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Developing automatic biometric authentication system using intelligent machine learning algorithm form Dorsal hand vein Feature

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Abstract: Now-a-days most of the applications are requires the effective security system for managing the transaction details and other information. Other than the CCTV security process, biometric systems are utilized in several application to monitor the people activities and helps to authenticate the person. Even though, the biometric systems are failing to authenticate the right person some times which reduces the efficiency of authentication system. For achieve this goal, in this paper dorsal vein biometric features are used to authenticate the user information. Initially, dorsal vein images are collected from different person, which are processed by applying the median filter that eliminates the noise from image. After that vein regions are located with the help of the deep learning approach which recognize the vein information using different layers. From the extracted vein region, various statistical features are derived that are processed by the intelligent classifier called ant colony optimized compositional neural network which train the features and authenticate the user information effectively. Then the efficiency of the system is evaluated using experimental results such as FAR, FRR and ERR.

***Index Terms* – Biometrics system, authentication, Dorsal vein, Median filter, Deep learning approach, Intelligent machine learning technique.**

I. Introduction

Now-a-days biometric authentication system [1] is one of the effective security systems which helps to recognize the person using their personal behaviors. The biometric system utilizes different traits [2] such as palm print, face, iris, fingerprint, gait, signature, dorsal vein and so on. Even though different biometric features are involved in the system, finger knuckle print, iris, retina, face, signature, dorsal vein [3]and palm print features are providing enough security to the system. These human traits are effectively satisfying the universality, peculiarity, permanence and collectability property. Among the different biometric features, finger vein [4] ins one of the effective biometric features that successfully recognize the person and authenticate the user identity with effective manner. More ever, vein traits [5] presented inside of the human body which is varied from person to person. Due to the peculiar biometric traits, it is difficult to hack by intermediate user, so, the vein biometric features are providing more authentication to user details. This vein based biometric identification [6] process is also named as vascular technology because it establishes the authentication to user details by examining the blood vessels patterns.

During the dorsal vein biometric process, infra-red (IR) [7] is used to capture the hand vein image and the CCD image sensor is utilized to capture the other part of vein image. Unlike the other biometric trait scanner, vein requires the special device because, the vein features are captured in extraordinary speed but scanning is low than a second. Due to the inside part the vein [8] establishes more security and authentication to data when compared to other biometric features. According to the discussion, the sample hand vein image is depicted in figure 1.

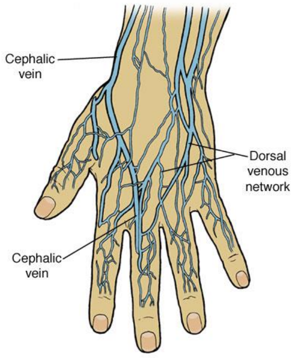

Figure 1: Sample hand vein image

The captured vein images are processed by applying different processing techniques [9] and steps such as image preprocessing, region identification, feature extraction and matching process. These steps are successfully process the vein image and the extracted features are saved in the database as template that is used for person authentication process. By considering these steps various researchers analyze the hand vein biometric image to improve the security to the data. Here few researcher opinions are discussed to understand the processing steps. (Gupta P., et al., 2014) [10] creating the effective and secure authentication system using palm dorsa vein biometric features. Initially, dorsa vein biometric images are captured with the help of infrared-light camera. Th captured images are processed by multi-scale matched filtering techniques. This algorithm successfully eliminates the noise present in the image. Then the different features are derived which are stored in the database. Finally, image registration matching algorithm is applied to authenticate the user information. Then the efficiency of the system is evaluated using 840 images and 140 different classes of images. The created vein biometric system ensures the more security to the user details compared to other existing approaches.

(SujataKulkarni, et al., 2016)[11] developing the effective biometric system using hidden biometric features. In this work, author choses the finger vein pattern because it is difficult to hack by unauthorized person. The vein images are captured using NIR finger vein capturing device. The collected images are processed by bilateral and contrast limited histogram equalization approach which eliminates the image noise and enhance the quality of the image. Then different features are derived by using the local binary pattern. After that the testing features are matched with trained features using matching algorithm. Then the efficiency of the system is evaluated using experimental results in which system ensures the 94.34% of security to the personal details compared to other biometric features.(Huang D., et al., 2013) [12] implementing the effective authenticating system using the hand vein biometric features. Initially, hand vein images are collected from NCUT database, the gathered images are processed by applying oriented gradient map approach. Then the vein texture and patterns are derived by SIFT local matching approach. In addition to this patterns, various key points are extracted that are stored as the template in the database. Finally, the matching process is done by applying the oriented gradient map approach. Then the efficiency of the system is evaluated using experimental results in which biometric system provides the maximum authentication accuracy.

Jalilian E., Uhl A. (2020)[13] developing automatic biometric authentication system using the improved convolution neural network with fused training labels. First the hand vein biometric images are collected from person, which are processed by applying the convolution neural network. The neural network effectively derives the vein region and the various features are extracted from the image. The extracted features are fused and providing the proper training, which is stored in the databases. Then the matching process is performed to authenticate the user details. Finally, the efficiency of the system is evaluated using experimental analysis. According to the various researcher opinion, hand vein biometric features are providing the enough security to the user information. The captured biometric images are processed by applying different techniques to minimize the deviation error while authenticating the user information. By considering their opinion, in this work, deep learning and optimized compositional neural network techniques are used to recognize the user traits. Then the efficiency of the system is evaluated using the MATLAB based experimental results.

Then the rest of the manuscript is arranged as follows, section 2 discusses about the deep learning and optimized compositional neural network techniques vein biometric authentication system, section 3 evaluated the efficiency of the system and conclusion is described in section 4.

II. INTELLIGENT MACHINE LEARNING TECHNIQUE BASED DORSA VEIN BIOMETRIC SYSTEM

In this section discusses about the intelligent machine learning techniques-based dorsa vein biometric system. In this work, Hong Kong Polytechnic University Contactless Hand Dorsal Images Database [14] is used to create the effective biometric system. Traditional discussed methods are authenticating the user information but they are failing to minimize the false acceptance rate and false rejection rate. In addition to this, those methods are less accuracy while providing security [15] to data. For overcoming these problems, in this work intelligent techniques such as deep learning with optimized compositional neural network is used to maximize the authentication accuracy also reduce the error rate. Based on the discussion, the general working structure of dorsa vein biometric authentication system structure is depicted in figure 2.

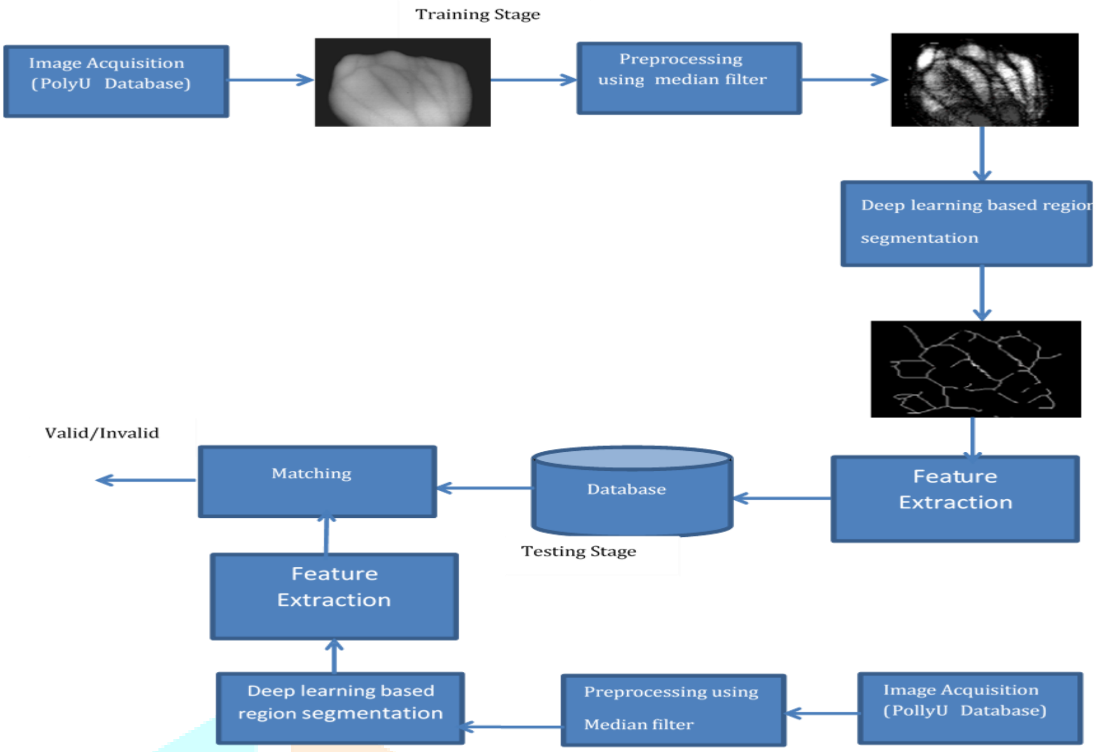

Figure 2: dorsa vein biometric systems structure

From the figure 2 illustrated that the dorsa vein biometric system structure which consists of several steps such noise removal, vein region location, feature extraction and matching process. Here every step is discussed in details for ensuring better authentication process.

2.1 Image Noise removal process

The first step of the work is vein image collection, here, Hong Kong Polytechnic University Contactless Hand Dorsal dataset images are used. The dataset consists of almost 2505 hand dorsal images which are collected from 501 subjects. The collected images have several unwanted pixel information that reduces the efficiency of authentication system. So, in this work, median filter [16] is used for removing noise from the image because it removes the random and distortion noise effectively. In addition to this, method utilizes minimum measurement process that reduces the complexity while removing noise from image. Due to this reason, in this work median filter is used for noise removal process. This filter [17] computes the target noise pixels by comparing the pixel value with the threshold value. If the pixel value is deviated from the threshold value, it must be replaced by applying median value. The median value is estimated by sorting the neighboring pixel and middle value is chosen as the median value. Once the median value is estimated which used to replace the noise pixel value in the dorsa vein image. After eliminating the noise from image, dorsal vein region must be located which is discussed as follow.

2.2 Dorsal Vein region segmentation

Second step of the work is dorsal vein region segmentation process because the vein part is played an important role while authenticating the user information. In this work, deep learning neuralnetwork [18] is used for dorsal vein region location segmentation process. Here two-dimensional U-net deep learning concept is used for segmenting the vein region from the collected hand vein image. The utilized deep learning network structure is depicted in figure 3.

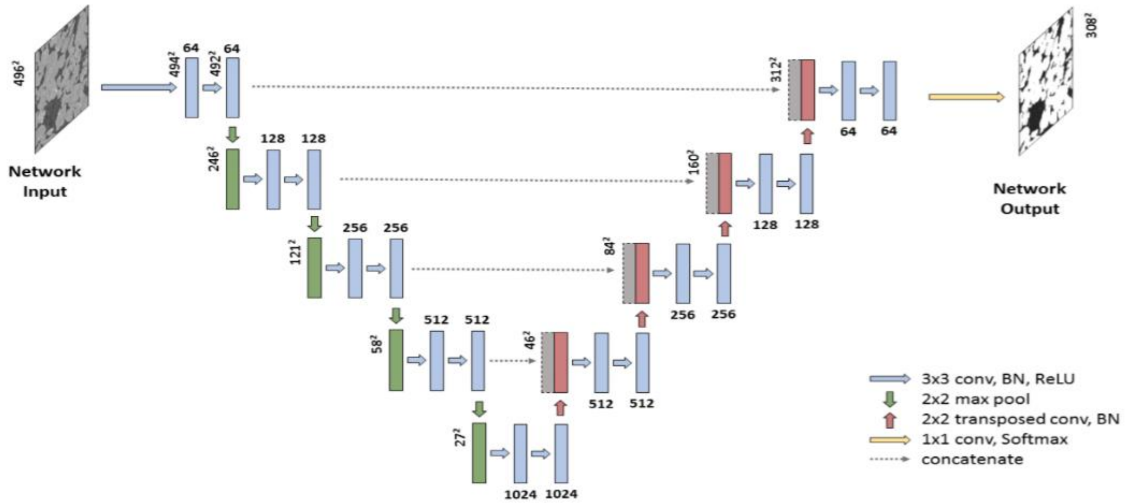

Figure 3: 2D-U net deep learning neural network structure

According to the above figure 3, the network follows as same as the convolution neural network [19] which includes the two 3*3 valid convolution (encoder), followed by rectified linear unit, max pooling operation (2*2) and down sampling. These layers are successfully analyzing the pixels in the image and doubles the number of pixel channels. As same as encoder, the decoder part also having the many decoder unit that consists of up-convolution layer (2*2). The up-convolution layer double of the pixel feature map in the spatial resolution, 2-convoluton (3*3) and followed by rectified linear unit. In addition to this encoder and decoder units, cropping process is performed to determine the border area of vein image. Finally, 1*1 convolution layer is utilized to map each feature with the respective segmented region class. During the segmentation process, batch normalization layer [20] is added in before computation of rectified linear unit for maximize the network convergence speed. In addition to this, log-loss objective function is used to analyze each pixel characteristics which helps to group the pixel according to the objective value. This process is repeated for several iteration until to segment the vein region. More than 100 iterations are performed to predict the exact vein region, during this process 0.9 is chosen as deep learning rate and gradient descent momentum is used for optimizing the vein region segmentation process. This process is repeated to segment the dorsal vein region.

2.3 Feature extraction

After segmenting the dorsal vein region, different meaningful information needs to be extracted to creating the template for authentication purpose. In this work, several statistical features [21] are extracted which are listed in table 1.

Table 2.1: Statistical features

Features	Related Formula
Entropy	$\sum_{i,j=0}^{n-1} -\ln(P_{ij})\,P_{ij}$
Correlation	$\sum_{i,j=0}^{n-1} P_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2}$
Energy	$\sum_{i,j=0}^{n-1} (P_{ij})^2$
Variance	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}(i-\mu)^2.p(i,j)$
Mean	$\sum_{i=0}^{2(n-1)} i.p_{x+y}(i)$
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 above table 1 different features are extracted from the dorsal vein region which are trained and create the template for developing the biometric authentication system.

2.4 Feature training and matching process

Final step of this work is to train the extracted feature for improving the authentication process. In this work ant colony optimized compositional neural network is used for feature training process. The neural network is one of the effective artificial networks[22] which works according to the genetic algorithm. The extracted features are processed by three layers such as input, hidden and output layers. During the feature process, the network uses both gaussian and sigmoid activation function for predicting the output value. Sometimes, the features regularities and patterns are determining the activation function to get the output value. At the time of feature training process, network is optimized by updating the weight and bias value. In this work ant colony optimization algorithm [23] is used to improve the overall training process. For this purpose, pheromone parameters are need to be initialized. After that feature weights related transition probability value must be computed using eqn (3.1)

$$P_i^k(t) = \left\{ \frac{|t_i(t)|^{\alpha}|n_j|^{\beta}}{\sum_{\mu}|t_i(t)|^{\alpha}|n_j|^{\beta}} \quad if\ i\ \epsilon j^k \right. \qquad (3.1)$$

In eqn (1), feature set is represented as j^kn, t is pheromone values and the heuristic information is represented as β.

Based on the probability value, best weight and bias value is selected according to the maximum fitness value. This process is repeated until to select the optimized one. For every updating process, pheromone probability value must be updated as follows.

$$\Delta t_i^k = \begin{cases} \phi.\gamma(s^k(t)) + \frac{\phi.(n-|S^k(t)|)}{n} & if\ i\ \epsilon\ s^k(t) \\ 0 & otherwise \end{cases} \qquad (3.2)$$

In eqn (3.2), $s^k(t)$ is selected feature related parameter. This process is repeated and the respective features are stored in the database with respective output value.

If the new person enters the system, their biometric traits are recorded and features are extracted from the image. The derived features are need to be matched with the template features. If the matching process having minimum difference value, then the person is authenticated and allow to the system else they are terminated. Then the efficiency of the system is evaluated using MATLAB based experimental results and discussion.

III. Results and Discussion

In this section discusses about the excellence of intelligent deep learning with compositional neural network (DLCNN) based dorsal vein biometric authentications system. As discussed earlier, in this work, The Hong Kong Polytechnic University Contactless Hand Dorsal dataset images are used to examine the above discussed biometric methodology steps. The dataset consists of totally, 2505 images in which 1000 images are used for testing and 1505 images are used for training purpose. Based on the discussion, here few hand dorsal vein images are depicted in figure 4.

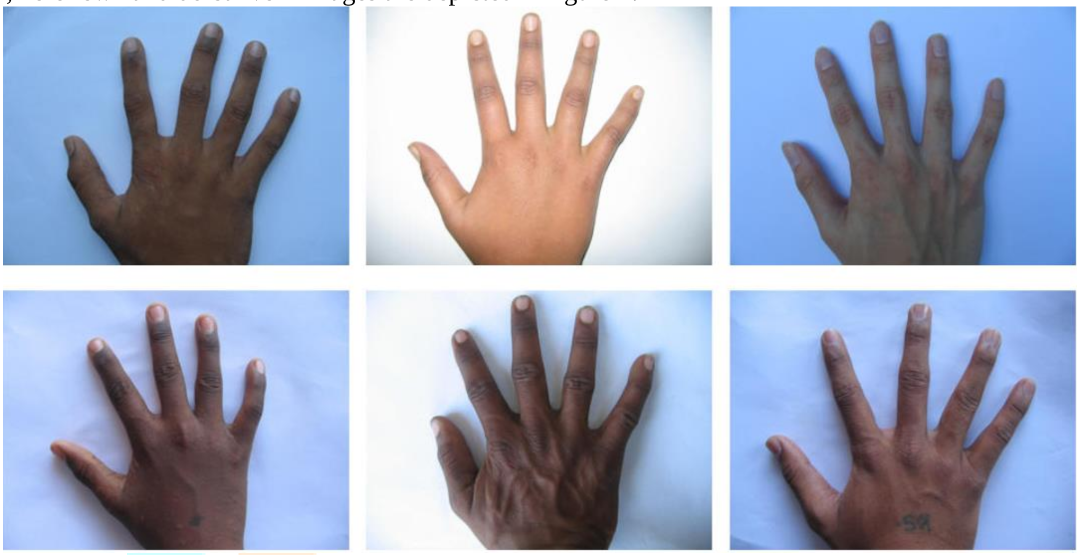

Figure 4: Sample hand dorsal vein images

These hand vein images are processed by above discussed processing steps and the template is created for performing the matching process. This process is developed by MATLAB tool and the excellence of the system is analyzed using different metrics such as false acceptance rate, rejection rate, equal error rate and accuracy. Based on the discussion, the false acceptance rate is computed by taking the ratio of number of features accepted and number of features tested. The respective calculation is shown in eqn (3.3).

$$FAR = \frac{Number\ of\ features\ accepted}{Number\ of\ features\ tested} \times 100 \qquad (3.3)$$

Based on the calculation, FAR value is shown in figure 5.

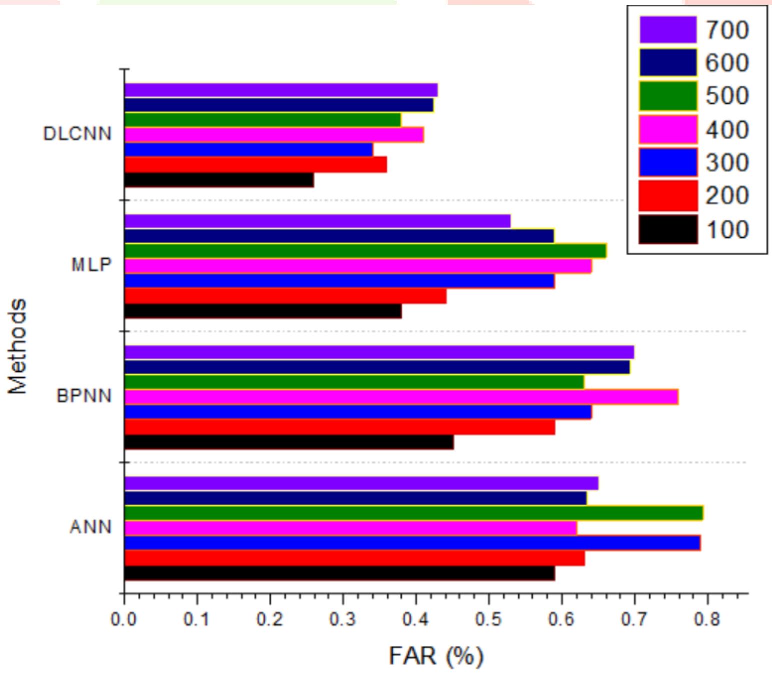

Figure 5: False Acceptance Rate-DLCNN

The figure 5 demonstrated that the false acceptance rate efficiency of deep learning with compositional neural network (DLCNN). The DLCNN approach ensure minimum FAR value compared to other methods such as ANN, BPNN and MLP approach. Due to the inside biometric traits and effective segmented dorsal vein regions are minimize the false acceptance rate (0.21%) compared to Artificial Neural Network (ANN) (0.53%) [24], Back propagation Neural Network (BPNN)(0.46%) [25] and Multi-layer Neural Network (MLP) (0.376%) [26].In addition to this, rejection rate of the DLCNN system must be calculated for improving the efficiency of the biometric system. The FRR rate is computed by taking the ratio of number of original features rejected and number of original features tested. Based on the discussion, eqn (3.4) is written as follows.

$$FRR = \frac{Number\ of\ \ original\ features\ rejected}{Number\ of\ original\ features\ tested} \times 100 \qquad (3.4)$$

So, the false rejection rate value is computed using eqn (3.4) and the graphical representation is shown in figure 6.

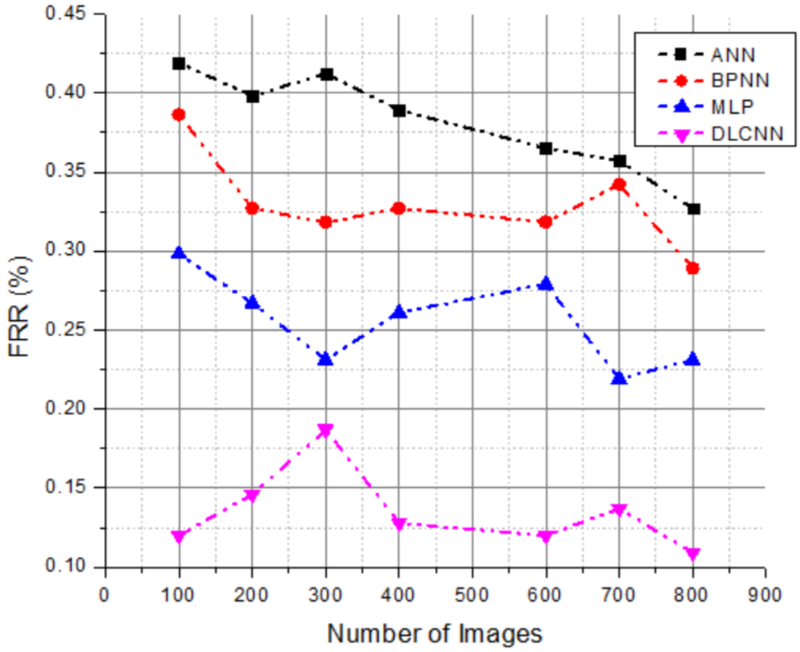

Figure 6: False Rejection Rate-DLCNN

The figure 6 clearly shows that the false rejection rate value of deep learning with compositional neural network (DLCNN). The DLCNN approach ensure minimum FRR value compared to other methods such as ANN, BPNN and MLP approach. The extraction of dorsal vein region and respective feature derivation and optimized learning process minimize the rejection rate (0.187%) compared to Artificial Neural Network (ANN) (0.53%) [18], Back propagation Neural Network (BPNN) (0.36%) [20] and Multi-layer Neural Network (MLP) (0.3176%) [19]. Along with this FRR and FAR, the DLCNN approach Equal error rate value is estimated and shown in figure 7.

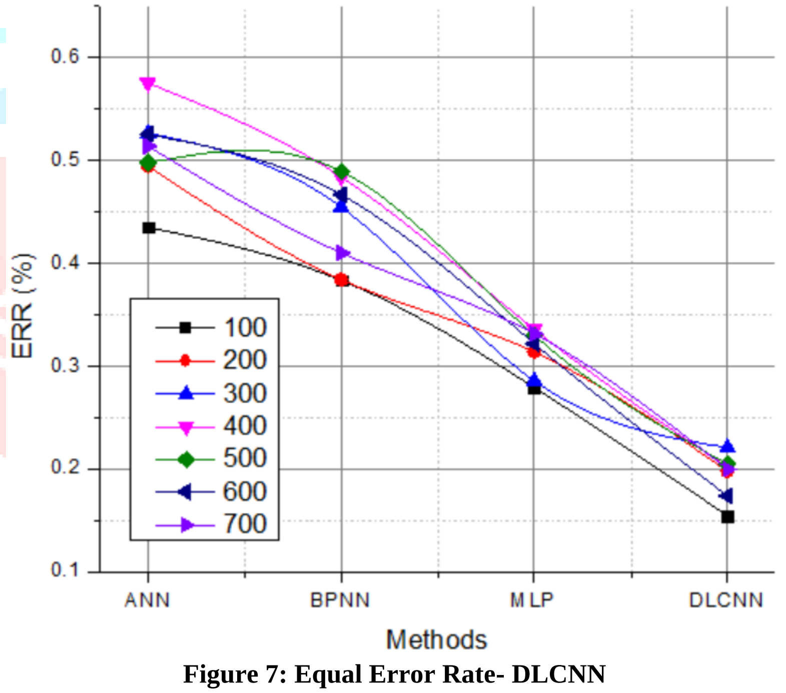

Figure 7: Equal Error Rate- DLCNN

The figure 6 clearly shows that the equal error rate value of deep learning with compositional neural network (DLCNN). The DLCNN approach ensure minimum ERR value compared to other methods such as ANN, BPNN and MLP approach. Along with these metrics, the obtained accuracy value is illustrated in table 2

Table 3.1: DLCNN-Authentication Accuracy

Sl. No.	Methods	Authentication Accuracy
1	Artificial Neural Networks (ANN)	95.5
2	Back propagation Neural Network (BPNN)	96.2
3	Multi-layer perceptron (MLP	97.28
4	deep learning with compositional neural network (DLCNN)	98.89

From the table 2 it clearly depicted that the deep learning with compositional neural network (DLCNN) obtains highest authentication efficiency (98.89%) when collated with other approaches.

IV. Conclusion

Thus, the manuscript analyzes the deep learning with compositional neural network (DLCNN) based dorsal vein biometric system. Initially, dorsal vein images are collected from polyU image dataset. The collected images are analyzed pixel by pixel and eliminating the noise pixels by computing the median value. Then the dorsal vein regions are segmented with the help of convolution layers. From the derived region various statistical features are extracted that are trained by layer of compositional neural network. The network uses both gaussian and sigmoid activation function while performing the feature learning process. Then the ant colony optimization algorithm is applied to optimize the neural network function and the matching process is performed with testing and training features. At last the efficiency of the system is evaluated using MATLAB based results in which system ensures the 98.89% of security to the user data. further, the biometric system is improved by including the optimized feature selection process.

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