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Finger Knuckle Print based Biometric System Creation using Dual Clustering with Radial Basis-Manhattan Length Approach

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Abstract: Authentication is important factor in most of the application to perform the verification process. There are several factors are used to verify the personal identifies but biometric characteristics are most important one because everyone are having specific biometric features. Due to the easy access, minimum cost, stable features are leads to chose the finger knuckle print for authentication purpose. Initially, finger knuckle print images are collected from people which are processed by applying mean filter. Then the finger knuckle region is located by applying the optimized dual clustering approach. Then the various features are extracted which are trained with the help of the sigmoid activation function with radial neural network. Finally, the extracted features are matched with the trained feature using Manhattan length. This described matching process helps to authenticate the users. At last efficiency of the system is evaluated using MATLAB based experimental results such as false acceptance rate, equal error rate and false rejection rate.
Keywords: Authentication, biometric characteristics, finger knuckle print, sigmoid activation function with radial neural network, Manhattan length

I. INTRODUCTION

Now-a-days most of the applications utilizes the authentication system [1] for managing the user information and providing security to their details. For maintaining security, biometric systems are played a vital role because it effectively authenticates the person information and granted the access permission. The biometric system [2] utilizes the user traits, characteristics and identities for analyzing the authorized user in the application. There are several traits such as signature, DAN, palm veins, face, foot print, retina, hand print, hand geometry, dorsal vein, voice, rhythm, gait and finger knuckle print [3] are used to maintain the user information.

With the help of these biometric features different applications such as hospital systems, educational institutions, sports management system, bank management systems are creating the secure system. Among the different biometric features, in finger knuckle biometric features having specific in texture information, contact less, stable one, easy to capture and easy to acceptance. Due to this specific characteristic most of the application uses the finger knuckle print [4] for biometric authentication system. In addition to this, the finger knuckle print biometric features have varied from one person to other person in terms of both key point and connectivity between the key points. So, the finger knuckle print feature ensures almost maximum security to user details in the application. According to the discussion, the general representation of finger knuckle print figure is depicted in figure 1.
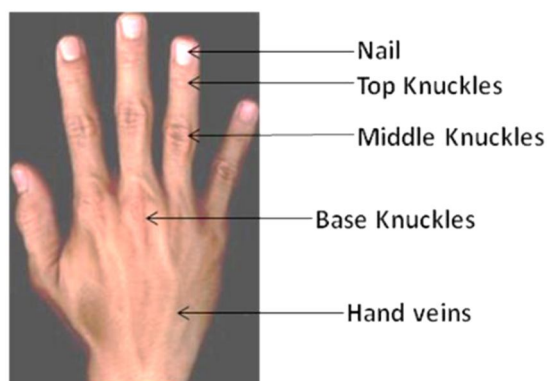

Fig. 1 Sample image for finger Knuckle Print Biometric Feature

Figure 1 demonstrated that the sample image for finger knuckle print biometric feature [5]. The images consist of several knuckles such as top, middle and base knuckle. Each knuckle having the different key points which are different from person to person. So, as discussed earlier, the finger knuckle print ensures the maximum security to the data. This captured biometric images are processed by applying different image processing [6] and machine learning techniques. The techniques are extract the meaningful information which are used to match the test biometric feature with trained biometric feature. According to the discussion, the captured finger knuckle print images are processed by different researcher to provide the security to data. Here, few research author opinions are analyzed to get idea about finger knuckle print biometric system.

(Xiong M., Yang W., Sun C. (2011))[7] creating effective finger knuckler print biometric authentication system using local Gabor binary pattern approach. The captured images are processed by applying the binary pattern approach which successfully recognize the finger print images and matching the testing features with training features. This knuckle print based recognition process ensures the authentication when compared to other methods. (Attia, A et al., 2018) [8] developing person recognition system in bank using finger knuckle pattern and multi scale binarized statistical texture features. Initially, finger knuckle print images are captured from person which are processed by region of interest approach which extract the knuckle region. Then the binarized statistical image features are derived from knuckle region which are trained with the help of convolution filters. The continuous learning process improves the overall person identification rate. In addition to this, principle component analysis with linear discriminate analysis technique to minimize the dimensionality of features. Finally, the persons are identified with the help of nearest neighbor with Mahalanobis distance measure. Then the created system efficiency is evaluated using Poly finger knuckle print database and the developed system ensure the maximum recognition accuracy.

(Bahmed F., et al., 2019) [9] analyzing different multi-biometric hand recognition system for improving security in airports as well as companies. This work survey different biometric features among that fingerprint features are having unique characteristics which helps to create the effective biometric modalities.

The created hand biometric modalities system ensures the maximum authentication results compared to other biometric features. Hossain E., Chetty G. (2013) [10] developing the human identification system using the multi-model feature learning along with gait biometric features. Initially, the gait features are collected from CASI Multiview multispectral and UCMG Multiview database. The collected biometric features are processed and different statistical features are derived using principle component analysis and linear discriminate analysis approach.

Then the extracted features are trained by applying the deep learning process that successfully train the features to performing the person identification process. Finally, the identification process is done by applying different techniques such support vector machine, multilayer perceptron and neural network techniques. Thus, the introduced system successfully recognizes the person due to the deep learning-based feature training process. According to the various author's opinion, the effective biometric system needs to be created to minimize the unauthorized access. For ensuring this objective, in this work, intelligent neural network approach is introduced to process every step involved in the biometric authentications system.

Then the rest of the section is arranged as follows, section 2 discusses about the introduced intelligent neural network based biometric authentication system. Section 3 analyze the efficiency of introduced biometric authentications system and conclusion is discussed in section 4.

II. FINGER KNUCKLE PRINT BIOMETRIC AUTHENTICATION SYSTEM

The finger knuckle print biometric authentication [11]system is created using intelligent neural network. The developed system effectively analyzes each user traits to providing the authorization for accessing the information or application. As discussed above, the finger knuckle print having effective characteristics, fine texture and other reasons are main intension to this biometric feature for providing authentication. During the biometric authentication polyU knuckle print image set is used for evaluating the created system efficiency.

According to the discussion, the general processing step for knuckle print biometric authentication system structure is depicted in figure 2.

The above figure 2 illustrated that the finger knuckle prints biometric authentication system structure. The biometric system consists of several steps such as image collection, noise removal, knuckle region extraction, feature extraction and feature matching process. These steps are effectively analyzing the captured knuckle print image and recognize the authorized users successfully. The detailed explanation of the processing procedures is discussed as follows.
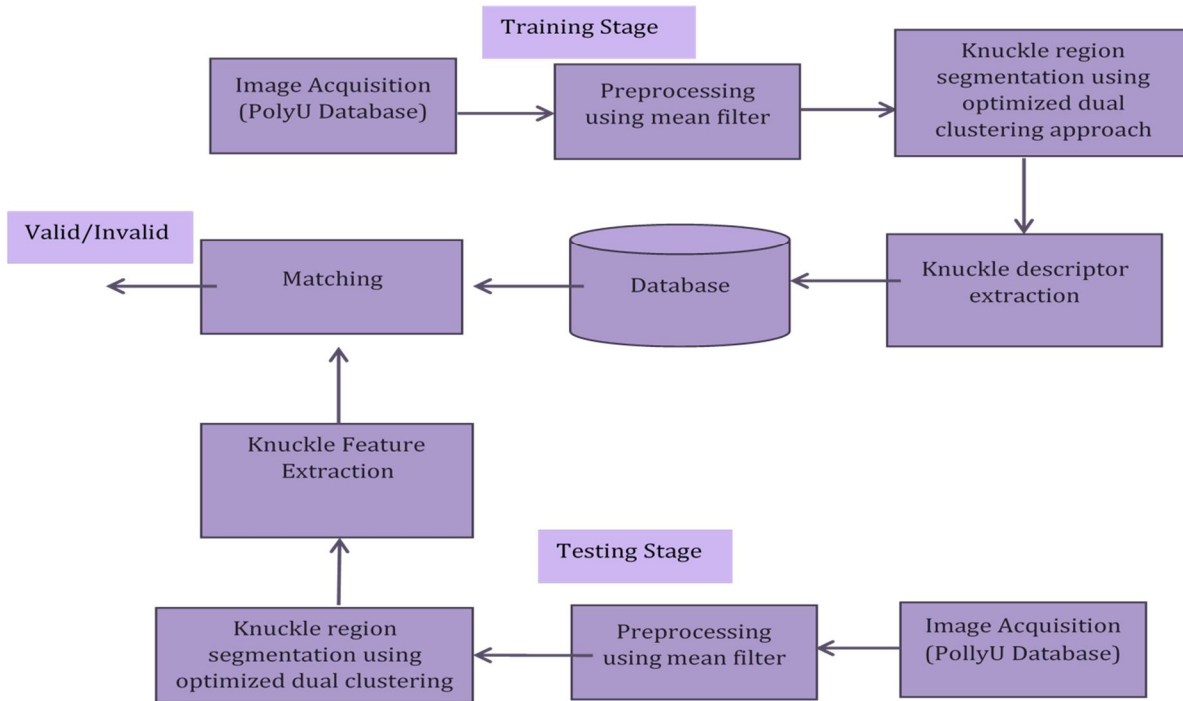
Fig. 2 Finger Knuckle print Biometric Authentication System Structure

A. Image Nose Removal

Initially, the finger knuckle print images are collected from Poly image dataset [12]. The collected images are having several unwanted pixel information due to the low resolution, image shake, name and low capturing process. These unwanted information damage the entire biometric system efficiency. So, the noise present in the knuckle print image is eliminated by applying the mean filter [13]. The captured image pixels are analyzed and compared with the threshold value which is determined according to the pixel range. If the pixel range is deviated from the threshold values, that should be replaced with the help of mean value. The mean value is estimated by considering the neigh boring pixel details. This process is continued to entire image pixel for replacing the unwanted or inconsistent image pixels. Based on the discussion, the noise removed finger knuckle print images are shown in figure 3.
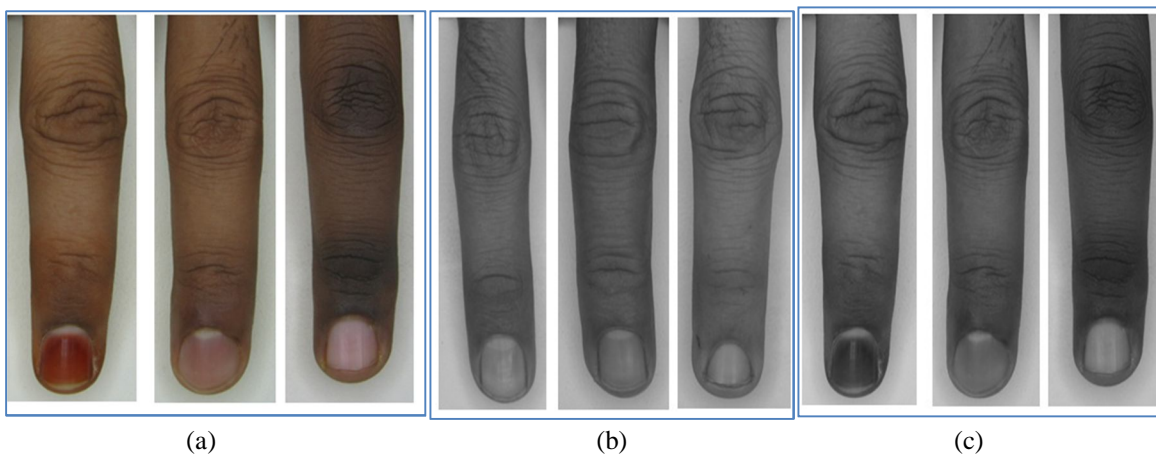

Fig. 3 (a) PolyU data base image   (b) grayscale converted image   (c) noise removed image

After eliminating the noise present in the image, knuckle region must be identified because it played a vital role in person authentication.

B. Knuckle Region Segmentation

The second step of the work is to segmenting the knuckle region from the noise removed finger knuckle print biometric features. In this work dual clustering approach [14] is used for segmenting the knuckle regions. The introduced method works according to 3 characteristics which helps to improve the overall region identification process. Initially, image histograms are identified using the probability density and cumulative density value.

Based on the histogram value, images are divided into different clusters. The formed clusters having the high gradient value of borders that helps to identify the exact knuckle region.

This cluster formation consists of two spaces, the first space uses the one-dimensional histogram value for representing the image brightness level H=HB). Next space uses the dual three-dimensional space which denote the original finger knuckle print image that is represented as B=B(x,y).

The one-dimensional space is analyze the images according to the image brightness value and how effectively the brightness of the image is distributed are analyzed which is done by using the minimal clustering process (Kmin). After that the threshold brightness (T) value related minimal cluster values is identified which is represented as the binary image (black-white image). Generally, the formed cluster bitmap is represented as,

$$b = \varphi(x, y) \tag{1}$$

$$\begin{cases} \varphi(x, y) = 0 & if \ B(x, y) < T \\ \varphi(x, y) = 1 & if \ B(x, y) \geq T \end{cases} \tag{2}$$

From the computed cluster, bitmap b is represented as the object in dual space. The estimated bitmap value helps to identify the distribution of black or white pixels in image.

The main intension of the bitmap process is used to predict the exact and good border for knuckle region. So, the entire image threshold value T, the dual clustering process for image is computed using eqn (3).

$$M_{DC} = \frac{G}{(k*L)} \tag{3}$$

In eqn (3), k represented as the brightness difference between background and object,

L is border length.

G is border mean gradient value. MDC is represented as the maximum of clustered region.

Based on the above dual clustering analysis, knuckle region along with borders are identified effectively. Based on the discussion, the sample segmented knuckle region is represented in figure 4.
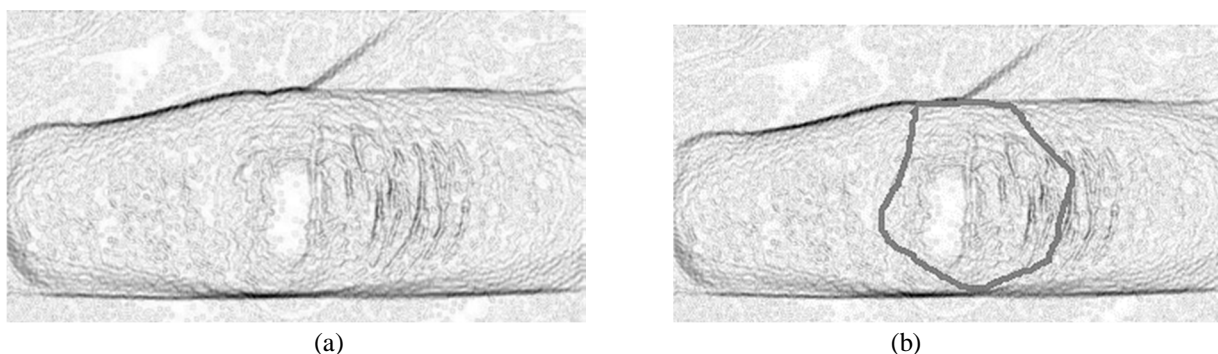

(a)   (b)

Fig. 4 Sample Knuckle region segmented image

C. Finger Knuckle Region – Feature Extraction

Third step of the work is to deriving the meaningful features from the extracted knuckle region. Here different statistical features [15] are derived to understand the characteristics of knuckle segmented region. The list of extracted knuckle features is listed in table 1.

TABLE I

Knuckle Region-Extracted Features List

Features	Related Formula
Entropy	$\sum_{i,j=0}^{n-1} - \ln(P_{ij}) P_{ij}$
Correlation	$\sum_{i,j=0}^{n-1} P_{ij} \dfrac{(i-\mu)(j-\mu)}{\sigma^2}$
Energy	$\sum_{i,j=0}^{n-1} (P_{ij})^2$
Contrast	$\sum_{i,j=0}^{n-1} P_{ij}(i-j)^2$
Cluster Shade	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i+j-\mu_x-\mu_y)^3 . p(i,j)$
Variance	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i-\mu)^2 . p(i,j)$
Mean	$\sum_{i=0}^{2(n-1)} i . p_{x+y}(i)$
Cluster Prominence	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i+j-\mu_x-\mu_y)^4 . p(i,j)$
Inertia	$\sum_{i,j=0}^{n-1} (i-j)^2 . p(i,j)$
Skewness	$\sigma^{-3} \sum_{i=0}^{n-1} (i-\mu)^3 . p(i)$
Kurtosis	$\sigma^{-4} \sum_{i=0}^{n-1} ((i-\mu)^4 . p(i)) - 3$

Based on the table I, different statistical features are extracted from knuckle region which are more helpful to authenticate the user information. The extracted features are trained and stored in the database for making the matching process.

D. Feature Training and Matching Process

Fourth step of the work is to performing the feature training or learning process because it provides the proper guidelines while matching the testing and training process. In this work, sigmoid activation function with radial neural network is used to feature training purpose. Radial basis neural network [16] is one of the effective supervised artificial networks which process the non-linear inputs and produces the output in terms of linear form. It is one of the fastest learning algorithms and produces the output using three layers such as input, hidden and output layer. The section 2.3 extracted features are taken as non-linear inputs and transferred into the hidden layer. In hidden layer radial basis (radbas) activation function is used to process the consumed input. During the computation process, number of hidden layers are chosen according to the number of neurons involved in the input layer. These hidden layers are successfully analyze the input features using radbas function to get the output in the hidden layer. Then the graphical representation of radbas activation function is represented in figure 5.
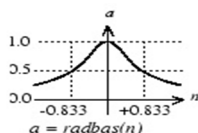

Fig. 5 Radial basic activation function representation

In addition to this activation function, center and spread factors are utilized in the feature training process to improve the overall matching process. The centers are determined according to the k-means clustering process which is computed using eqn (4).

$$argmin \sum_{i=1}^{k} \sum_{x \in s_i} \|x - \mu_i\|^2 \qquad (4)$$

In eqn (4)μ_i is the mean at the center point s_i. According to the center value, the incoming features are trained using the radbas activation function. Further the exact output for input is determined by applying the sigmoid activation function. Then the output value of input is estimated using eqn (5).

$$s(x) = \frac{1}{1+e^{-x}} \qquad (5)$$

In eqn (5) x is the input to the network. According to the computation, the output value is estimated for each input and stored as template in the database. Finally, the matching process is performed to maintain the authentication. When the new person enters the system, their finger knuckle print images are collected processed according to section 2.1 to 2.3. The extracted features are matched with the template features which is done by applying the Manhattan lengthmeasure[17]. This distance measure also called as the taxicab geometry that usually predict the distance between the template and testing features. The distance computation is done by using eqn (6).

$$d_1(p, q) = \|p - q\|_1 = \sum_{i=1}^{n} |p_i - q_i| \qquad (6)$$

In eqn (6) p and q is represented as the training and testing features in the list. Based on the computation, the minimum distance between the features are selected as the valid features else the users are restricted to entered the system. Then the overall efficiency of the introduced system is evaluated using experimental results and discussion.

III. RESULTS AND DISCUSSIONS

The efficiency of introduced finger knuckle print biometric authentication system (DCRBML) efficiency is evaluated in this section. As mentioned earlier, in this work, polyU finger knuckle print image dataset is used for analyzing efficiency of biometric system. The dataset consists of around 7920 images that was captured from 125 male and 40 females. Here the sample polyU dataset images are depicted in figure 6.
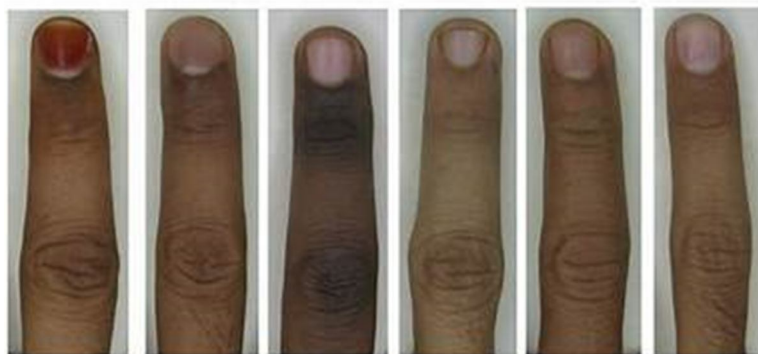

Fig. 6 Sample PolyU FKP-images

The gathered FKP images are processed according to the section 2.1 to 2.4 discussion and the matching process is done by using the Manhattan length measure. This discussed process is developed using MATLAB tool and the excellence of the system is evaluated using different metrics such as false acceptance rate, equal error rate, accuracy and false rejection rate. False acceptance rate is nothing but how effectively developed system reject the false person biometric features. The eqn (7) used to compute the false acceptance rate.

$$FAR = \frac{Number\ of\ features\ accepted}{Number\ of\ features\ tested} * 100 \qquad (7)$$

According to eqn (7) computation, the estimated FAR value related graphical analysis is shown in figure 7.

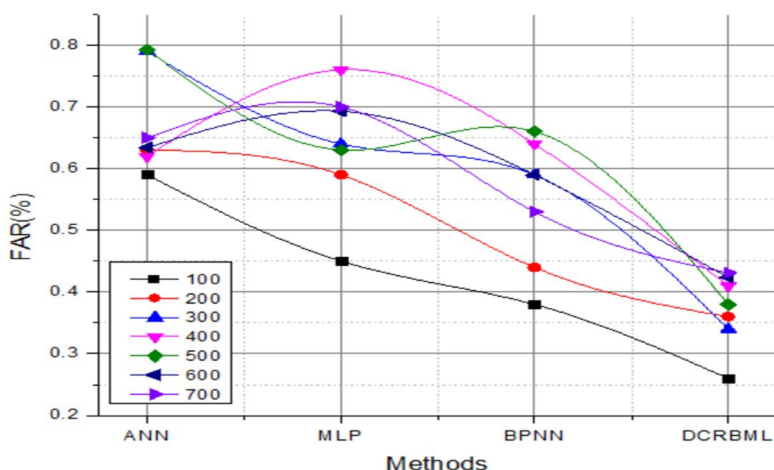Fig. 7 False Aceptance Rate - DCRBML

The figure 7 clearly illustrate that the dual clustering with radial basis-Manhattan lengthapproach (DCRBML) attains low false acceptance rate. The obtained results are low compared to other recognition method such as Artificial Neural Network (ANN)[18], Multi-layer Neural Network (MLP) [19] andBack propagation Neural Network (BPNN) [20]. The successful detection of knuckle region, borders accept the false features with minimum rate (0.312%) compared to other approaches such as ANN(0.64%), MLP(0.53%) and BPNN (0.48%). Along with the FAR value, false rejection rate of introduced system must be computed. Rejected rate nothing but how effectively introduced system reject the right feature when access the system. The rejection rate is computed using eqn (8).

$$FRR = \frac{Number\ of\ original\ features\ rejected}{Number\ of\ original\ features\ tested} * 100 \qquad (8)$$

Depending to the eqn (8) computation, the estimated false rejection rate related graphical analysis shown in figure 8.
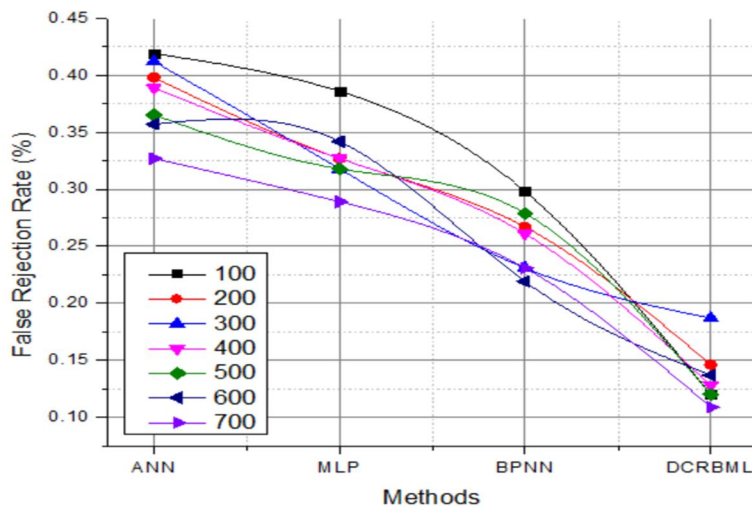

Fig. 8 False Rejection Rate-DCRBML

The figure 8 clearly illustrate that the dual clustering with radial basis-Manhattan lengthapproach (DCRBML) ensures minimum false rejection rate. The obtained results are low compared to other recognition method such as Artificial Neural Network (ANN)[26], Multi-layer Neural Network (MLP) [27] and Back propagation Neural Network (BPNN) [28]. The effective derivation of knuckle region related features are used to reject the right features with minimum rate (0.135%) compared to other approaches such as ANN(0.35%), MLP(0.31%) and BPNN (0.255%). In addition to this FAR, FRR, the system equal error rate must be computed which is depicted in figure 9.
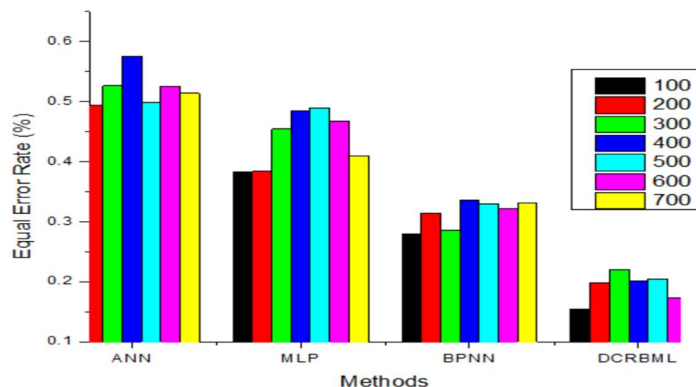
Fig. 9 Equal Error Rate-DCRBML

Figure 9 demonstrated that the dual clustering with radial basis-Manhattan length approach (DCRBML) has low equal error rate collated with the other recognition method such as Artificial Neural Network (ANN), Multi-layer Neural Network (MLP) and Back propagation Neural Network (BPNN). In addition to these, error rate, the finger knuckle print based biometric authentication system accuracy level need to be evaluated. Then the obtained authentication accuracy value is depicted in table II.

Table II

Authentication Accuracy

Sl. No.	Methods	Authentication Accuracy
1	Artificial Neural Networks (ANN)	94.23
2	Multi-layer Neural Network (MLP)	94.87
3	Back propagation Neural Network (BPNN)	95.78
4	dual clustering with radial basis-Manhattan length approach (DCRBML)	98.76

From the table II it clearly depicted that the dual clustering with radial basis-Manhattan lengthapproach (DCRBML) ensures maximum authentication accuracy compared to other methods. Due to the effective segmentation of knuckle region, knuckle features help to maximize the matching process and authentication process.

IV.CONCLUSIONS

Thus, in this manuscript analyze the dual clustering with radial basis-Manhattan length approach (DCRBML) based biometric authentication system. Initially, polyU finger knuckle database images are collected and the noise present in the images are eliminated with the help of mean value. Then image region is located by computing the image histogram and border value. Based on these values, the knuckle region is identified and segmented. From the segmented region different features are extracted which are trained using radbas activation with sigmoid activation function based radial neural networks. Finally, the testing features are compared with the trained features using Mahanta length measure. The discussed system is developed using the MATLAB based simulation results in which system ensures 98.76% of authentication accuracy with minimum deviation rate. Further, the work is improved using the meta heuristic optimization neural network.

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