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A Novel Deep Learning Lacunarity Texture Analysis System Using Mid-Point ROI Extraction Algorithm for Palmprint Recognition System

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The palmprint comprises multiple unique patterns that are distinct in detecting human identity. There are numerous algorithms proposed by past researches for recognizing Two-dimensional Palmprint Region of Interest (2DPROI) images. In this research, an innovative Deep Learning Lacunarity Texture Analysis System (D2LTA) is developed for recognizing the accredited persons at higher recognition rate. To impart the D2LTA model, Two-dimensional palmprint hands' ROI images are segmented using Mid-point ROI generation algorithm, produced a peculiar feature vector using lacunarity approach in a state-of-the-art manner, and then Deep Learning ConvNet classifier is proposed for D2LTA system to justify the accredit person. The key principle of the Mid-point ROI generation approach is to determine the perfect straight line on the center of the palm. Based on the straight line in the palm, determine the pixel values of the ROI's rectangular box. To catch the perfect straight line, line mid-point method is used. To do this research, 2D-palm hands are procured from three different datasets such as BMPD, CASIA and IIT palm datasets and 2DPROI images are secured from PolyU, Hong Kong Polytechnic University, Hong Kong. The proposed model has been assessed with diverse dimensions to prove the acquirement 99.25% of higher precious authentication rate.

Keywords: Two-Dimensional Palmprint Region of Interest - Deep Learning ConvNet Classifier - Mid-point ROI Extraction Algorithm - Lacunarity approach.

1. Introduction

Biometric is an automated technique of recognizing a person based on physiological or behavioral characteristic. A biometric framework is a pattern recognition system which matches the striking or biased highlights of procured image (test picture) with the elements of pre-put away images (display picture) [1]. There are several biometric traits available. Amid those, palmprint biometric trait is wealthy in actual qualities due to its ease of use and availability, climate adaptability, non-intrusiveness, permanent structure and durable structural traits, and segregating skill [2]. In palmprint trait, each person possesses the unique characteristic, no two persons should share the same characteristic features. Characteristic features are readily presentable to a system and easily quantifiable.

Palmprint images contain rich exceptional elements for human identification. It makes an extremely serious theme in biometric research [2]. Palmprint is the skin examples of the inner surface of the human hand and it presents in the region from the wrist to the foundation of the fingers. There are three main lines in the palm - the head line, the principle (heart) lines, and the life line—are formed by flexing the hand and wrist in the palm. Those are considered as the highlights of the individual palmprint identification. The determination of palmprint highlights is a crucial issue in dependable palmprint identification [3].

During the recognition phase, the recognition system captures the characteristic of the individual palmprint highlights and converts it to the digital format, which is further processed by the feature extractor to produce the same representation as the template. The resulting representation is fed to the feature matcher that compares it against the template(s) to establish the identity of the individual.

For the identification of palmprints, the ROI extraction is a vital process [4]. The process of performing a series of adjustments and key point locations for various palmprint and palm vein images is referred to as ROI extraction [4]. The core idea is to extract the ROI is to employ the valley points between the fingers to establish a coordinate system and then obtain the ROI of palmprints [5]. Following this, the effective area of the centre is selected to extract features, and the final matching is completed for the recognition.

The first important step for palmprint identification is ROI extraction. Some of the authors used the concept of fixed size ROI. Tangent based approach is used to find the reference points in fixed size ROI approach [6]. This approach is based on two boundaries such as one from point finger to middle finger and other from little finger to ring finger. Fixed size ROI approach has two main limitations. Those are: 1. can not to adjust the ROI size as we need, and 2. easily capture the irrelevant image into the ROI frame. Those reasons lead the less usage of fixed size ROI approach compare than the dynamic ROI extraction approach.

Dynamic or adaptive ROI extraction approach segment the requisite palm area along with more contents [7]. In concept of dynamic ROI first locate the points of finger tips, finger root points based on these points then developed a localized ROI [8]. In the dynamic ROI, establish the ROI area coordinate points based on the key points values. Hence, it can be easily adjustable and acquire an exact ROI area as we required [9] [10]. Even though, Dynamic ROI extraction algorithms are stipulated to do complex process. And it is the sophisticate algorithms for adjusting its keypoint values, and creating the sensitive parameter values.

Several ridges, lines, wrinkles present in the palmprint images. And those are to be treated as texture features [11] [12]. Spatial arrangement in the pixel intensities of the image provides more rich and distinct information for classifying the complex patterns. Most used texture feature analysis approach is Fractal Dimension (FD) approach [13]. It is best for analyzing the texture depiction, in several applications like the signature recognition, palmprint recognition, and written identification etc [14] [15]. [16] this research is proved that the texture features of huge datasets in the image processing are received unique information using FD approach. In 1983, Mandelbrot invented the fractal geometry for expounding the fractals as the sets of self-identical texture [13]. But in the FD estimation approaches, stipulation of same dimensions values of several parts of the image surface are identical (similarity values), and obtained correlated features that causes low precious categorization [6]. Mandelbrot introduced the method in 1983 to estimate the various texture values of same dimension patterns using lacunarity texture analysis approach [17]. [18] This paper ensured that estimation of FD values using Gliding-Box algorithm in lacunarity approach brought the better result in image classification.

Machine Learning (ML) and Deep Learning techniques (DL) are the vital extension of AI technology [6]. [19] this paper stated that Back-Propagation Feed-Forward Neural Network (BPNN) impart the 99.99% of recognition rate compared to other machine learning techniques. ML is difficult to learn and train the large volume of data due to the lack of definable in the decision-making [20]. DL overcomes all possible ML problems with higher authentication rate [21]. DL has multiple layers to train the system [20]. Each layer learns the huge data and train the system efficiently using Deep Neural Network (DNN) architecture with input and output layers, as well as numerous hidden layers[22], [23]. [24] this paper is explored that DL approach conceded the better Authentication Accuracy Rate in PRS.

In this research paper, a novel palmprint recognition system D2LTA is proposed. In D2LTA system, Mid-point ROI extraction algorithm, lacunarity texture analysis approach, and Deep Back-Propagation Neural Network algorithm are developed to segment the exact 2DPROI area, extract the unique qualified relevant features of 2DPROI, and classify the fake and genuine persons' authorization. It is effectively elucidated in the Section 2 of proposed methodology. Section 3 describes the experiment of this research, and Section 4 and 5 deals with the discussion and conclusion.

2. Proposed Methodology

In this research, D2LTA system is developed in four phases. First phase is data acquiring phase; where research data is taken from existing datasets or using real-time data capture technology. Second phase is pre-processing phase; where the captured input data is refining and smoothing in order to the need of doing further process easily, accurately and in low computation. Third phase is image feature extraction phase; where image information is brought out to classify the each and every single image. Fourth Phase is Classification phase, where the extracted image information is categorized or recognized for performing the identification. And finally, the performance of image classification is evaluated to know the efficiency of proposed system for authentication process. Fig.1.a, and 1.b. portrays the diagrammatic representation of D2LTA system's testing and training processes.

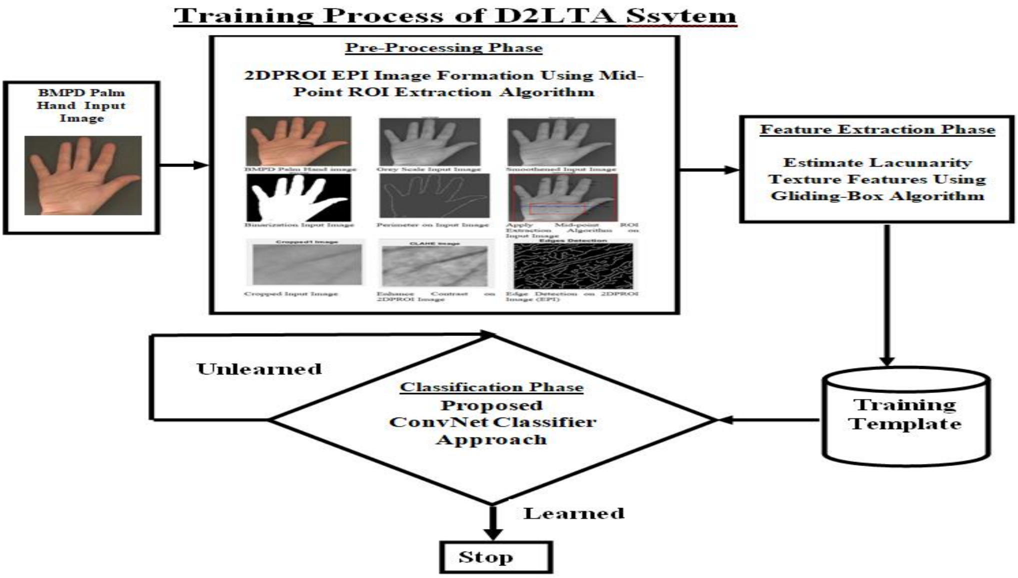


Fig.1.a. Diagrammatic Representation of D2LTA System’s Training Process

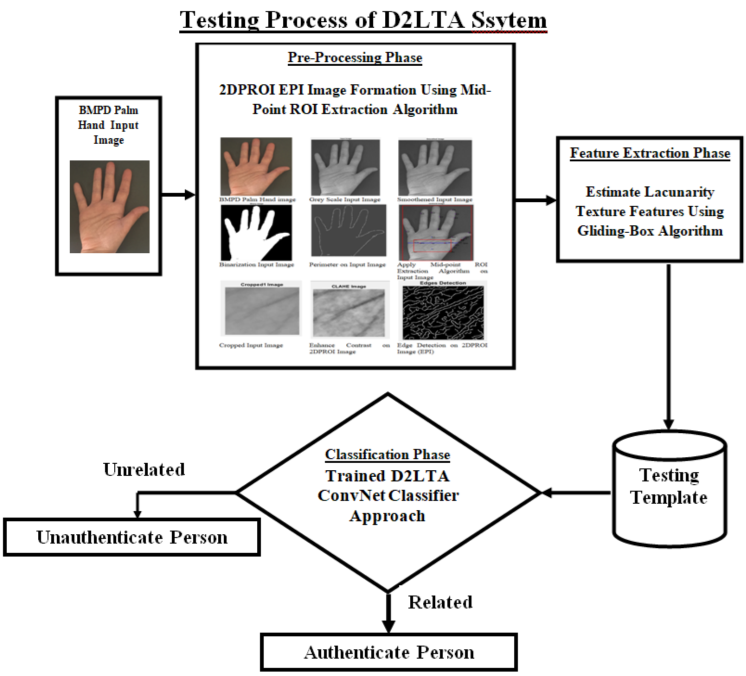


Fig.1.b. Diagrammatic Representation of D2LTA System’s Testing Process

a. Data Acquiring Phase

The overall research is explored on 2DPROI images of various datasets such as IIT, BMPD, PolyU, and CASIA palm database. Each datasets are captured the human palm images in its own principles, which are discussed in below.

BMPD Dataset

The Birjand University Mobile Palmprint Database (BMPD), has 1640 photos of 41 Iranian girls. Those photos are taken in two sessions. In the first session, participants were asked to place their hand on a black backdrop, and six free-flowing photographs of each palm were captured at a distance of 20 cm from the participant's hand. 16 pictures were obtained of each user's palm in the second session. Sample BMPD database is displayed in Fig.2.b.

Fig.2.a. IIT Delhi Touchless Palmprint Database

Fig.2.b. Birjand University Mobile Palmprint Database

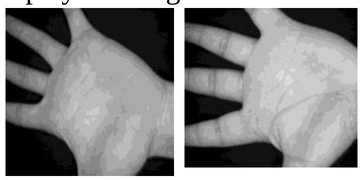


Fig.2.c. CASIA Palmprint Database

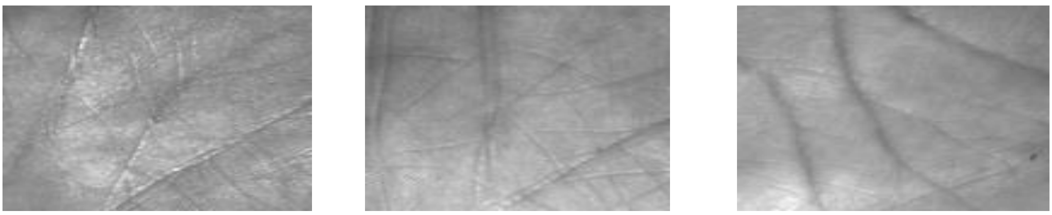


Fig.2.d. PolyU 2DPROI Database

CASIA Dataset

CASIA Multi-Spectral palmprint image database is released in order to promote the research and progress on multiple spectral imaging of biometric modalities. The 5,502 palmprint pictures of 312 individuals are present in 8 bit gray-level JPEG image file format. We take pictures of the left and right palm prints for every individual. CASIA database is made available only for academic and research purposes. It is shown in Fig.2.c.

IIT DATASET

The hand images of IIT palmprint database are collected from the students and employees of IIT Delhi in NewDelhi, India. The images in the currently accessible database are came from 230 users in bitmap (*.bmp) format. Every subject in the database is between the ages of 12 and 57. Each figure is photographed seven times, once from the left and once from the right hand, in various hand posture variants. Higher image scale fluctuations are the outcome of touchless imaging. Every user has had their captured photos consecutively numbered with an integer identifying number. All of these photographs are available in bitmap format and have a resolution of 800 * 600 pixels. It is shown in Fig.2.a.

PolyU Datasets

In PolyU datasets, 8000 normalized 2DPROI .bmp image format files are available. Those images are collected from 400 volunteers' left and right palm hands and stored those images into two separate sections. In each section, 10 2DPROI images of same palm hand are captured to identify the miscellaneous noises on the same image. Sample of PolyU dataset's 2DROI images are shown in Fig.2.d.

b. Pre-Processing Phase

Pre-processing is the vital key step for constructing the competent input image due to the presence of ill effects of noises, and shadows. The pre-processing involves the following steps such as, a. the original RGB image is converted into gray +scale image; b. Remove the noise and adjust the smooth boundary using Wiener filtering technology, as per in the image Fig.3.a, b; c. The 2DPROI image is extracted using Mid-point ROI extraction algorithm; d. Contrast of 2DPROI is enhanced using adapthiseq() function in Matlab software; e. Edge Preprocessed Image (EPI) is formed using Canny edge detection algorithm [25]. Cropped 2DPROI image and EPI formations are delineated in the Fig.4.a, 4.b, 4.c, 4.d, 4.e, and 4.f. Table.1 shows the pictorial representation of novel Mid-Point ROI extraction approach procedures.

Fig.3.a. Conversion of input image into grayscale image

Fig.3.b. Smoothen the image after filtering

Proposed Mid-Point ROI Extraction Algorithm

This algorithm is enacted by executing the following steps

i. Detect the border boundaries using binary conversion process.

ii. The perimeter pixel of an object is found to catch the border boundaries.

iii. Regionprops() function property is used to asset the centre pixel value of an entire palm image and it is marked as CI.

iv. The centre point of palmar surface is extracted by implementing the below following steps:

a. Mid-point pixel value M1 is calculated by finding the average between the centre point of image $CI_{x1,y1}$ and border point of wrist W(x2,y2) using (1).

$$M1_{x,y} = \frac{CI_{x1,y1} + w_{x2,y2}}{2} \quad (1)$$

b. The centre point of palmar surface (CP) is point-out by measuring the midpoint pixel value between the points CI and M1.

v. To fetch the exact region of 2D-PROI by drawing a horizontal line from the pixel point of LHM to RHM based on CP. LHM and RHM pixel points are noted as follows:

a. Mark the end point of the left palmar side border at the x-axis as LHM.

b. Determine the mid-point pixel value between the CP and LHM and marked as ML1.

c. Similarly, mark the RHM pixel point and pointed the MR1 point.

d. Find the mid-point pixel value (MLHM) between the ML1 and LHM and the mid-point pixel value (MRHM) between the MR1 and RHM using (1).

vi. Based on the points of MLHM and MRHM, mark all coefficient points (BLP, ULP, BRP, and URP) of the rectangular box to crop as an exact 2D-PROI.

Fig.4.a. Binary Conversion

Fig.4.b. Perimeter pixels of the Image border

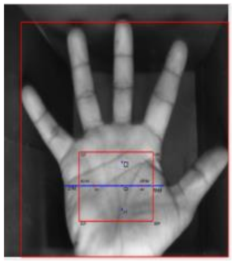


Fig.4.c. Perfect ROI Segment Area Extraction

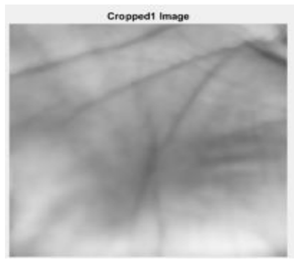


Fig.4.d.Cropped 2D-PROI Image

Fig.4.e. Contrast Enhancement on Cropped 2DPROI Image

Fig.4.f. Edge Preprocessed Image (EPI) on Cropped 2DPROI Image

c. Feature Extraction Phase

After getting the 2DPROI images, main elements of the palmprint images such as ridges, principle lines, and wrinkles are captured to make the unique feature vector [25]. It can be shown in Fig.5.a, 5.b. For that, canny edge detection algorithm is used. The output of the canny edge algorithm is edge pre-processed 2DPROI image (EPI). EPI is clearly display in Fig.5.c. From the EPI image, variations of the spatial intensity arrangement of the pixels are noted and formed it as the training and testing templates. It can be accomplished using lacunarity texture analysis approach. In this paper [26] Gliding-box algorithm is proved its dominant by revealing the heterogeneity of rough texture features. As the reference of paper [27], lacunarity value is estimated using mass distribution function on Gliding-box algorithm.

Procedures for estimating the Lacunarity (L) Value on EPI

a. In the Gliding-box procedure, L value can be determined on each gliding box. Gliding box is formed on each sliding move by sliding one edge at the foremost edge and reducing edge at the lower edge in the hyper-plane in the form the non-overlapping gliding box with the size $\psi \times \psi$, ($\psi = 1, \ldots, \frac{\Lambda}{\Omega}$) from the upper left corner of the image E_{PI} ($\Lambda \times \Lambda$). Ω is a scale interval value ranges from 1 to log2(Λ)/2.

b. At each gliding box, estimate the mass distribution values ($m_{(\psi,\Omega)}$) using dividing the occupied gray-scale pixels (P_ψ) of each overlapping boxes by box count values N_ψ [sixth, 26]. It can be done using the equation 1.

$$m_{(\psi,\Omega)} = \sum_{i=1}^{\log 2(\Lambda)/2} \frac{p_\psi}{N_\psi} \quad | \Omega = 1, \ldots, \text{and } \log 2(\Lambda)/2| \quad |\psi = 1, 2, \ldots, \frac{\Lambda}{\Omega}| \qquad (1)$$

Lacunarity (L_Ω) at different scales Ω can be calculated using the equation 2

$$L_\Omega = \frac{\sum_{i=1}^{\log 2(\Lambda)/2} m_{(\psi,\Omega)}{}^2 \times EPI_{(\psi,\Omega)}}{\sum_{i=1}^{\log 2(\Lambda)/2} [\, m_{(\psi,\Omega)} \times EPI_{(\psi,\Omega)}\,]^2} \quad | \Omega = 1, \ldots, \text{and } \log 2(\Lambda)/2| \; | \psi = 1, 2, \ldots, \frac{\Lambda}{\Omega}| \qquad (2)$$

Thus, Lacunarity L_Ω feature vector is gathered with the dimension 1 × 3 for a test image. Similarly, find the L_Ω values for all training and testing images. Then, stored those all as the training and testing templates. Those templates are used to do the authentication and identification process of D2LTA system.

D. Classification Phase

Utilizing Matlab Deep Learning ToolBox, proposed Convolution Neural Network or ConvNet classifier is constructed. To learn the training template, ConvNet architecture is structured with adjustable parameters. Table.2, 3, 4, and 5 depicts the used adjustable parameters' values in the proposed ConvNet classifier. Passing the values of adjustable parameters to the trainingOption() function to set the array of input, output, and hidden layers. After fixing the ConvNet structure tentatively, classifier network starts its learning process by adjusting the number of hidden layers' values, filter values and the epoch values in the trainNetwork() function. Thus, the D2LTA system is learned. This learning process is finished till the learning accuracy reached the 100% and loss 0% at some specified epoch iteration in the training progress chart. Figures. 7., 8., 9., and 10, are embellished that the training progress charts for all kinds of databases used in this research. Figures. 7., 8., 9., and 10, and Tables. 2, 3, 4, and 5 are delivered that the D2LTA system is learned the various kind of palm database's features at different level of adjustable parameters of proposed ConvNet classifier. At ultimate, D2LTA system recognized all output data according its training and testing input.

After finishing the learning process of D2LTA system, testing process is started to authenticate a person. In testing process, testing template feature vector is applied to the trained ConvNet classifier of D2LTA system to enumerate the Authentication Accuracy Rate (AAR).

3. Experimental Analysis

This research paper explores its experiment on three different set of palm datasets. In this research paper, a novel Mid-point ROI extraction algorithm is used for extracting the perfect 2DPROI area from the entire palm hand. Fig.5.a. shows the implementation of Mid-Point ROI extraction algorithm on a palm hand image, Fig 5.b shows the cropped 2D-PROI using Mid-Point ROI extraction algorithm and Fig.5.c shows the edges on 2DPROI.

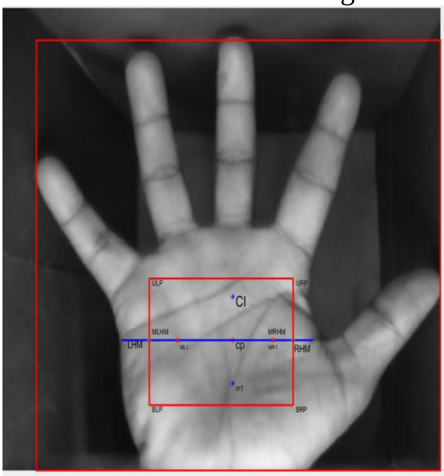
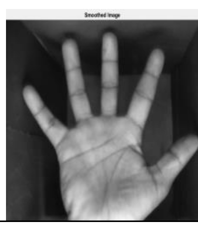
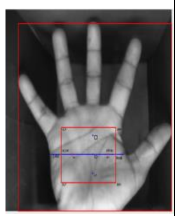
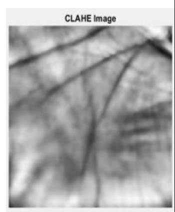


Fig. 5. a. Extraction of 2D-PROI Image Using Mid-Point ROI Extraction Algorithm

Fig. 5. b. Cropped 2D-PROI Using Mid-Point ROI Extraction Algorithm

Fig. 5. c. Edges on cropped 2D-PROI Image Using Canny Edge Detection Algorithm

Table 1. Pictorical Representation of Mid-Point ROI Extraction Approach on Various Datasets

Various palmprint Datasets	2D-PROI Input Images	Smoothen Image	Binary Convert Image	Segmented ROI Area Marked Using Mid-Point ROI Extraction Algorithm	Contrast Extracted 2D-PROI Image
IITD Touchless Palmprint image					

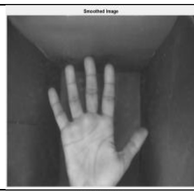
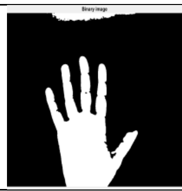
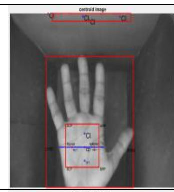
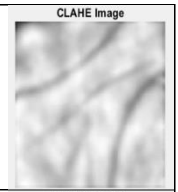
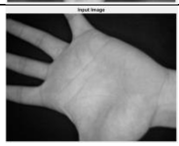
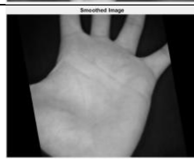
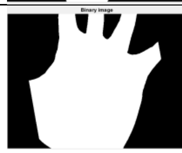
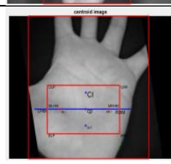
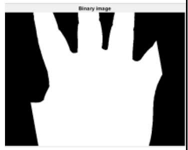
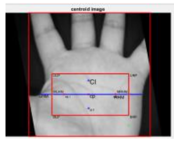
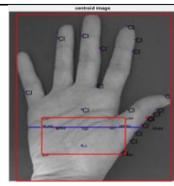
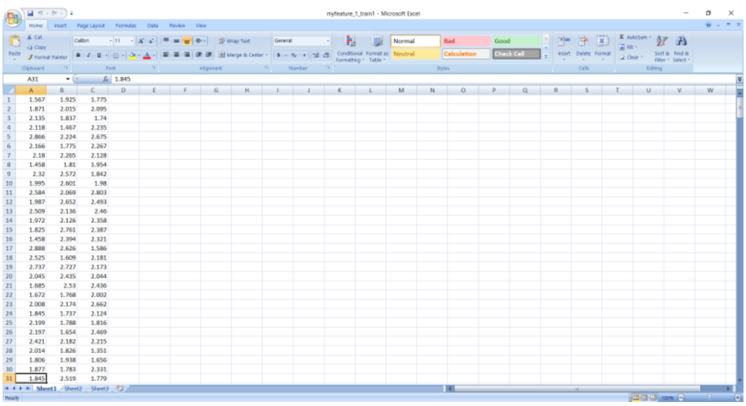
IITD Touchless Palmprint image					
CASIA Palmprint image					
CASIA Palmprint image					
BMPD Palmprint image					

Table.1. displays the pictorial representation of segmenting the 2DPROI images from different palm hand image datasets. In this research experiment, 400 palm hand images are occupied from IITD, CASIA, and BMPD palm hand databases. Then, 2DPROI area is segmented using the proposed novel Mid-Point ROI extraction algorithm. 400 2DPROI images are occupied directly from PolyU database. From the occupied 400 2DPORI images, 80% and 20% of the 2DPORI images are served as training and testing samples. All taken training and testing 2DPROI images are made as feature vector using proposed lacunarity texture analysis approach. A sample training feature vector is shown in Fig.6.



	A	B	C
1	1.567	1.925	1.775
2	1.871	2.015	2.095
3	2.135	1.837	1.74
4	2.118	1.467	2.235
5	2.866	2.224	2.675
6	2.166	1.775	2.267
7	2.18	2.265	2.128
8	1.458	1.81	1.954
9	2.32	2.572	1.842
10	1.995	2.601	1.98
11	2.584	2.069	2.803
12	1.987	2.652	2.493
13	2.509	2.136	2.46
14	1.972	2.126	2.358
15	1.825	2.761	2.387
16	1.458	2.394	2.321
17	2.888	2.626	1.586
18	2.525	1.609	2.181
19	2.737	2.727	2.173
20	2.045	2.435	2.044
21	1.685	2.53	2.436
22	1.672	1.768	2.002
23	2.008	2.174	2.662
24	1.845	1.737	2.124
25	2.199	1.788	1.816
26	2.197	1.654	2.469
27	2.421	2.182	2.215
28	2.014	1.826	1.351
29	1.806	1.938	1.656
30	1.877	1.783	2.331
31	1.845	2.519	1.779

Fig. 6. Created Training Feature Vector for 400 2DPROI Images Using Lacunarity Texture Analysis Approach

Training vector of 400 2DPROI images in all datasets are learned using proposed ConvNet classifier. Learning process is completed, when the training progress chart shows the acquirement of 100% of recognized accuracy to all kinds of dataset's 2DPROI images. This is shown in the Fig.7, 8, 9, and 10.

Table 2. Proposed ConvNet Classifier's Adjustable Parameters Variables for the of 400 IITD 2DPROI Training Images

Num. Features	Num. Filters	Filter Size	Num. HiddenUnits	Num. Classes	Max Epochs	Mini BatchSize	Learning Rate
1×3 ×1	10	[5 5]	30	400	100	10	0.001

Table 3. Proposed ConvNet Classifier's Adjustable Parameters Variables for the of 400 BMPD 2DPROI Training Images

Num. Features	Num. Filters	Filter Size	Num. HiddenUnits	Num. Classes	Max Epochs	Mini BatchSize	Learning Rate
1×3 ×1	13	[3 3]	50	400	100	10	0.001

Table 4. Proposed ConvNet Classifier's Adjustable Parameters Variables for the of 400 CASIA 2DPROI Training Images

Num. Features	Num. Filters	Filter Size	Num. HiddenUnits	Num. Classes	Max Epochs	Mini BatchSize	Learning Rate
1×3 ×1	15	[4 4]	45	400	100	10	0.001

Table 5. Proposed ConvNet Classifier's Adjustable Parameters Variables for the of 400 PolyU 2DPROI Training Images

Num. Features	Num. Filters	Filter Size	Num. HiddenUnits	Num. Classes	Max Epochs	Mini BatchSize	Learning Rate
1×3 ×1	12	[3 3]	35	400	100	10	0.001

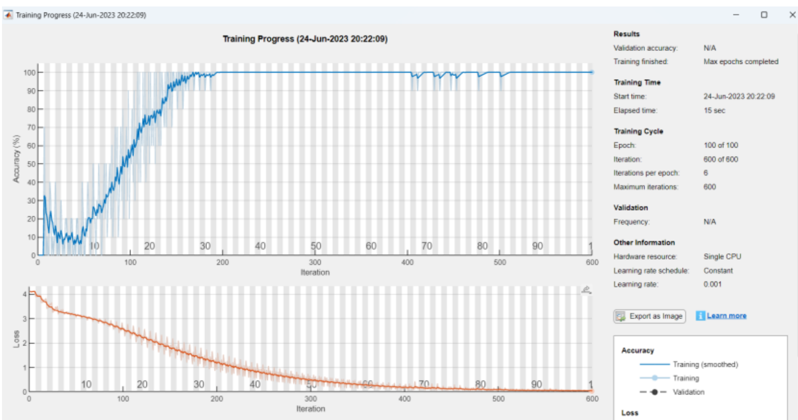


Fig. 7. Training or Learning Progress Chart of IITD Palm Hand Datasets Using D2LTR System

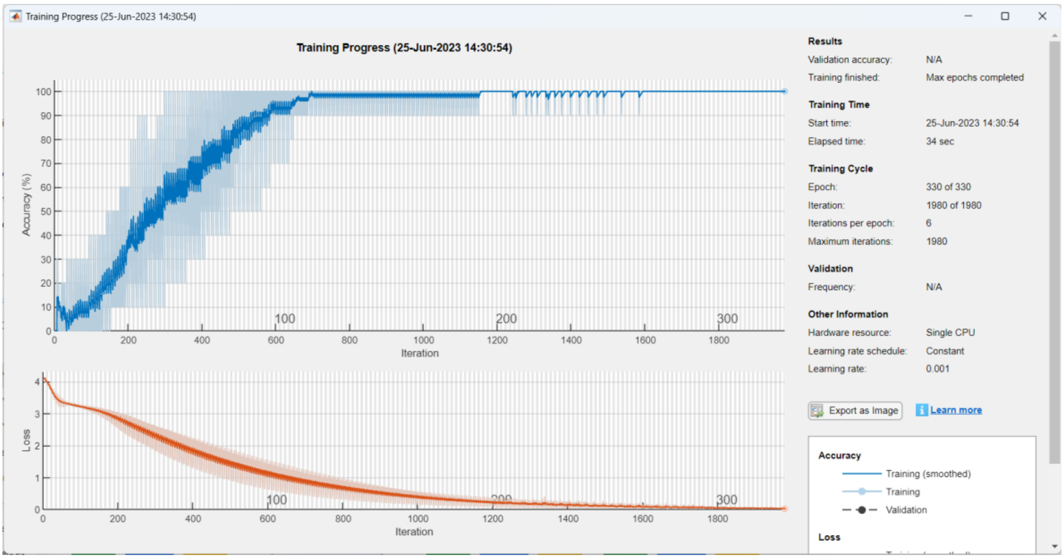


Fig. 8. Training or Learning Progress Chart of BMPD Palm Hand Datasets Using D2LTR System

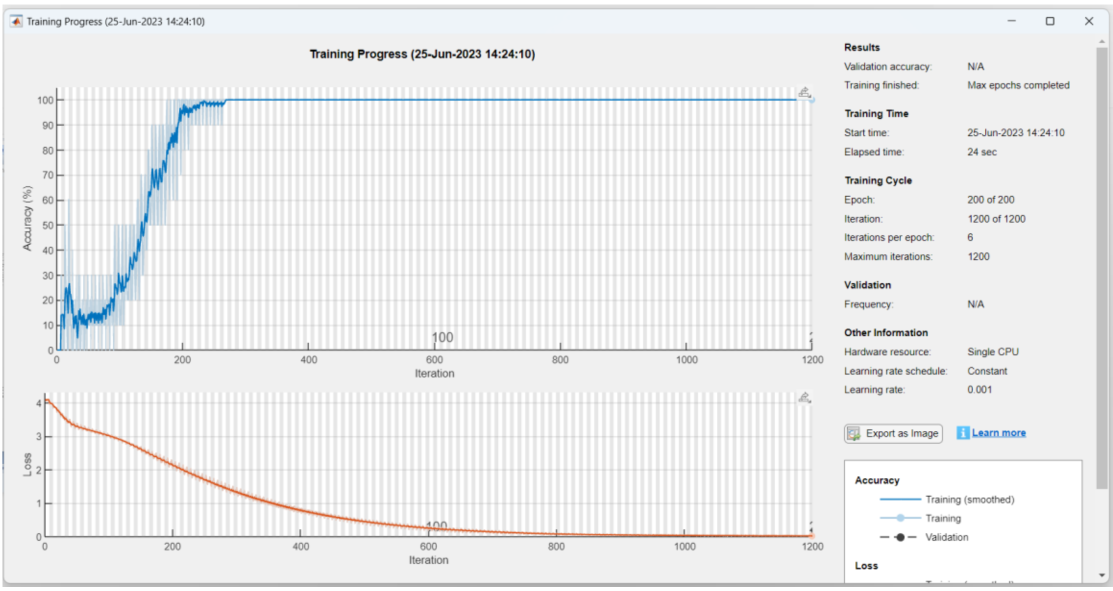


Fig. 9. Training or Learning Progress Chart of CASIA Palm Hand Datasets Using D2LTR System

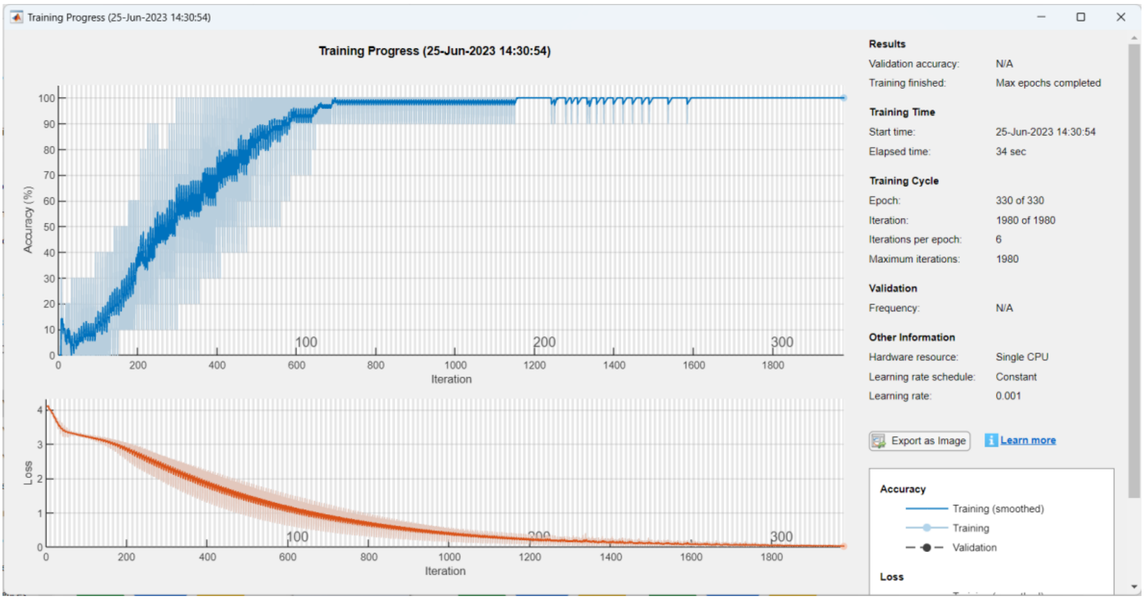


Fig. 10. Training or Learning Progress Chart of PolyU 2DPROI Datasets Using D2LTR System

After the training of the D2LTA system, testing template features are identified. The measurement of the identification accuracy rate is evaluated using confusion matrix approach. Confusion matrix metrics such as accuracy, specificity, and precision values are calculated using (3), (4), and (5). To calculate the confusion matrix metrics, number of True Positive, True Negative, False Positive, and False Negative values can be counted by comparing the matched training features against with the testing features during the testing experiment.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Postive} + \text{False Negstive}} \qquad (3)$$

$$\text{Precision} = \frac{\text{False Negative}}{\text{True Positive} + \text{False Negative}} \qquad (4)$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Postive}} \qquad (5)$$

Thus, training and testing experiments are done on all datasets.Table.6 illustrates the obtained recognition accuracy, precision, and specificity rate for all datasets. It is proved that the proposed D2LTA system is an efficient system to authenticate the any kind of palm datasets.

Table. 6. Confusion Matrix Metrics' Values of D2LTA System

400 testing 2DPROI samples of Various Datasets	TP	TN	FP	FN	Precision	Specificity	Authentication Accuracy Rate (AAR)
IITD	393	4	2	1	99.49%	66.67%	99.25%
BMPD	388	8	2	2	99.49%	80.00%	99.00%
CSAIA	370	27	2	1	99.46%	93.10%	99.25%

PolyU	390	7	4	1	98.98%	63.64%	98.76%

4. Discussion

Table.6. and Fig.11 depicts AAR for all kinds of palm hand databases. It reveals that CASIA and IITD palm hand image datasets has gotten 99.25% of AAR and BMPD palm hand image datasets has gotten 99% of AAR. And PolyU 2DPROI image datasets has gotten 98.76% of AAR, which got lower AAR compare than other three datasets due to the presence of same identical data presentation by the acquirement of large size 2DPROI area. D2LTA system attained all stages of PRS implementation with the achievement of better AAR rate (99.25%). It can be suggested as one of the best contributed PRS system to the society. Fig.12 is shown the analyses of AAR of proposed D2LTA system with the existing PRS approaches. And it reports that the proposed D2LTA system is the better PRS system to make the proper palm hand image segmentation, 2DPROI image feature extraction, classification and matching processes using its proposed novel approaches.

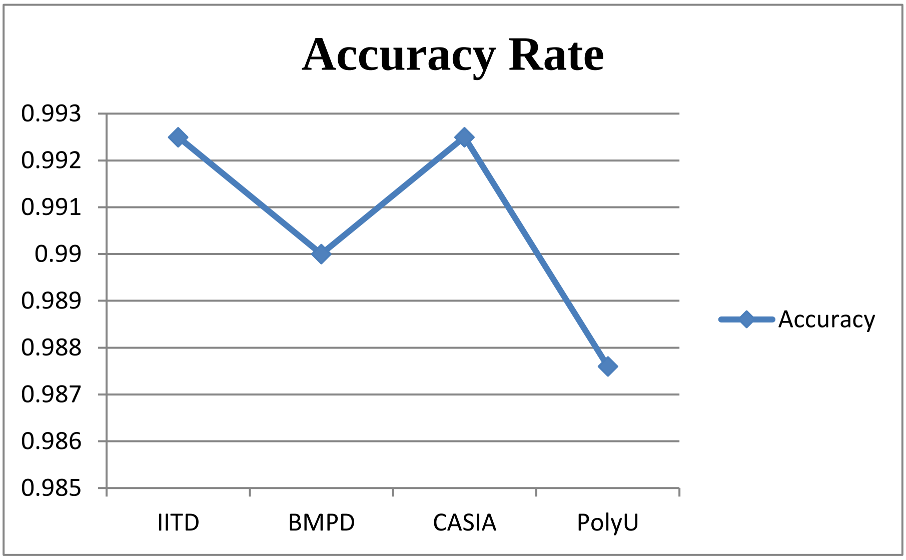


Fig.11. Chart Representation for depicting the AAR to all kinds of Palm Hand Database images

5. Conclusions

In our research, an innovative D2LTA system is evolved to bring the well regulated biometric secure PRS system to the society. It can be accomplished using developed novel approaches in the D2LTA system. Mid-point ROI extraction approach, lacunarity texture analysis approach, and peculiar ConvNet classifier approach are proposed to execute the D2LTA system. Table.1. reveals that the perfect elevated 2DPROI images using the proposed Mid-point ROI extraction approach from the three different palm hand datasets. Table.6 manifests the attainment of better 99.25% AAR for IITD and CASIA palm hand datasets. At ultimate, this research employed all the implementation phase of PRS at higher AAR using the perfect D2LTA approaches. Yet, this research is not reached the 100% achievement in AAR, due to the presence of analogous image features in the training process of D2LTA system. It causes a few mismatches in authentication process. In future, this drawback can be reduced using hybrid approach of feature extraction technique to capture the dissimilar image features.

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