Fingerprint Recognition By GWO Optimized ANFIS Classifier

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Abstract: The Automatic Fingerprint Recognition System plays a significant role in forensics and law enforcement applications. The objective of the proposed system in the current study is to identify and separate fingerprint images automatically using a Fuzzy Inference System (FIS) with heuristic algorithm Grey Wolf Optimizer (GWO). We have implemented our work by doing firstly image refinement and segmentation using block based segmentation, second feature extraction to create feature table, third testing and training data using fuzzy logic with GWO and compare our method's performance using ANFIS classifier. The intention of feature selection approach is to select a small subset of features. The features extracted from fingerprint images are second order and third order features such as homogeneity, ridge orientation etc. This work finds finger prints recognition for fingerprint obtained with label or class, so that during testing, error can be minimized. Our proposed method of fingerprint recognition fits good enough when compared to fingerprint using ANFIS classifier only.

Keywords: fingerprint classification, Grey Wolf Optimisation, ANFIS, fuzzy logic

I. INTRODUCTION

In this world as the digitalization is increasing, the need of reliable personal authentication is also increasing and it has become an important human computer interface activity. Passwords or token-based approaches such as swipe cards and passports are knowledge-based approaches upon existing security measures depend. Token cards may be stolen or shared and PIN numbers and passwords may be stolen electronically. So, these approaches are not very secure and have less accuracy. It is also very difficult to find the difference between a person having access to the tokens and authorized user.

1.1 Biometrics

These are more reliable than token or knowledge based authentication methods. Biometrics verifies the identity of an individual through physiological measurements or behavioral traits and these are associated permanently with the user. Biometrics has so many advantages over traditional security approaches. These are:

- 1. Accuracy and Security
- 2. Non-repudiation
- 3. Screening.

The various biometric modalities can be broadly categorized as:

Physical biometrics: This involves some form of physical measurement and includes modalities such as face, fingerprints, irisscans, hand geometry etc.

Behavioral biometrics: It measure a user's way in which he performs certain tasks. These are usually temporal in nature. This includes modalities such as speech, signature, gait, key-stroke dynamics etc.

Chemical biometrics: This is still a nascent field and involves measuring chemical cues such as odour and the chemical composition of human perspiration.

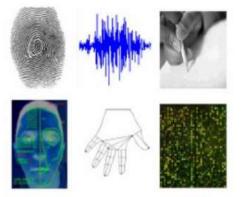


Figure 1.1: Various biometric modalities: Fingerprints, speech, handwriting, face, hand geometry and chemical biometrics

1.1.1 Biometrics and Pattern Recognition:

Biometrics has evolved through interaction of different fields. Fingerprint recognition emerged from the application of pattern recognition. By computer vision community, face detection and recognition was researched. Biometrics is primarily considered as application of pattern recognition techniques. It has so many differences from conventional classification problems as discussed below:

- 1. In biometric recognition, choosing a proper feature representation is the primary task. After choosing the features carefully, the verification process is fairly straightforward but signal and image processing for the features extraction is the main problems in the biometric identification.
- 2. Conventional problems such as optical character recognition (OCR), as compared to the number of samples available for each class, the number of patterns to classify is small. In case of biometric recognition, the number of patterns to classify is as large as the set of users in the database.
- 3. Since biometric templates represent personally identifiable information of individuals, security and privacy of the data is of particular importance unlike other applications of pattern recognition.
- 4. 4. Modalities such as fingerprints, where the template is expressed as an unordered point set (minutiae) do not fall under the category of traditional multi-variate features commonly used in pattern recognition.

1.2 Objective:

Keeping these points in consideration following will be our objectives:

- To study the previous work done on overlapped fingerprint recognition
- improve the accuracy of ANFIS system by use of PSO optimisation algorithm which classifies the overlapped and normal image in the considered database
- To separate the fingerprint using block based segmentation rather than simple morphological methods

II. LITERATURE REVIEW

[1] proposed a very simple algorithm that uses Laplacian of Gaussian (Log) filter, edge filter (Log based) and morphological operations. Block wise computation of mean and variance is not required for this algorithm. In paper [2]proposed various regions of a fingerprint image like high-quality ridge region, low-quality ridge region, unrecoverable ridge region, non-ridge region and remaining ridges where high and low quality ridges are considered as foreground and unrecoverable ridge region is considered as background. In paper [3] designed a segmentation algorithm by computing

local gray mean, variance, gradient and Gabor response with the use of Hidden Markov Model. In paper [4] used energy of Gaussian Hermite moment for fingerprint segmentation. A number of pixel-based segmentation methods have been developed, along with the block based segmentation. A PSO-ANFIS algorithm proposed for wind power prediction of a micro grid farm in china. In this, adaptive Neuro-fuzzy inference system (ANFIS) is based on PSO (particle swarm optimization)[5]. In paper [6] proposed an effective threshold selection method of image segmentation based on particle swarm optimization (PSO), which is embedded into two-dimensional Otsu algorithm. We proposed a Fourier transform [7] and relaxation labeling techniques to separate out the overlapped fingerprints into component or individual fingerprints. In paper [8] transformed the discrete spectrum into the continuous spectrum by proposing a sampling theorem and artificial immune network into the fingerprint image ridge distance estimation method. In paper [9] dealt with extraction of fingerprint features directly from gray scale images by the method of ridge tracing. The proposed method allows using the contextual information to better handle noisy regions. In [10]

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presented a new fingerprint ridge line extraction approach by way of ridge line tracing. In paper [11] proposed an orientationbased ridge descriptor, and uses it for fingerprint image matching. Web Banking or Internet Banking to describe banking transactions through internet application [12]. We used fingerprint databases that are FVC2000 and FVC2002. The FVC2002 database performs better outcomes as compared with FVC2000 database [13]. In paper [14] studied frequency domain methods implemented for gender identity from fingerprints. It showed that DWT is widely used and also in aggregate with SVD and PCA for gender identity from fingerprints. We proposed a unique approach for fingerprint ROI (vicinity of hobby) segmentation using Fourier coefficients computed over non-overlapping photograph segments and used to study a neural community [15]. In [16] recommended robust orientation area estimation algorithm (called the basic set of rules) for overlapped fingerprints. The effectiveness of the proposed technique has been evaluated now not best on simulated overlapping prints, however additionally on real overlapped latent fingerprint photos [17]. In [18] endorsed a hierarchical matching gadget. Level three functions, such as pores and ridge contours, are mechanically extracted the use of Gabor filters and wavelet rework and are domestically matched the usage of the iterative closest factor (ICP) algorithm. We studied the Branchy Net structure that used several well-known networks (Le-Net, Alex-Net, Res-Net) and data-sets (MNIST, CIFAR10) [19]. In fingerprint recognition machine, fingerprint function extraction algorithm requires good satisfactory fingerprint snap shots to supply precise effects [20]. We studied [21] about fingerprint ridge structures encoded in phrases of orientation patch and continuous phase patch dictionaries to enhance the fingerprint reconstruction. In this technique, first the local capabilities are extracted by Speeded-Up Robust Feature (SURF) algorithm. Then the capabilities of the test fingerprint photo are as compared in opposition to two or more exiting template picture capabilities for matching [22]. Researchers have recognized several important demanding situations in latent fingerprint recognition: 1) low information content material; 2) presence of background noise and nonlinear ridge distortion; 3) want for an established scientific procedure for matching latent fingerprints [23]. We proposed palm print matching algorithm has been evaluated on a latent-to-complete palm print database which includes 446 latent and 12,489 heritage complete prints [24]. Restriction of mild nonlinear distortion is likewise considered for this sort of descriptor. To assess the overall performance of the proposed descriptor, it experiments on FVC2000 DB1. A comparison is made among the proposed descriptor and a maximum broadly used minutia descriptor [25].

III. PROPOSED WORK

The objective of the proposed system in the current study is to identify and separate fingerprint images automatically using a Fuzzy Inference System (FIS) with meta-heuristic algorithm Grey Wolf Optimizer (GWO). We have compared our results with ANFIS classifier to check and validate our results. Different categories of features are extracted from the segmented fingerprint images. The features extracted from fingerprint images are real values. Overall working can be divided in following points.

3.1 Pre-processing of Fingerprint Image:

- Input a finger print image
- Conversion to gray scale image
- Binarization
- Histogram base equalization
- Noise removal using median filter
- Segmentation using block based technique

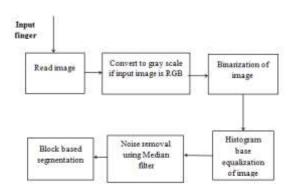


Figure 3.1: Pre-processing steps

3.2 Feature Extraction from fingerprint Image:

There are various features of segmented fingerprint image but to avoid many complexities we have taken essential 5 features for comparison purpose. These features are second order and third order features.

1. *Correlation:* Correlation is a statistics term which is defined as a mutual relationship or connection between two or more things. This technique is a promising approach for fingerprint matching using matching of ridge shapes, breaks etc. General expression for correlation of two images is shown below.

$$Correlation = \sum_{i,j=0}^{N-1} pi_{,j} \left[\frac{i - \mu i(j - \mu j)}{(\sigma i^2)(\sigma j^2)} \right]$$

2. *Energy*: It gives the sum of square elements in GLCM (Gray Level Co-occurrence Matrix) generated in MATLAB. Its range is [0,1]. The equation of energy is

$$energy = \sum_{i=1}^{k} \sum_{j=1}^{k} P^{2}_{ij}$$

3. *Homogeneity*: It gives the value that calculates the tightness of distribution of the elements in the GLCM to the GLCM diagonal. For diagonal GLCM its value is 1 and its range is [0,1]. The equation of homogeneity is

homogeneity =
$$\sum_{i=1}^{k} \sum_{j=1}^{k} P_{ij}$$

3.3 Grey Wolf Optimization (GWO):

In previous chapter working and mathematical models of the social hierarchy, tracking, encircling, and attacking prey in GWO are already provided. GWO is used here to tune the membership functions of Sugeno FIS. GWO can be complex if taken more no. of wolves, iteration or alpha wolves' size. However, we have kept the GWO algorithm as simple as possible with the fewest operators to be adjusted. GWO is meta-heuristic optimization algorithm which is used to minimize a cost function for optimum values which are to be tuned.

3.4 Performance Evaluation Parameters:

In order to evaluate performance of FIS-GWO and ANFIS, we have chosen two performance measures

- 1. Mean square error of trained and tested output
- 2. Accuracy of output w.r.t. testing input labels.

Details of classifiers are out of scope of this study so we put off this segment for reader as self-exploration.

Before applying to ANFIS, we divided our feature data in

- 1. 80:20 ratio and 80% data is used as training data and remaining 20% is used as testing data.
- 2. 70:30 ratio and 70% data is used as training data and remaining 30% is used as testing data.
- 3. 60:40 ratio and 60% data is used as training data and remaining 40% is used as testing data.

Following parameters are used to compare performance of different techniques.

- 1. Accuracy
- 2. Mean Square Error (MSE)

The accuracy of fuzzy inference system is the precision of the fuzzy logic model. It is highly related to the measurement of correct estimation of a fuzzy model for a real system. Commonly, accuracy is evaluated as percentage of correct classifications of a given data set, the mean square error (MSE) is also considered as second important performance evaluation measure. It is for the reason we have taken MSE as our cost function in GWO.

Accuracy% = $\frac{\sum_{j=1}^{N} \delta_{y_j, t_j}}{N} \times 100$

Mean Square Error (MSE)= $\frac{1}{N}\sum_{j=1}^{N}(y_j - t_j)^2$

Where $\delta_{kl} = 1 \text{ or } 0$ according to whether k=l or k \neq l respectively; N is the size of data set, y_j is the system output for *j*th data point, t_i is true, desired output for the *j*th data point.

IV. RESULTS & DISCUSSION

In our work we have proposed fingerprint matching using fuzzy logic which was tuned by meta-heuristic algorithm Grey Wolf Optimization (GWO). The proposed work is implemented in MATLAB R 2016a. Inbuilt functions in MATLAB make the use easier and save our time to build our code from scratch, so we can use that time in problem solution of research.

4.1 Pre-processing of MRI Image:

Fingerprint database is taken from public access data base FVC2002_DB1_B. This is 80 fingerprints database which is of 10 person's fingerprint. Here first we read fingerprint image, second noise is removed using median filter third histogram equilization is done and last finger print is segmented using block based segmentation technique. Image segmentation is the process of dividing an image into several parts. This is used to identify objects or other information in digital images. There are many ways to perform image segmentation.

4.2 Case-1- When training and testing data set are in 80:20 ratio:

The fingerprint data base with 5 features are randomly divided between training testing data set with ratio 80:20 for this training data set. A sugeno type FIS system is created having 5 input as feature of fingerprint and 3 MF of each input. The input MF have the range from 0 to 1 are shown below

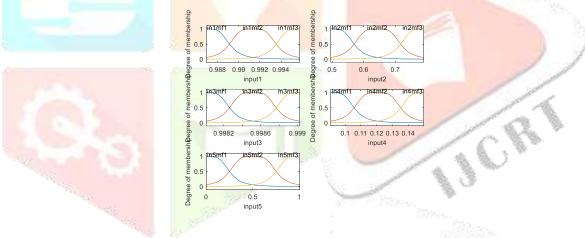


Figure 4.1 Input membership function of FIS

Now, membership function of FIS are tuned using GWO algorithm. The cost function of GWO is MSE between output and input labels which is to be minimized. Output MF are shown below.

Membership function for input and output are shown in figure 4.1 and 4.2. It is observed the change or modified values of membership function.

GWO conversions curve for minimizing cost function is shown below.

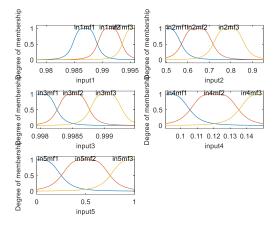


Figure 4.2 Output membership function of FIS.

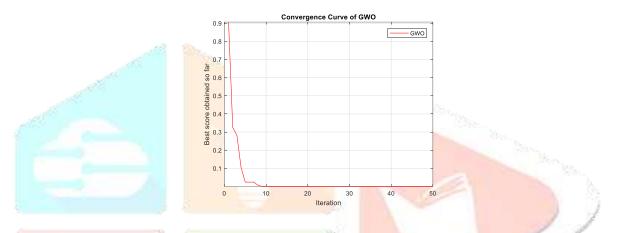


Figure 4.3 Convergence curve of GWO based on cost function

It can be seen that GWO curve converges within 50 iterations to its best value results of tested data using FIS with GWO is shown in figure. We have implemented a bar graph showing the difference between actual labels and predicted labels using FIS with GWO and is shown in figure 4.4

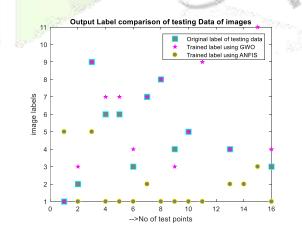


Figure 4.4 FIS using GWO and ANFIS based classified labels

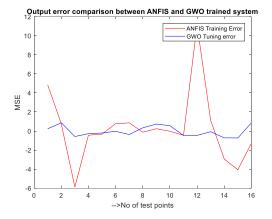
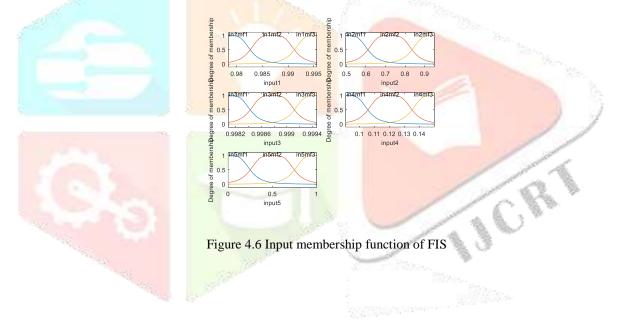


Figure 4.5 MSE Error plot of FIS with using GWO and ANFIS

4.3 Case-2- When training and testing data set are 70:30

The fingerprint data base with 5 features are randomly divided between training testing data set with ratio 70:30 for this training data set. A sugeno type FIS system is created having 5 input as feature of fingerprint and 3 MF of each input. The input MF have the range from 0 to 1 are shown below. Now, membership function of FIS are tuned using GWO algorithm as explained in chapter 5. The cost function of GWO is MSE between output and input labels which is to be minimized. Output MF are shown below.



GWO conversions curve for minimizing cost function is shown below.

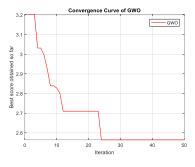


Figure 4.7 Convergence curve of GWO based on cost function

It can be seen that GWO curve converges within 50 iterations to its best value results of tested data using FIS with GWO is shown in figure. We have implemented a bar graph showing the difference between actual labels and predicted labels using FIS with GWO and is shown in figure.

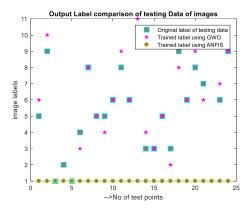


Figure 4.8 FIS using GWO and ANFIS based classified labels

It can be observed from bar graph that label matching using GWO with actual labels is more than that of ANFIS based labels. Now this trained FIS system is tested against a testing data.For the same training data set classification is also done using ANFIS classifiers and FIS classifier with 3 MF"gbellmf" having 243 rules. Training and testing errors using ANFIS are shown in figure

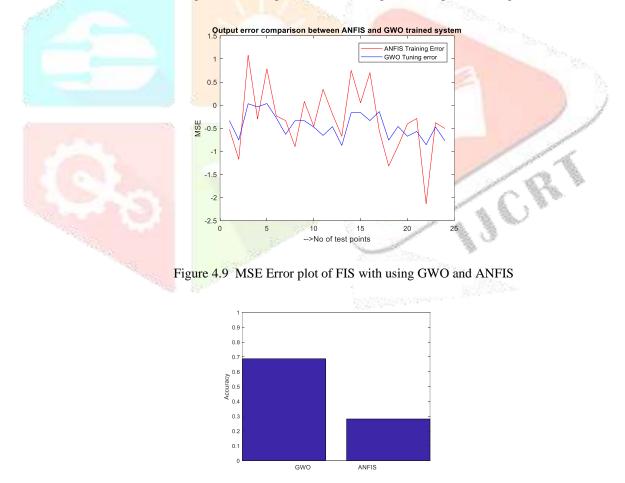


Figure 4.10 Accuracy of proposed GWO and ANFIS based techniques

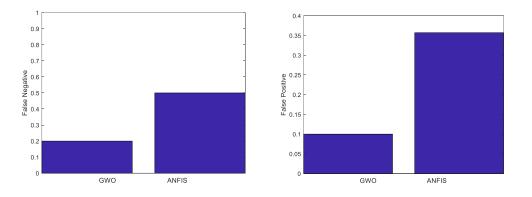


Figure 4.11 False Negative and False positive rates of GWO and ANFIS techniques

It can be seen that the MSE using GWO tuned FIS varies between 0 to 2 whereas, variation of ANFIS based error have large variations.

V. CONCLUSION

Our work presented fingerprint identification and verification based on fingerprint features. The work is done in sequence start from the first stage which is pre-processing which is used to remove unwanted data and increased the clarity of ridges of fingerprint image. The second step is the feature extraction which is used to extract the fingerprint features. The third step of this work is the matching which is divided into two parts identification process one by means of FIS using GWO and another is ANFIS classifier. The experiments are tested on fingerprint databases FVC2002.

The result of proposed work is good comparing with ANFIS based classification. The future work is to do fingerprint identification and verification by using neural network and fuzzy logic in order to enhance and evaluate the best performance of fingerprint recognition system and to create our own database for testing our work on it. The proposed system can yield improved results as compared to the existing methods implemented so far. The Result obtained for proposed system has more accuracy and less MSE error, as compared to existing methods using ANFIS.

VI. REFERENCES

1]. S. Mohammedsayeemuddin, P. V. Pithadia and D. Vandra, "A simple and novel fingerprint image segmentation algorithm," 2014 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), Ghaziabad, 2014, pp. 756-759.

2]. Kawagoe, M., Tojo, A, "Fingerprint pattern classification Pattern Recognition", 17(3), 295-303 (1984).

3]. Klein, S. Bazen, A. Veldhuis, "Fingerprint image segmentation based on hidden markov models", In 13th Annual Workshop on Circuits, Systems, and Signal Processing, pp. 310–318 (2002).

4]. Wang, L.; Dai, M.; Geng, G.H.: Fingerprint image segmentation by energy of Gaussian hermite moments. In: Li, S.Z.E.A. (ed.) Sino biometrics, Lecture Notes in Computer Science, vol. 3338, pp. 414–423. Springer, Berlin Heidelberg (2004).

5]. H. Li, A. T. Eseye, J. Zhang and D. Zheng, "A Double-Stage Hierarchical Hybrid PSO-ANFIS Model for Short-Term Wind Power Forecasting," 2017 Ninth Annual IEEE Green Technologies Conference (GreenTech), Denver, CO, 2017, pp. 342-349.

6]. K. Wei, T. Zhang, X. Shen and J. Liu, "An Improved Threshold Selection Algorithm Based on Particle Swarm Optimization for Image Segmentation," *Third International Conference on Natural Computation (ICNC 2007)*, Haikou, 2007, pp. 591-594.

7]. F. Chen, J. Feng and J. Zhou, "On separating overlapped fingerprints," 2010 Fourth IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS), Washington, DC, 2010, pp. 1-6.

8]. Xiaosi Zhan, Yilong Yin, Zhaocai Sun and Yun Chen, "A method based on continuous spectrum analysis and artificial immune network optimization algorithm for fingerprint image ridge distance estimation," *The Fifth International Conference on Computer and Information Technology (CIT'05)*, 2005, pp. 728-733.

9]. D. Arpit and A. Namboodiri, "Fingerprint feature extraction from gray scale images by ridge tracing," 2011 International Joint Conference on Biometrics (IJCB), Washington, DC, 2011, pp. 1-8.

10]. R. Ma, Yaxuan Qi, Changshui Zhang and Jiaxin Wang, "A novel approach to fingerprint ridge line extraction," *IEEE International Symposium on Communications and Information Technology*, 2005. ISCIT 2005, 2005, pp. 2-5.

11]. Hui Chen, Jianping Yin, Xin Shu, Chunfeng Hu and Yong Li, "An orientation-based ridge descriptor for fingerprint image matching," 2010 International Conference OnComputer Design and Applications, Qinhuangdao, 2010, pp. V1-288-V1-292.

12]. R. Priya, V. Tamilselvi and G. P. Rameshkumar, "A novel algorithm for secure Internet Banking with finger print recognition," 2014 International Conference on Embedded Systems (ICES), Coimbatore, 2014, pp. 104-109.

13]. M. M. H. Ali, V. H. Mahale, P. Yannawar and A. T. Gaikwad, "Fingerprint Recognition for Person Identification and Verification Based on Minutiae Matching," 2016 IEEE 6th International Conference on Advanced Computing (IACC), Bhimavaram, 2016, pp. 332-339.

14]. S. R. Shinde and S. D. Thepade, "Gender classification with KNN by extraction of Haar wavelet features from canny shape fingerprints," 2015 International Conference on Information Processing (ICIP), Pune, 2015, pp. 702-707.

15]. B. Stojanović, A. Nešković and O. Marques, "Fingerprint ROI segmentation using fourier coefficients and neural networks," 2015 23rd Telecommunications Forum Telfor (TELFOR), Belgrade, 2015, pp. 484-487.

16]. F. Chen, J. Feng, A. K. Jain, J. Zhou and J. Zhang, "Separating Overlapped Fingerprints," in *IEEE Transactions on Information Forensics and Security*, vol. 6, no. 2, pp. 346-359, June 2011.

17]. Q. Zhao and A. K. Jain, "Model Based Separation of Overlapping Latent Fingerprints," in *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 3, pp. 904-918, June 2012.

18]. J. Feng, Y. Shi and J. Zhou, "Robust and Efficient Algorithms for Separating Latent Overlapped Fingerprints," in *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 5, pp. 1498-1510, Oct. 2012.

19]. Q. Zhao and A. K. Jain, "Model Based Separation of Overlapping Latent Fingerprints," in *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 3, pp. 904-918, June 2012.

20]. M. F. Hassanin, A. M. Shoeb and A. E. Hassanien, "Grey wolf optimizer-based back-propagation neural network algorithm," 2016 12th International Computer Engineering Conference (ICENCO), Cairo, 2016, pp. 213-218.

21]. S. Teerapittayanon, B. McDanel and H. T. Kung, "BranchyNet: Fast inference via early exiting from deep neural networks," 2016 23rd International Conference on Pattern Recognition (ICPR), Cancun, 2016, pp. 2464-2469.

22]. S. A. Sudiro, M. Paindavoine and T. M. Kusuma, "Image enhancement in simple fingerprint minutiae extraction algorithm using crossing number on valley structure," 2007 International Conference on Intelligent and Advanced Systems, Kuala Lumpur, 2007, pp. 655-659.

23]. U. Hany and L. Akter, "Speeded-Up Robust Feature extraction and matching for fingerprint recognition," 2015 International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, 2015, pp. 1-7.

24]. A. Sankaran, M. Vatsa and R. Singh, "Latent Fingerprint Matching: A Survey," in *IEEE Access*, vol. 2, no. , pp. 982-1004, 2014.

25]. L. Haloui, N. Dad, N. En-Nahnahi, S. E. Ouatik and M. Oumsis, "Improvement of fingerprint matching by describing the minutiae neighborhood using a set of Quaternion Disc-Harmonic Moments," 2014 IEEE/ACS 11th International Conference on Computer Systems and Applications (AICCSA), Doha, 2014, pp. 273-279.