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A Novel Deep Supervised Contour Fractal Dimension Analysis Model for Palmprint Recognition

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ABSTRACT

A novel Palmprint Recognition System (PRS) using Deep Supervised Learning (DSL) classifier is proposed in this research work. To divulge the novelty, a Deep Supervised Contour Fractal Dimension Analysis Model for Palmprint Recognition (DCFPR) is put forward. That has a novel Region-based Contour Fractal Dimension (RCFD) feature extraction approach and a Deep Supervised Learning (DSL) classifier approach for acquiring the higher recognition and identification accuracy rate. To accomplish the RCFD approach, traced all the edges/contours of 2D Palmprint Region of Interest (2D-PROI) image using Canny edge detection algorithm and then split into several regions. At each region, Fractal Dimension (FD) and the Slope value (S) are computed in an idiosyncratic manner using the Box-Counting procedure and then accumulate all FDs and Ss of all regions to create a distinctive feature vector. Classify this feature vector using Deep Supervised Learning (DSL) classifier approach to authenticate the genuine person of the taken palmprint at a higher accuracy rate. In this research, the multi-spectral 2D-PROI image database derived from PolyU, Hong Kong Polytechnic University, Hong Kong. The proposed model has been examined and evaluated with various metrics and found with 98% of authentication accuracy.

Keywords: Palmprint Recognition System, Deep Supervised Learning Classifier, Region-Based Contour Fractal Dimension, Canny's Edge Detection algorithm, Box-Counting, Fractal Dimension.

1. Introduction

Biometric imparts a secured technique of substantiating identification [1]. Biometric Authentication and Identification systems (BAIS) are typically necessary to protect the emerging digital aspects of the IoT world. Accordingly, the benefaction of this research is to make adequate preparation for furnishing an optimal remedy for the following: a, To overcome the demands of users who are wanted to secure their e-information and worthy assets at low cost in a more truthful and opportune manner, b, To provide the finest security to our society from the unauthorized intruders' hacking. c, To provide a perfect solution to avert illicit access to digital information.

BAIS is a programmed real-time application of human identification which can be possible by acquiring; determining and scrutinizing the digital data of human corporeal and logical characteristics [2]. Researchers are exploring several biometric traits to earn the peculiar BAIS. However, many researchers are impleading their exploration into PRS due to its singularity, stability and high-performance characteristics [3]. The large space of the palmprint area includes principle lines and wrinkles which provide lots of unique information compared to the fingerprint area. Human palm print principle lines, and wrinkles can be treated as edges or contours for receiving the feature information. And those edges are not identical to each palm in a human hand. The Canny edge detection algorithm classifies the perfect set of edges of various sizes in an entire image [4].

Authors in [5] proposed segmentation-based fractal analysis to apply fractal model at low computation time compared to other techniques. Fractal dimension (FD) approach is considered as a widely applied descriptor, especially for analyzing the texture representation, in several fields like the signature recognition, palmprint recognition written identification etc [6],[7]. Authors in [8] stated that the fractal-based feature extraction technique has been proved as the agreeable approach in a computer-aided diagnosis system with a huge dataset. In 1983, Mandelbrot introduced fractal geometry to define fractals as the sets of self-identical. Fractal dimension is a ratio that describes the asymmetry and the difficulty of the stochastic models, indicating the pattern changes feature at the various scale [9]. The Box-counting algorithm is the most progressive and straightforward technique to measure the fractal dimension of the image [10],[1]. It works well for both linear and nonlinear fractal images and derives the deformity patterns on the surface of the images [11],[12].

A set of feature vectors is created and stored for identification and recognition processes by the DSL classifier algorithm which is the sub-area of Artificial Intelligence (AI) technology. Authors in [13] proved that feed-forward neural network with Back-Propagation achieved the higher authentication precision of 99.99% compared to other machine learning techniques used in this paper. Authors in [14] showed that the deep learning method has yielded higher recognition rate for palm print images. Machine learning algorithms forecast the outcome in higher accuracy using anterior knowledge of content. Nevertheless, massive datasets are not learned thoroughly in the machine learning algorithms that cause the lack of limpidity, interpretability in the decision-making. To overcome these drawbacks, researchers have extended their view

JOURNAL OF ALGEBRAIC STATISTICS
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ISSN: 1309-3452

of perception towards the next level that is the deep learning classifier approach [15] described in section 2. Deep learning on massive datasets is being most potent in the medical, biometric field and its enhanced techniques train the datasets faster and accurately [16].

Consequently**,** this paper employs an innovative RCFD feature extraction approach to brand the simple and fast computation. It computes the fractal dimension and slope values from the contours of the 2D-PROI images in an idiosyncratic manner to discrete the distinct features. That is explained in the section 3. A suitable DSL classifier algorithm and its configuration are designed for setting the higher rate of recognition and verification precision rate at a low time, which is explained in section 4.

2. General Description of Deep Supervised Learning (DSL) Classifier

A Deep Neural Network (DNN) is an Artificial Neural Network (ANN). It learns large input for predicting the exact outcome at a low error cost [17]. The general DNN architecture and the implementation of DSL classifier algorithm is discussed below.

2.1 DNN Architecture

DNN architecture includes an input layer (x^i) where *i* refers to the value of training template i-vector values from 1 to N (i.e. N is the maximum number of input data), an output layer (y^j) where *j* refers to the target j-vector values from 1 to M ((i.e. M is the maximum number of output data), and the multiple hidden layers hk^p where k refers to the number of hidden layers, p refers to the number of hidden perceptrons. The value of k and p are regulated progressively until least error rate is reached at a minimum training time. The learning rate value α and the epoch value $E\gamma$ are used to decrease the gradients and to know the number of iterations needed to attain the least mean square error through the whole dataset where *γ* refers to the maximum number of iterations. Next, the weight matrices are assigned to all the layers of DNN that are labeled as W_{m1}, W_{m2}, and $W_{m(k-1)}$ where m refers to the number of weight matrices and k refers to the number of hidden layers in the network. The basic DNN architecture is shown in Fig.1.

2.2 Implementation of DSL algorithm

Implementation of the DSL algorithm is done in two aspects: 1. Training aspect, and 2. Testing aspect. At the training aspect, the supervised learning algorithm is applied on DNN where two processing stages are performed in each epoch. In the first stage, the signal passes from the input perceptrons (x^i) to the first hidden layer h^p perceptrons along with the output using the equation (1) and (2). Similarly, the output of all hidden layers is gained till the output perceptrons are reached. In the output layer, output is calculated using (3) and to get the final output p^j. Each hidden unit determines its error by using the output unit's error.

$$h_j^p = w_m \times x^i |i = 1, \dots, N||m = 1, \dots, (k-1)||j = 1, \dots, k| \quad (1)$$

$$h_j^p = \beta (h_j^p) \quad |j = 1, \dots, k| \quad (2)$$

$$p^j = \beta(w_{m(k-1)} \times y^j)|m = 1, \dots, (k-1)||j = 1, \dots, M| \quad (3)$$

The dissimilarity between the exact output y^j and the final output of the network p^j is computed as an error Δ^j using (4).

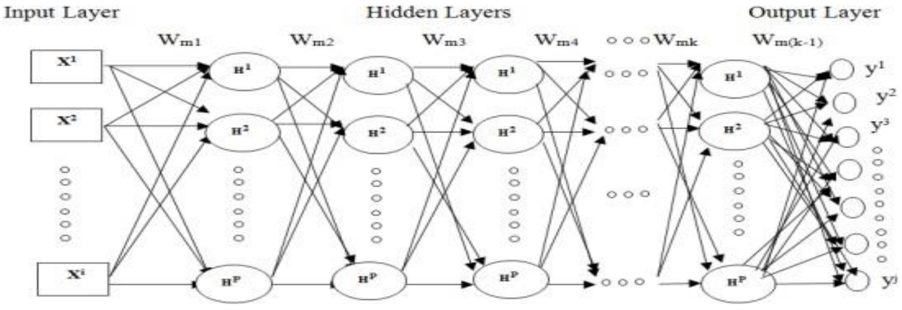
$$\Delta^j = y^j - p^j|j = 1, \dots, M| \quad (4)$$

In the second stage, the weights of all layers are updated using (5) in the backward direction along with the reverse processing procedure of the first stage to decrease the gradient.

$$w'_m = \alpha \times \Delta^j \times y^j|m = k-1, k-2, \dots, 1||j = 1, \dots, M| \quad (5)$$

Similarly, the first and second stage processes are repeated iteratively with the updated weights until the least Mean Square Error (MSE) rate between the prediction and true class values is achieved. Thus, the DSL classifier algorithm is tuned to learn the input and map the output exactly for the recognition process.

Fig.1. Basic Architecture of DNN



JOURNAL OF ALGEBRAIC STATISTICS
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And at the testing aspect, tuned DSL classifier with the obtained weight values is used to determine the verification accuracy.

3. Proposed Methodology

The proposed Deep Supervised Contour Fractal Dimension Analysis Model for Palmprint Recognition (DCFPR) has been performed in four levels: 1. Data acquiring level, 2. Pre-processing level, 3. Feature extraction level, and 4. Classification or Matching level [1]. The recognition and verification processes of DCFPR are depicted in Fig. 2, and Fig. 3.

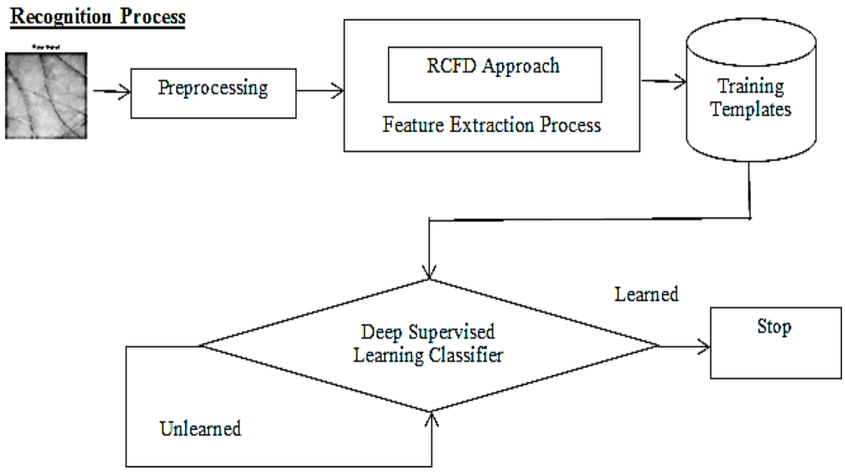

Fig.2. Block Diagram of DCFPR Recognition Process

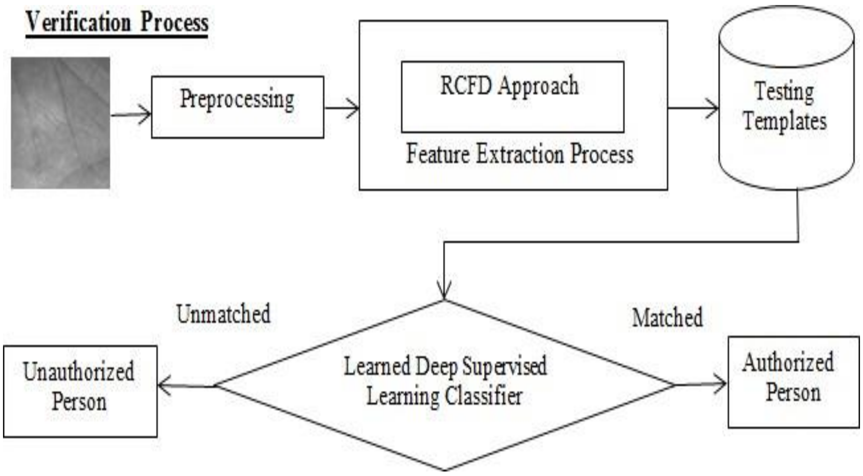

Fig.3. Block Diagram of DCFPR Verification Process

3.1 Data Acquiring

This research explores the 2D-PROI images of a multi-spectral 2D-ROI palmprint image database at the biometric research center (UGC/CRC) in POLYU, Hong Kong. That is comprised of 8000 segmented and normalized BMP image files of 400 volunteers' left and right hands' palms, store in two separate sections. Each section has 10 images of each palm and some of these sample 2D-PROI images are shown in Fig.4.

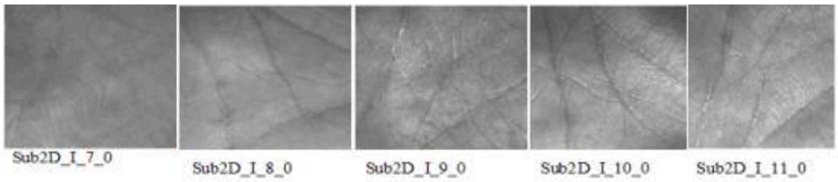

Fig.4. POLYU 2D-PROI Bitmap Images

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 1074 - 1083
https://publishoa.com
ISSN: 1309-3452

3.2 Pre-processing

The input image is molded to the well-defined quality image by doing the following processes: 1. Convert the input image into gray-scale image, 2. Remove the unfavorable data in the image, 3. Increase the spatial intensity level of the image. By pre-processing, the tiny creases, lines and ridges of palm print are spotted out more visibly as shown in Fig. 5. Then Canny edge detection algorithm is applied for tracing the lines, ridges, and curves and the resultant image is represented as Contour palm print Image (CI), shown in Fig.6.

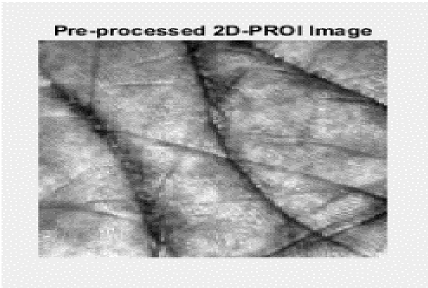

Fig.5. Pre-processed Image of 2D-PROI image

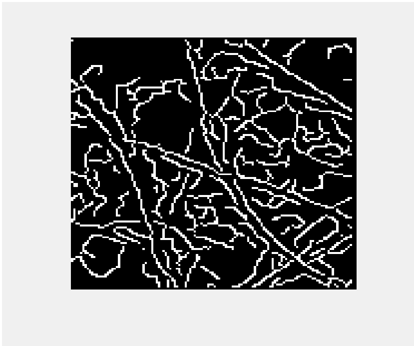

Fig.6. Canny Edge Detection on the Pre-processed Image

3.3 Feature Extraction level

A set of discrete Model based texture features of an image can be effectively excerpted by exploiting the Fractal Dimension (FD) approach [7]. This paper is explored and furnished the RCFD feature extraction approach to appraise the FD values of an input image in an idiosyncratic manner. The first step of the implementing the RCFD approach is to split the Contour palm print Image (CI) into four quarters (one-fourth) of non-overlapping regions with the equal size ʎ × ʎ where ʎ refers to the dimension of each region [18]. Each region is labeled as (CI_r) where r refers to the number of regions

i.e. r =1, 2, 3, and 4, which is shown in Fig.7. Next, the fractal dimension FD_r and slope S_r values for all regions (CI_r) are found by exploiting Box-Counting algorithm in a novelty manner. Finally, the representative FD and its S values are determined as discussed in the below subheading and Fig. 8. depicts the Graphical representation of RCFD approach.

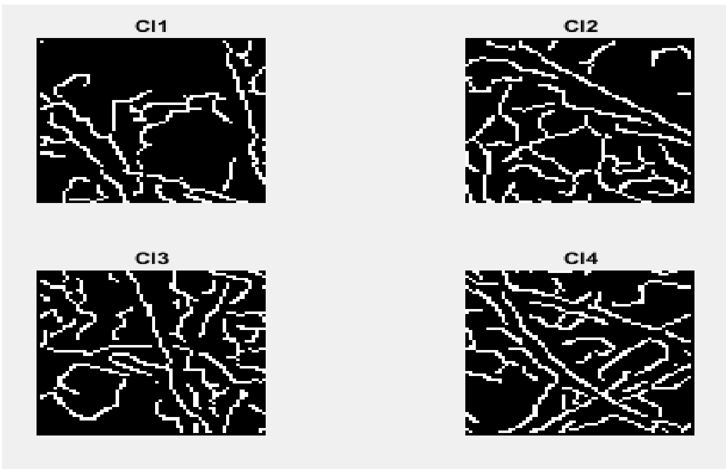

Fig.7. Equal Quarter Size Non-Overlapping Regions of CI (labeled as CI1, CI2, CI3, and CI4)

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 1074 - 1083
https://publishoa.com
ISSN: 1309-3452

3.3.1 RCFD approach

The procedure adapted in RCFD approach is given below.

3.3.1.1 The Fractal Dimension (FD_r) and its Slope (S_r) for each region of CI is calculated using the Box-Counting algorithm in a specific manner.

3.3.1.2 Determine the mean value of all edges' length (μ_Φ) in all square boxes $\Phi \times \Phi$ of set ε, where $\Phi = \Lambda/\varepsilon$ at various box scale intervals ε, (ε=1, ….., Ψ) where ψ refers to the maximum box scale interval value (i.e., log2(Λ)/2) using (6).

$$\mu_{\Phi,\varepsilon} = \sum_{\varepsilon=1}^{\Psi} \frac{\sum_{\Phi=1}^{\frac{\Lambda}{\varepsilon}} L_\Phi}{E_\Phi} \left|\Phi = 1, \ldots, \frac{\Lambda}{\varepsilon}\right| |\varepsilon = 1, \ldots, \Psi| \quad (6)$$

where L_Φ and E_Φ refer to the edge length and the total number of edges within square boxes $\Phi \times \Phi$ of set ε.

3.3.1.3 Find the Probability Mass Function (PMF_ε) of each set ε using (7).

$$PMF_\varepsilon = \sum_{\varepsilon=1}^{\Psi} \frac{\sum \mu_{\Phi,\varepsilon}}{N_\varepsilon} \left|\Phi = 1, \ldots, \frac{\Lambda}{\varepsilon}\right| |\varepsilon = 1, \ldots, \Psi| \quad (7)$$

where N_ε refers to the total number of boxes in the set ε.

3.3.1.4 Estimate the (FD_r) and its slope value (S_r) of each set ε for all regions of CI using (8)

$$FD_{r,\varepsilon} = \sum_{\varepsilon=1}^{\Psi} \frac{log(PMF_\varepsilon)}{log\left(\frac{1}{2^\varepsilon}\right)} |r = 1,2,3, and\ 4||\varepsilon = 1, \ldots, \Psi| \quad (8)$$

And this log transformation yields a straight line with slope $S_{r,\varepsilon}$ for each set ε to know more even spatial distribution and degree of high intensity values in an image.

3.3.1.5 Finally, calculate the representative fractal dimension (RFD_{CI}) and slope

(RS_{CI}) values of CI by using (9) and (10).

$$RFD_{CI} = \sum_{r=1}^{4} \frac{\sum_{\varepsilon=1}^{\Psi} FD_{r,\varepsilon}}{\sum\sum_{\varepsilon=1}^{\Psi} FD_{r,\varepsilon}} |r = 1,2,3,4||\varepsilon = 1, \ldots, \Psi| \quad (9)$$

$$RS_{CI} = \sum_{r=1}^{4} \frac{\sum_{\varepsilon=1}^{\Psi} S_{r,\varepsilon}}{\sum\sum_{\varepsilon=1}^{\Psi} S_{r,\varepsilon}} |r = 1,2,3,4||\varepsilon = 1, \ldots, \Psi| \quad (10)$$

Thus, RFD_{CI} and S_{CI} values are made out and stored as the training and testing template datasets using RCFD approach.

4. Classification or Matching level

According to the general description of the DSL classifier algorithm described in section 2, the DSL classifier is developed and tuned with the suitable activation functions, hidden layers, and its weight values to absorb the training template accurately in the recognition process. This tuned DSL classifier uses ReLU activation function to calculate the output of the hidden layers for avoiding the problem of vanishing gradient, and rise up the translational invariance to reinforce the output [16] and the Sigmoid activation function is used to find the output perceptrons' values in the output layer for setting the probability of the output data range between 0 and 1.

5. Experimental analysis

This research is appropriated 400 2D-PROI images of 20 volunteers in POLYU database, on that 80% of training image samples and 20% of testing image samples are deployed for the palm print identification process. In the testing phase, initially, 100 image samples has been taken and further increased in steps of 100 for each testing. Primarily, training and testing templates are generated using RCFD feature extraction approach. Fig. 9. shows the resultant measurement of fractal dimension FD_1 and its slope S_1 values of CI_1 of the test image. Likewise, FD and its S values for all regions of CI of the test image are estimated using (8). Finally, using (9) and (10) RFD_{CI} values 1.5920, 0.3878, and -0.0734 and S_{CI} value 0.9059 are evaluated which revealed the degree level of grey intensity values in the test image.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 1074 - 1083
https://publishoa.com
ISSN: 1309-3452

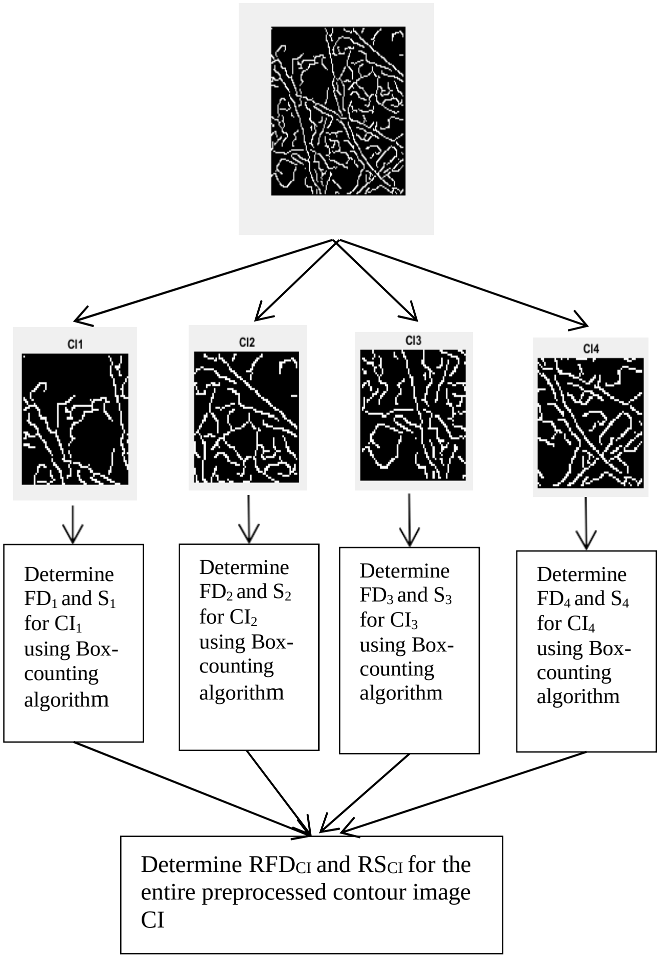

Fig.8. Graphical Representation of RCFD Approach

ε	2^{ε}	Φ × Φ	Nε	μΦ	pε	Log($1/2^{\varepsilon}$)	Log(pε)	FD1	S1
1	2	32 × 32	4	18.7750	9.3875	-0.6931	2.2394	-3.2310	
2	4	16 × 16	16	11.5490	2.8872	-1.3863	1.0603	-0.7648	1.9082
3	8	8 × 8	64	5.3307	0.6663	-2.0794	-0.4060	0.1952	

Fig. 9. Fractal Dimension (FD1) and its Slope(S1) Value of CI1 of a test image

In training and testing phases, DNN consists of five layers, where the first layer is the input layer that contains input nodes of the RCFD approach's feature i-vector consisting of three fractal dimension values and the corresponding slope values, the last layer is the output layer that carries ⌊log2n⌋+1 output nodes where n refers the number of bits required to denote the total number of training dataset, and three hidden layers are proposed in DCFPR system. As illustrated in

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 1074 - 1083
https://publishoa.com
ISSN: 1309-3452

section 2, DNN is trained with DSL classifier algorithm. The completion of the training process is assessed through the Mean Square Error (MSE) values. It is assumed that the DSL classifier algorithm trains the dataset very well if the MSE value is very least. The metric graph of the training process is shown in Fig.10. in that MSE values are approaching to the least MSE value at the epoch 9000. It can be effectuated by the salient parameters' values used in the DSL classifier algorithm, which is reported in Table 1.

Table 1. Salient Parameters' Values Used in the Training Phase of DRCPR System

Number of testing samples	**Number of Volunteers' Palms used**	**Number of Input Nodes**	**Number of Output Nodes**	**Epoch (γ)**	**Number of Hidden Layers**	**Number of Hidden Nodes or perceptrons**	**Learning Rate**
400	20	4	10	9000	3	33	0.00001

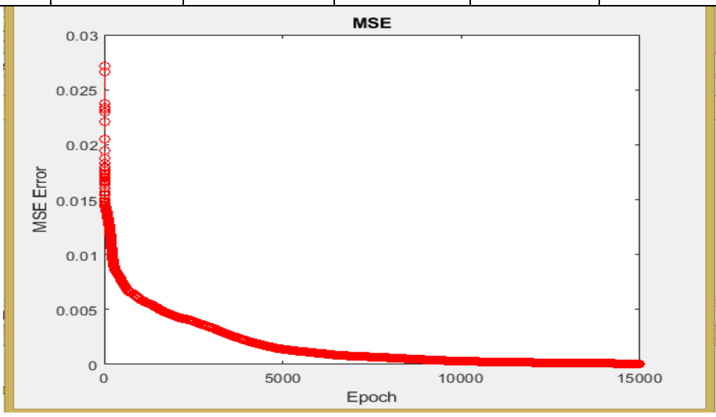

Fig.10. Metric Graph of DRCPR System Training Algorithm

The DCFPR system classifier performance is scrutinized through confusion matrix parameters such as Accuracy or Correct Positive Rate (CPR), True Positive Rate (TPR), False Positive Rate (FPR), Precision, and Specificity. In particular, the predicted values (True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)) are computed to measure the parameter values of the confusion matrix. Those values are obtained at the testing phase, where a set of the testing template compared with a set of the trained template and counted that how many testing datasets are matched correctly or not. Those predicted values are substituted in the confusion matrix parameters using (11), (12), (13), (14), and (15).

True Positive Rate (TPR)

$$TPR = \frac{TP}{TP + FN} \quad (11)$$

False Positive Rate (FPR)

$$FPR = \frac{FP}{FP+TN} \quad (12)$$

The Accuracy or Correct Positive Rate (CPR)

$$CPR = \frac{TP + TN}{TP+TN+FP+FN} \quad (13)$$

Precision

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

Specificity

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 1074 - 1083
https://publishoa.com
ISSN: 1309-3452

$$Specificity = \frac{TN}{TN+FP} \quad (15)$$

Fig.11. notifies the increasing value of True Positive (TP) in every increasing testing dataset. Table 2 and Fig. 12. signifies the parameters of the confusion matrix that shows the increasing range of testing image sample size (100, 200, 300, and 400), and its corresponding increasing value of TPR (0.90721, 0.97326, 0.993031, and 0.992385) and CPR values (0.90, 0.94, 0.9666 and 0.98). It implies that the increasing values of TPR and CPR are directly proportional to the increasing range of image samples [19]. That's demonstrated the proposed DCFPR system performs large datasets accurately and efficiently. As shown in Table 3, and Fig. 13., the proposed DCFPR system is executed well in its proposed feature extraction approach RCFD, which is revealed by analyzing other existing approaches along with its recognition accuracy rate.

6. Discussion

The motive of this research is to bring effective PRS by emphasizing an innovative recognition approach that consists of RCFD feature extraction and DSL classifier approaches. Table.2 is exposed the admissible performance of the approaches used in this system and analyzed it with the performance of other existing recognition approaches in Table.3 to know the achievement attained in its improvement. Data in the Fig.13, conspicuously proved that this system attained improvement with the hold of 98% recognition accuracy rate is higher than the other approaches used in the existing biometric technologies. Thence, this proposed DSFPR system can assent as a good reliable way of recognition in biometric technology.

Table 2. Predicted Values and Confusion Matrix Parameters

Number of testing samples	TP	T N	F P	F N	Precision	Specificity	TPR	FPR	CPR
100	88	2	1	9	98.8764%	66.6666%	90.7215%	33.3333%	90%
200	182	6	7	5	96.2962%	46.1538%	97.3262%	53.8461%	94%
300	285	5	8	2	97.2696%	38.4615%	99.3031%	61.5384%	96.666%
400	391	1	5	2	98.7373%	16.6666%	99.2385%	83.3333%	98%

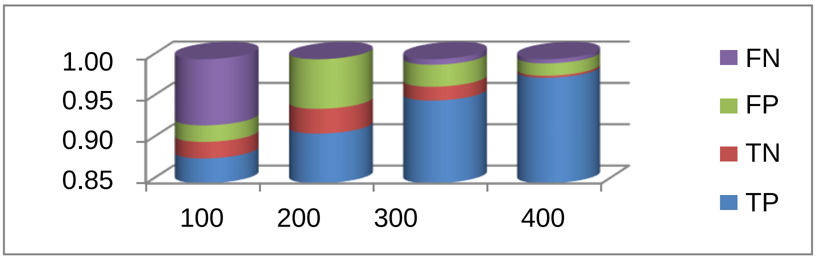

Fig.11. Predicted Values of the Confusion Matrix for Various Ranges of Testing Template

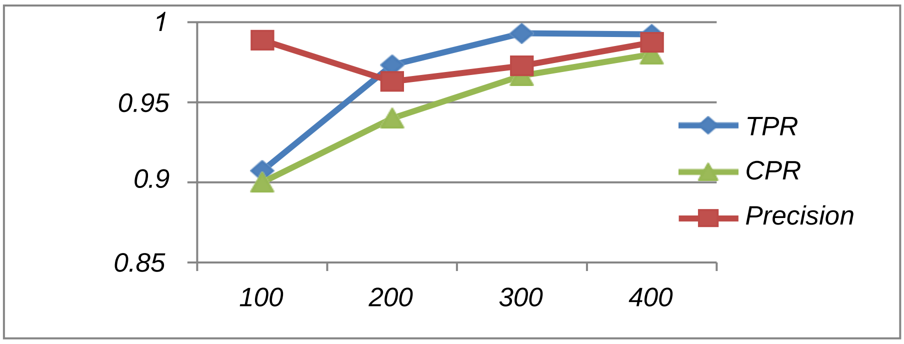

Fig.12. Confusion Matrix Parameter Values for Various Ranges of Testing Template

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 1074 - 1083
https://publishoa.com
ISSN: 1309-3452

Table 3. Analysis of Existing Approaches with Proposed Approach (RCFD)

S.No.	Recognition Approaches	Recognition Accuracy Rate	Publication Year
1.	Fractal Brownian Motion and K-means classifier approaches [12]	88.80%	2004
2.	Box-Counting Method (BCM) and double-threshold algorithm approaches [10]	94.61% & 93.23%	2005
3.	Contourlets-based Local Fractal Dimensions (CLFD) and Manhattan distance and the nearest neighbor classifier approaches [18]	97.80%	2008
4.	Box-Counting (BCM) and match score approaches [20]	92%	2014
5.	Box-Counting (BCM) and double-threshold algorithm approaches [21]	92%	2015
6.	Differential Box-Counting Method (DBC) and SVM classifier approaches [22]	97.9%	2017
7.	Fusion of Frequency, Model, and Statistical-Texture approaches with RF/SVM Classifier [7]	97.95%	2020
8.	Proposed Method (RCFD) and DSL classifier approaches	98%	----------

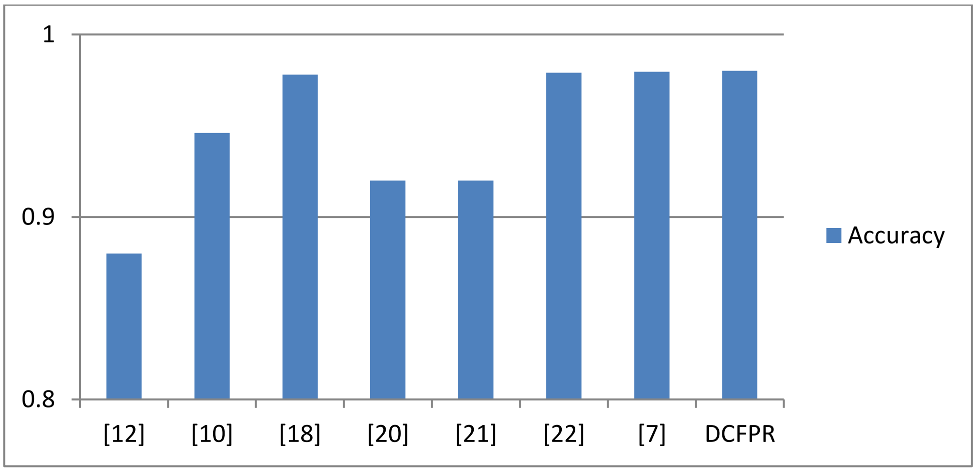

Fig.13. Performance Analysis of proposed Recognition approaches with Other Existing Approaches

7. Conclusion

The proposed DCFPR system is designed with a novel feature extraction approach (RCFD) to extract the distinct unique features of pre-processed 2D-PROI contour images and that fed to the DSL classifier algorithm. DRCPR system is experimented on 400 2D-PROI images of POLYU database with 80% of training and 20% of testing images and achieved a better accuracy of 98% in the authentication process. Hence, it can be used as one of the good feasible ways of BAIS. However, this proposed system exposed more self-similarity values for several datasets that tend to lack recognition accuracy. Hence, future work will be extended with deep study in the feature extraction techniques to improve the recognition and identification performance of the system.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 1074 - 1083
https://publishoa.com
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