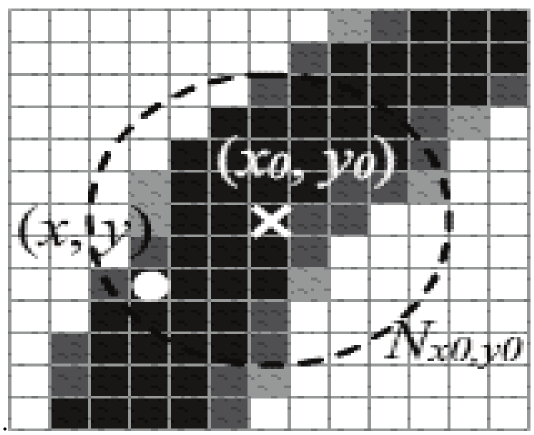

Figure 3. The circular neighborhood region

Feature Extraction

For feature extraction, we use the histogram of the gradient HoG approach [5].

Machine Learning

For the machine learning part, we compare the two famous classifiers extreme learning machine ELM (Huang et al., 2010)and fast learning network(Chow et al., 1999).

Extreme learning machine aims at training single hidden layer feed-forward neural network in three steps:

1. Random initialization of the weights in the input – hidden layer
2. Calculation of the output matrix
3. Calculation of the hidden output weights using Moore-Penrose inverse.

Fast learning neural network is similar in the topology to ELM, the only difference is the connections that exist between the input and output weights in FLN. The pseudocode of our methodology is provided in algorithm1.

ALGORITHM 1: PSEUDOCODE OF COMPARING ELM AND FLN

```
Input
training data
TestingData
Output
Evaluation Results
Start
For each number of hidden neurons
  For each type of activation function
     For each value of seed
            Train ELM
            Train FLN
             Test ELM
            Test FLN
  Add Testing to Evaluation Results
      End
    End
End

End
```

Experimental Works And Results

We compared both ELM and FLN using five types of activation functions: sigmoid, sin, hardlim, tribas, and radbas. Observing Fig. 4a until 4f we see that the performance of both ELM and FLN changes according to the activation function. Sigmoid type of activation function is the best performance among others. Another factor that plays an essential role in the classification result is the type of finger vein detection algorithm. Both MC and WLD have achieved better performance than RL. Also, we observe that changing the random weights in the input hidden layers which are corresponding in the x-axis in the figures does not change a lot in the performance given the activation function and the type of finger vein detection algorithm is the same. Looking at Fig. 5 shows that FLN gives better performance than ELM for most activation functions. The highest achieved accuracy for FLN was 68% when using the MC finger vein detection algorithm while ELM has achieved an accuracy of 67%. The reason is that each classifier is trained only on one feature type. Increasing the accuracy needs an ensemble learning approach.

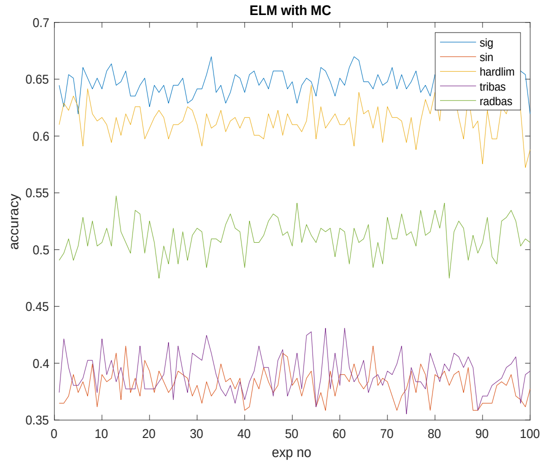

Figure 4a. Accuracy of ELM with MC using different activation functions

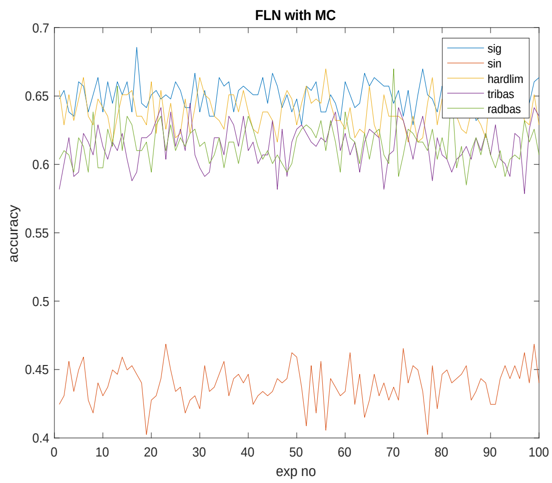

Figure4b. Accuracy of FLN with MC using different activation functions

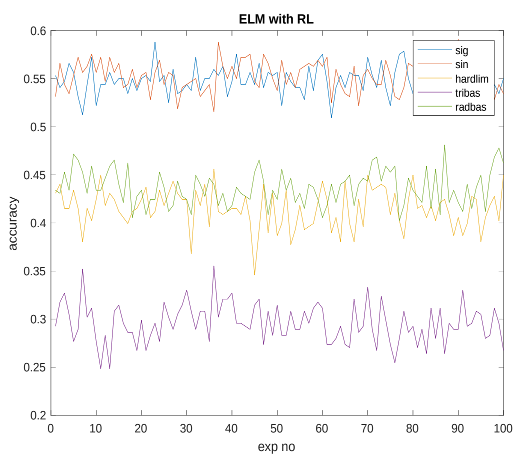

Figure 4c. Accuracy of ELM with RL using different activation functions

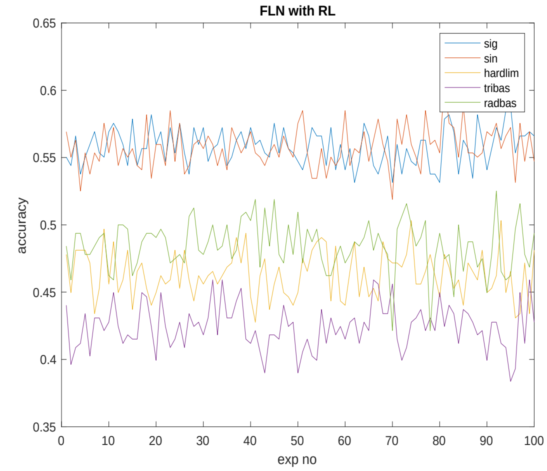

Figure 4d. Accuracy of FLN with RL using different activation functions

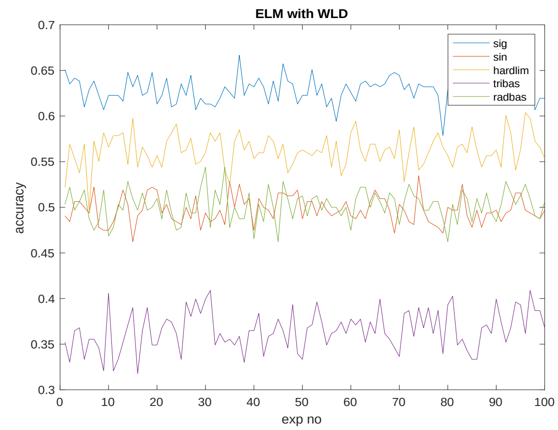

Figure 4e. Accuracy of ELM with WLD using different activation functions

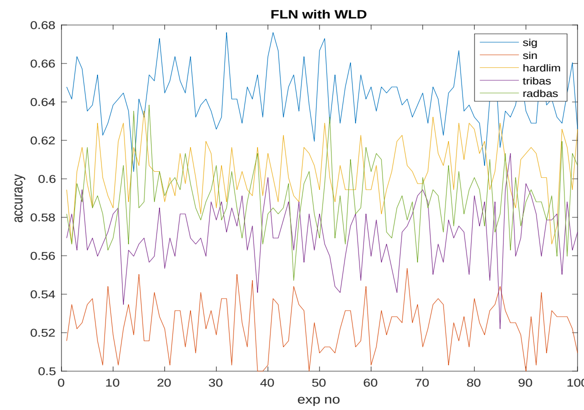

Figure 4f. Accuracy of FLN with WLD using different activation functions

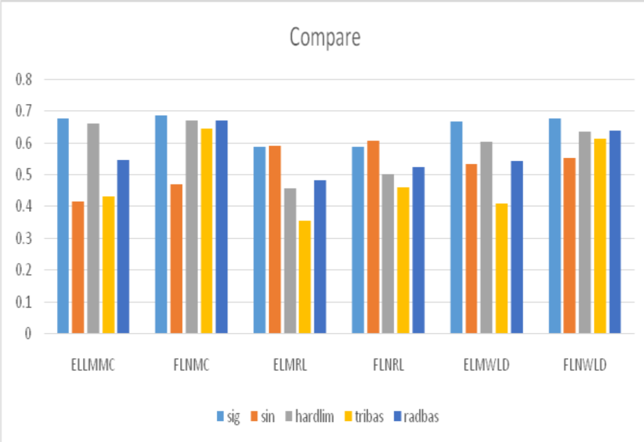

Figure 5. Accuracies of different ELM and FLN models

Conclusion

Finger vein-based identification has an increasing interest comparing with other biometrics identification techniques. The literature contains feature extraction wide range of approaches for finger vein. Nevertheless, the classifiers performance comparison has not received enough work. In this article, we adopt three-finger vein identification approaches MC, WLD, and RL. Besides, HoG feature extraction was used. Also, we compare two types of classifiers: ELM and FLN with different types of activation functions. Results, show the best-achieved accuracy was for FLN with MC detection method with an accuracy of 68% while the best accuracy of ELM was 67%. Future work is to do ensemble learning to combine all ELM and FLN classifiers for better performance.

Acknowledgment

The author would like to thank the Mustansiriyah university (www.uomustansiriyah.edu.iq) Baghdad-Iraq for its support in the present work.

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