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Contour Fractal Dimension Analysis using Square-Box ROI Extraction Approach with Convolution Neural Network Classifier for Palmprint Recognition System

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Abstract: Contour Fractal Dimension Analysis using Square-Box ROI Extraction Approach with Convolution Neural Network Classifier for Palmprint Recognition System ($CFDCNN_{Net}$) is proposed. To bring about the originality, Contour Fractal Dimension (CFD) feature extraction approach and a Convolution Neural Network (CNN_{Net}) classifier approach are employed. To impart the novelty the CFD feature extraction approach, Two Dimensional-Palmprint Region of Interest (2D-PROI) is captured from five different datasets using Square-Box ROI Extraction approach and point out all the edges/contours of 2D-PROI image (CP^I) using Canny edge detection algorithm and then estimate the Fractal Dimension (FD) values using Box-Counting algorithm to create a distinctive feature vector. Classify this feature vector using Convolution Neural Network (CNN_{Net}) classifier approach to identify the authorized person at a higher accuracy rate. This research explores on five different datasets such as CASIA, IITD, BMPD, SMPD and multi--spectral 2D-PROI image databases. The $CFDCNN_{Net}$ System model has been determined the authentication accuracy of different datasets with 98.66% of authentication accuracy.

Keywords: Palmprint Recognition System – Square-Box ROI extraction approach – Contour Fractal Dimension – Box-Counting – Fractal Dimension - Convolution Neural Network Classifier.

1. Introduction

Due to their distinctiveness and security, biometric recognition systems are widely used in many applications. Due to its stability, feature-richness, dependability, and improved user acceptability, hand-based person recognition has gained significant impetus in recent years [1]. Now-a-days, the authentication technology is preferred the biometric sensing. Biometric systems can be performed in either unimodal or multimodal system [2]. Unimodal biometric systems are facing the issues of spoof attacks, subpar sample quality, intra-class variability, and user acceptance plague [3]. The vast majority of these issues can be avoided by fusing data from many modalities [4].

Principal lines, valleys, wrinkles, and ridges on the palmar surface, are distinguishing the characteristics of palmprint to perform the authentication [5]. In recent years, several Convolution Neural Network (CNN) approaches have been presented in the palmprint recognition system [6]. A fascinating parameter to describe the roughness of an image is the fractal dimension [7]. It is able to be applied for information such as texture segmentation, three-dimensional (3D) shape estimate, and more [8]. [9] In this study, we employ a highly complex and cutting-edge technique of the fractal approach, to extract the characteristics of the palmprint texture information. This method has gained the popularity recently and is seen to be a hot topic for study in the field of image processing.

The fractal dimension (FD) technique is regarded for analyzing the texture representation, textual identification, palmprint and signature recognition [10] [11]. [12] This paper has proven the fractal-based feature extraction methodology to be the most acceptable method. Mandelbrot developed fractal geometry in 1983 to define fractals as collections of self-identical objects. The fractal dimension, which indicates the pattern changes characteristic at various scales, is a ratio that characterizes the asymmetry and the complexity of stochastic models [13]. The most advanced and user-friendly method to calculate the image's fractal dimension is the box-counting algorithm [14].

[15] shown that a better palmprint identification rate obtained using the deep learning approach. Machine learning algorithms use prior topic knowledge to more accurately predict the outcome. However, large datasets are not properly learnt by machine learning algorithms, resulting in lack of interpretability and clarity in decision-making [16]. In the medical and biometric fields, deep learning on large datasets is most effective, and its improved algorithms train the datasets more quickly and correctly [17].

Our proposed research constructs a novel $\text{CFDCNN}_{\text{Net}}$ classifier technique for the palmprint recognition system. To identify the different characteristics, it computes the fractal dimension values of the contours 2D-PROI image using canny edge detection algorithm. The input 2D-PROI image can be cropped using the novel square box ROI extraction algorithm. Proposed methodology of this research is discussed in the section 3. Classification level, and conclusion are described in section 3 and 6.

2. Proposed Methodology

Data acquiring phase, Pre-processing phase, Feature extraction phase, and Classification phase are the four vital phases of proposed palmprint recognition system ($\text{CFDCNN}_{\text{Net}}$) [1]. The identification and authentication processes of $\text{CFDCNN}_{\text{Net}}$ are illustrated in Fig.1, and Fig. 2.

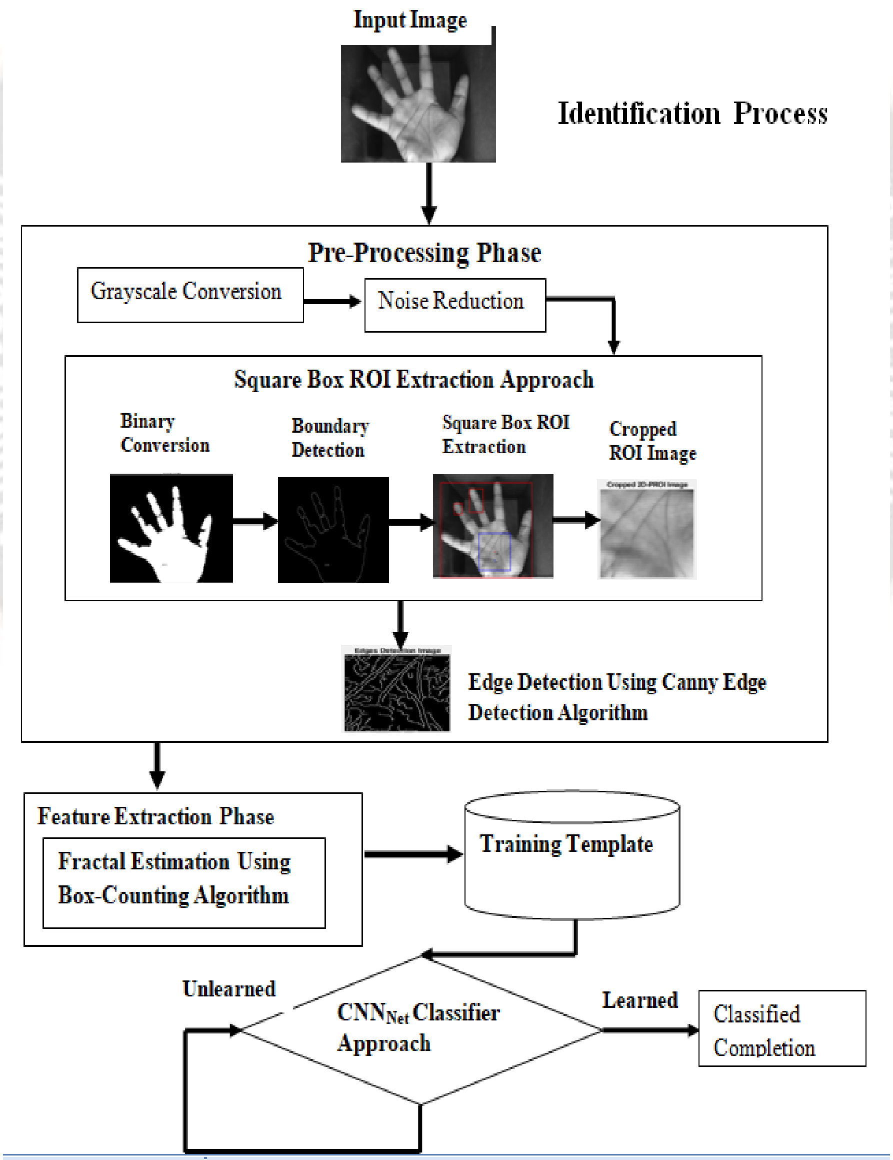

Fig.1. Block Diagram of $\text{CFDCNN}_{\text{Net}}$ Identification Process

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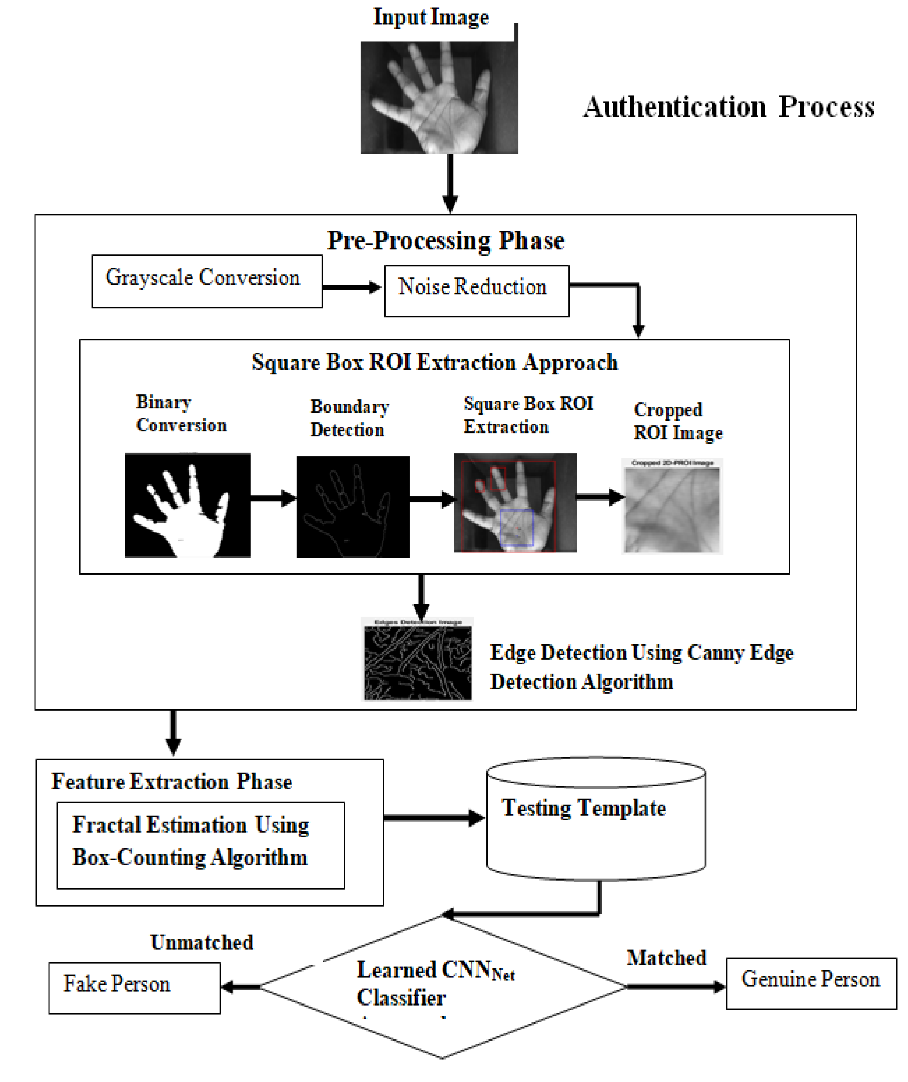

Fig.2. Block Diagram of CFDCNN$_{Net}$ Authentication Process

2.1. Data Acquiring

This research is scrutinized the palmprint images from various palm hand image datasets. Different datasets are derived from Indian Institutes of Information Technology (IIT) database, Birjand University Mobile Palmprint database (BMPD), CASIA palm database, Sapienza University mobile palmprint database (SMPD) database, and POLYU database.
The hand images took from 230 users of IIT Delhi students in New Delhi, India. All are stored in bitmap (*.bmp) format. Seven images of each subject, with their left and right hands in various hand poses are taken. It is shown in Fig.3.a.

5,502 palmprint images from 312 subjects are stored in the CASIA palmprint image database. Left and right palmprint images captured for each subject. It is shown in Fig.3.d.

8000 2D-PROI segmented and normalized BMP image files are accessed at the biometric research center (UGC/CRC) in POLYU, Hong Kong. 400 volunteers' left and right hands' palms are stored 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.

In the Birjand University Mobile Palmprint Database (BMPD), Left and right hands of 41 Iranian women images were collected. Totally, 1640 images are collected in two sessions with the interval of two weeks. Sample images of BMPD are shown in Fig.3.c.

110 international students' right hands images are taken from Sapienza and Tor Vergata universities in Rome. In this database, the distance between the palm and the smartphone is adjusted so that the best image quality can be obtained. It is shown in Fig.3.d.

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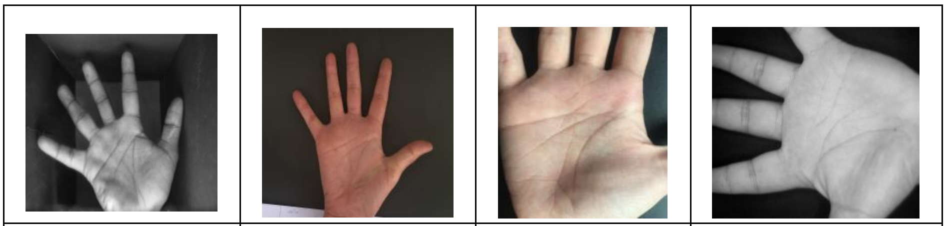

(a) (b) (c) (d)

Fig.3. a. IIT Dataset Image, b. BMPD Dataset Image, c. SMPD Dataset Image, and d. CASIA Dataset Image

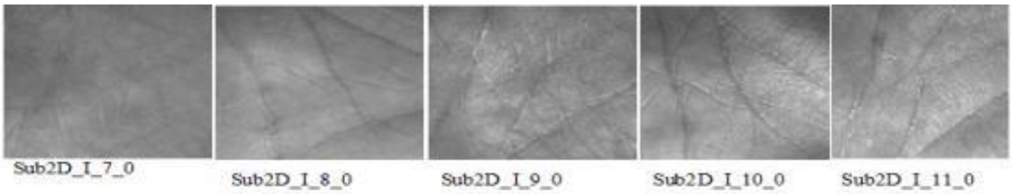

Fig.4. Sample 2D-PROI images from biometric research center (UGC/CRC) in POLYU, Hong Kong.

2.2. Pre-processing

The input image is pre-processed to make the input image quality in a well-qualified manner. It can be accomplished by performing the following steps: 1. Gray-scale conversion of image, 2. Detach the noise of data in the image, 3. Extract the 2D-PROI area using square-box ROI extraction approach to obtain the unique feature values and labeled as 2D-PROI image, 4. Rise up the spatial intensity level of the image to highlight the tiny creases, lines and ridges of palmprint, which are depicted in Fig. 5.a, 5.b, 5.c, 5.d, and 5.e. Finally, the resultant pre-processed image is labeled as Pre-processed 2D-PROI Image (CP^I).

Square-Box 2D-PROI Extraction Approach

The procedure adapted in the Square-box 2D-PROI extraction approach:

a. Separate the palm hand image from the background image using binary conversion.

b. Find out the perimeter pixels of an object to grasp the border boundaries of the palm image.

c. Marked the center region of the palm image (CI) using centroid property of Regionprops() function.

d. Extract the center point of palmar surface (CP) using the estimation of mid-point pixels value between the CI points and the endpoint pixel values of the palm's wrist at Y-axis, which is marked as WP. That is shown in Fig.6.

e. Pixel points of Left End Point (LEP) are attained at the x-axis of CP points, which is revealed in Fig.6.

f. Create the straight horizontal line between the end points of CP and LEP pixel values and set that length of the straight line value as the values of rectangular box's width and height. It produced the square-box area. Finally, cropped the image is kept inside the square-box area and labeled it as 2D-PROI image.

After attained the 2D-PROI image, canny edge detection algorithm is applied on 2D-PROI image to produce the contour 2D-PROI image and marked it as CP^I. It is shown as Fig.5.e.

(a) (b) (c)

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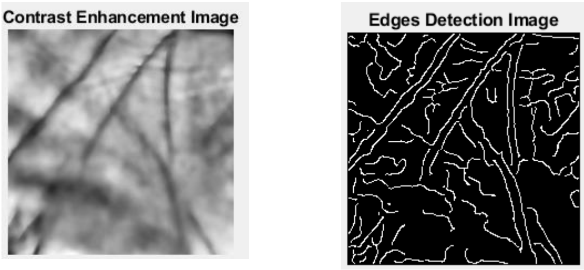

(d) (e)

Fig.5. a. IIT Dataset Input Image, b. Smoothen Input Image, c. ROI Extraction using Square-box ROI Extraction Approach, d. Cropped 2D-ROI image, e. Contour 2D-PROI Image CP^I

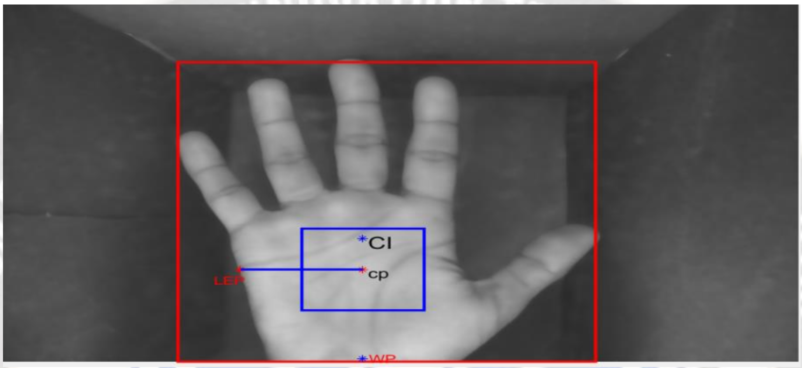

Fig.6. Pictorial Representation of Square-box 2D-PROI Extraction Approach

2.3. Feature Extraction level

Significant unique feature values are extracted from CP^I image using Box-Counting algorithm. A group of discrete Model-based texture characteristics of an image may be successfully extracted utilizing the Fractal Dimension (FD) estimation technique, [10]. This paper is extracted the distinct features of FD values in the PI input image using Box-Counting algorithm [11 -14]. Contour Pre-Processed Image (CP^I) of size (μ×μ) is used to estimate the FD values.

To accomplish the Box-Counting algorithm, estimate the mass value $M(i,N_\varepsilon)$ by finding and summing the probability of the pixel intensity values $P(I_i, \Lambda)$ of CP^I image covered within the counting boxes N_Ω of size $\Lambda \times \Lambda$ ($\Lambda = \frac{\mu}{\varepsilon}$) with the sets of interval ε from 1 to Ω (i.e., $\Omega = \log 2(\mu)/2$) where Λ refers to the size of each box, Ω refers to the highest range of interval value. It can be implemented using (1) and (2). Finally, the representative FD values are determined as the ratio of $\log(M(N_\Omega))$ divides $\log(1/2^\varepsilon)$ using (3).

$$P(I_i, \Lambda)_\varepsilon = \sum_{\varepsilon=1}^{\Omega} \frac{\sum_{\Lambda=1}^{\frac{\mu}{\varepsilon}} I_{i,\Lambda}}{N\Omega} \Big| \Lambda = 1,\dots,\frac{\mu}{\varepsilon} \Big| \; |\varepsilon = 1, \dots, \Omega| \quad (1)$$

$$M(i, N_\Omega) = \sum_{\varepsilon=1}^{\Omega} \sum_{i=1}^{\varepsilon} P(I_i, \Lambda)_\varepsilon \qquad |\varepsilon = 1, \dots, \Omega| \qquad (2)$$

where $I_{i,\Lambda}$ and N_ε refer to the pixel intensity values of CP^I image and the total number of boxes in the set ε.

$$FD_\varepsilon = \sum_{\varepsilon=1}^{\Psi} \frac{\log(M(i,N\Omega))}{\log\left(\frac{1}{2^\varepsilon}\right)} \qquad |\varepsilon = 1, \dots, \Omega| \qquad (3)$$

Where $M(i, N_\varepsilon)$ refers to the mass value of the image within the square box N_ε in the set ε. Thus, FD values are found out and stored as the training and testing templates using proposed approach.

2.4. Classification or Matching level

Proposed CNN_{Net} classifier was created using the Matlab Deep Learning Toolbox. The proposed approach CNN_{Net} classifier is built with the suitable odd parameters. That is obvious in Table 1. Table.1 reveals the CNN_{Net} parameters suitable for various dataset CP^I images. All CNN_{Net} parameters are substituted on trainingOptions() function. After setting the CNN_{Net}, the trainNetwork() method is used to carry out the CNN_{Net}'s training procedure. During the

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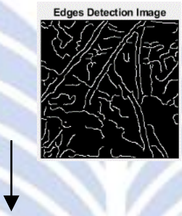
training process implementation of CNN_{Net} classifier, a training progress chart is created with the classification accuracy and loss percentages at each cycle of the epoch. The CNN_{Net} training process is ended based on the acquired high accuracy and low loss percentage result. Fig.10.a, 10.b, 10.c, 10.d, and 10.e show the training progress chart for all five test CP^I images from different datasets. During the testing phase, a trained CNN_{Net} classifier is employed.

3. Experimental analysis

This research is experimented on 2D-PROI images of five datasets such as CASIA, IITD, BMPD, SMPD and PolyU datasets. 300 training images are taken from each datasets and stored it as separate training and testing templates. From the 300 2D-PROI images, 80% and 20% of images are used for making training and testing templates. Totally, five training and testing templates are generated. Predominantly, training and testing templates are created using Square-Box ROI extraction and CFD feature extraction approaches. In PolyU datasets, 2D-PROI segmented and normalized images are obtained directly, which is shown in Fig.4. CASIA, IITD, BMPD, and SMPD datasets have 2D-palm hand images. Those are shown in Fig.3.a, 3.b, 3.c, and 3.d. Those 2D-Palm hand images are segmented to form the 2D-PROI area using Square-Box ROI extraction approach. Pictorial representation of Square-Box ROI extraction approach is shown in Fig.6. After the completion of Square-Box ROI extraction process, 2D-PROI images are captured and traced its contours using canny edge detection algorithm. That is depicted in Fig.5.e. Extracted Contour 2D-PROI images (CP^I) are fed into CFD feature extraction process to produce the unique feature vector.

2D-PROI image's Fractal Dimension (FD) values are extracted using (1), (2), and (3). Fig.7. reveals the resultant FD values for a test image (CP^I). Likewise, FD values are estimated on 300 2D-PROI images and formed training and testing templates. Fig.8. shows the extracted feature values for 300 CP^I images in the Microsoft Excel file.



ε	Ω	ʎ × ʎ	N_Ω	$M(i, N_\varepsilon)$	Log(1/2^ε)	Log($M(i, N_\varepsilon)$)	FD1
1	2	32 × 32	4	12.5730	0.6020	1.0994	1.8262
2	4	16 × 16	16	11.4810	1.2041	1.0599	0.8802
3	8	8 × 8	64	5.7807	2.7092	0.7619	0.2812

Fig.7. Resultant Fractal Dimension (FD) Values of CP^I test image

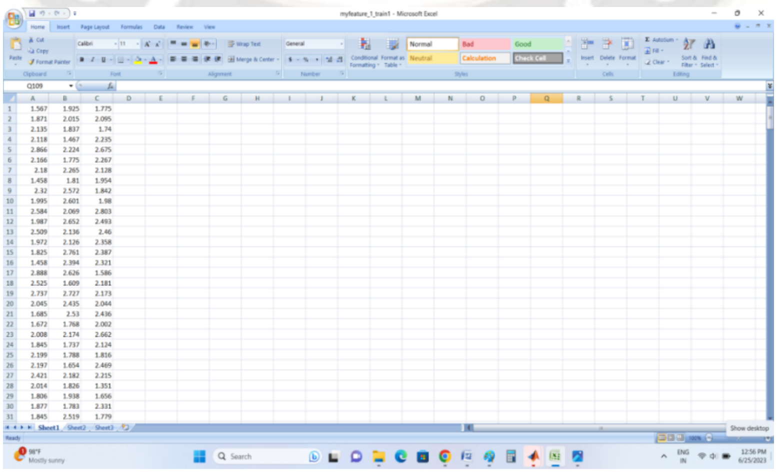


Fig.8. Extracted Proposed Feature values using $CFDCNN_{NET}$ approach

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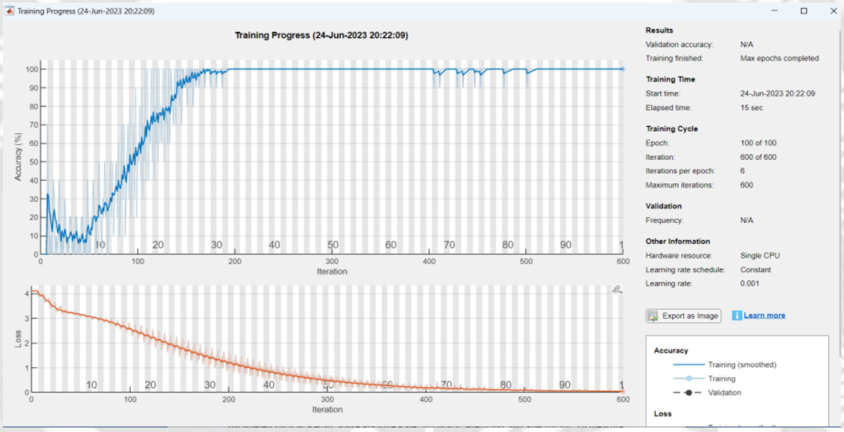
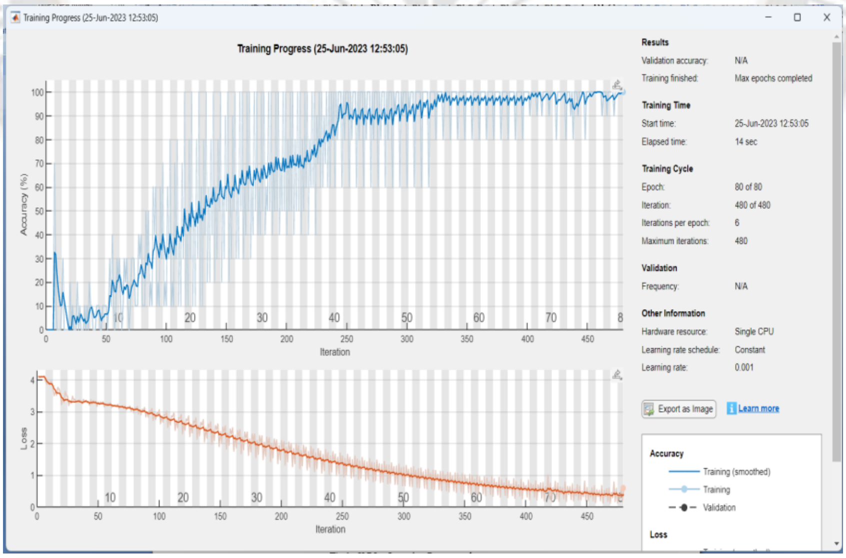
The CNN_{Net} classifier training performance charts are depicted in Fig.9.a, 9.b, 9.c, 9.d, and 9.e. It is shown the completed training process of all training templates. Those figures indicate that all various dataset training and testing templates are reached 100% accuracy and 0% loss in learning performance.

Table 1. Peculiar Parameters of CNN_{Net} for Recognizing the 300 Training Images of five different datasets

Peculiar Parameters of CNN_{Net}	**CASIA Datasets**	**IIT Datasets**	**BMPD Datasets**	**SMPD Datasets**	**PolyU Datasets**
Num. Features	1×3 ×1	1×3 ×1	1×3 ×1	1×3 ×1	1×3 ×1
Num. Filters	10	5	6	10	8
Filter Size	[5 5]	[8 8]	[5 5]	[5 5]	[6 6]
Num. Hidden Units	50	80	70	45	70
Num. Classes	300	300	300	300	300
Max Epochs	100	80	200	200	300
Mini Batch Size	10	10	10	10	10
Learning Rate	0.001	0.001	0.001	0.001	0.001



(a)



(b)

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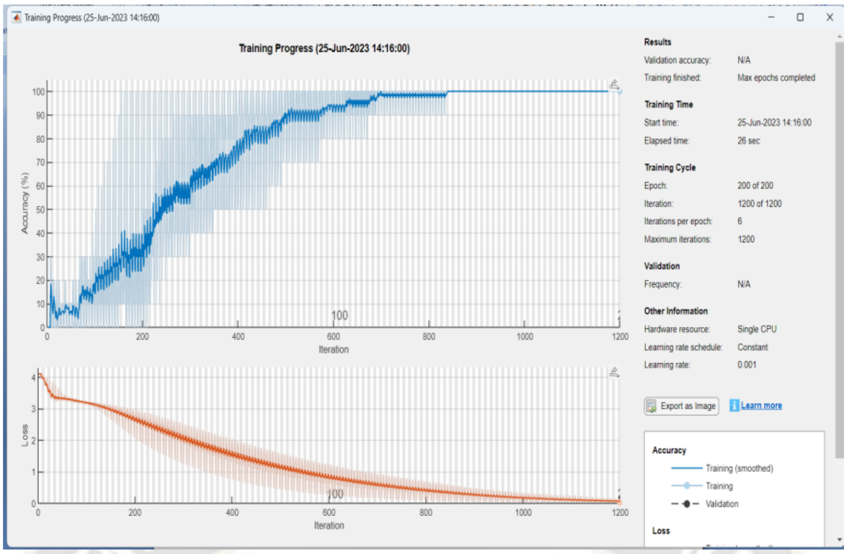
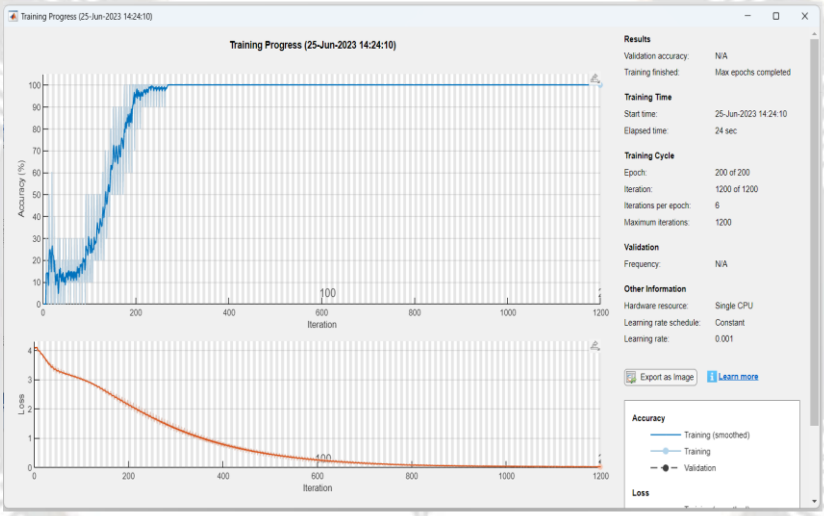
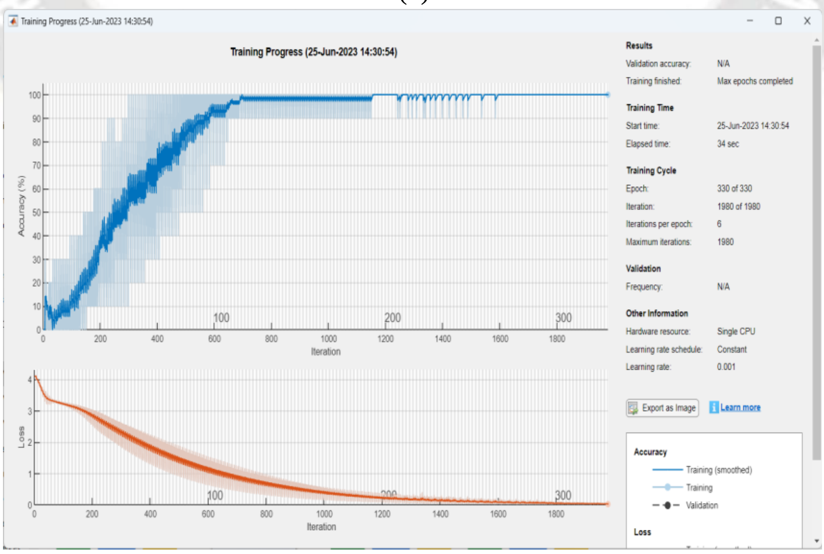


(c)



(d)



(e)

Fig.9. CNN_{Net} Learning Progress chart for Various Datasets Images, a. CASIA Dataset Images, b. IIT Datasets, c. BMPD Datasets, d. SMPD Datasets, e. PolyU Datasets.

Performance of our proposed system ($CFDCNN_{NET}$) is determined using confusion matrix parameters such as False Negative Rate(FNR), False Positive Rate(FPR), True Positive Rate(TPR), and Correct Positive Rate (CPR), Precision, and Specificity. To measure the parameter values of the confusion matrix, the predicted values (True Positive(TP), True Negative(TN), False Positive(FP), and False Negative(FN)) are in particular computed. These values are collected during the testing phase, when a set of the testing template is compared to a set of the trained template and a count is made of the number of testing datasets that are successfully matched or not. Using (4), (5), (6), (7), and (8), these anticipated values are substituted in the confusion matrix parameters.

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP+FN} \tag{4}$$

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP+TN} \tag{5}$$

$$\text{CPR} = \frac{TP+TN}{TP+FN+TN+FP} \tag{6}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{7}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{8}$$

The accuracy rate of recognition in every testing datasets is shown in Fig. 10. The suggested ($CFDCNN_{NET}$) system is executed successfully in its proposed feature extraction on various datasets which is disclosed by examining other current approaches as well as its recognition accuracy rate. Our proposed system ($CFDCNN_{NET}$) shows the best result accuracy rate in all datasets.

Table 2. Predicted Values of Confusion Matrix Parameters for five different testing templates

300 Testing samples from Five Different Testing Templates	**TP**	**TN**	**FP**	**FN**	**FNR**	**FPR**	**TPR**	**CPR**
CASIA Datasets	291	2	2	5	0.0168%	0.5%	0.9831%	0.9766%
IITD Datasets	288	6	1	5	0.0170%	0.1428%	0.98293%	0.98%
BMPD Datasets	290	5	3	2	0.0068%	0.375%	0.9931%	0.9833%
SMPD Datasets	292	2	1	5	0.0168%	0.3333%	0.9831%	0.98%
PolyU Datasets	292	4	2	2	0.0068%	0.3333%	0.9931%	0.9866%

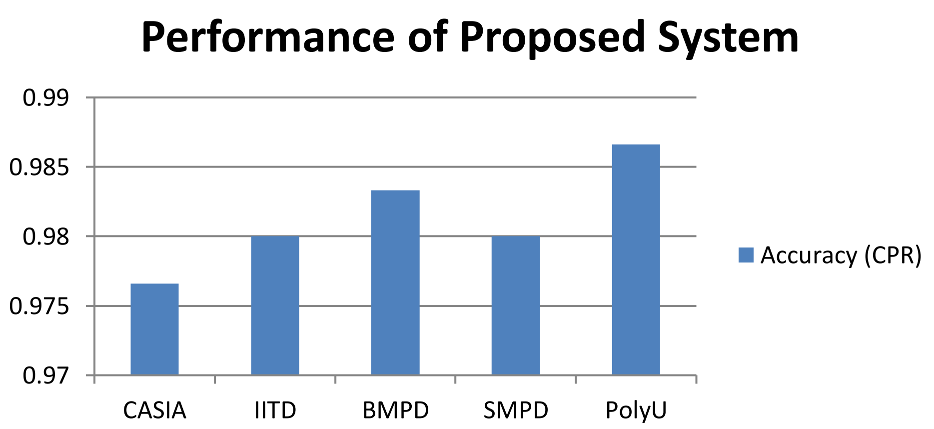


Fig.10. Chart Representation of $CFDCNN_{Net}$ System Classification Performance

4. Discussion

The goal of our research is a Contour Fractal Dimension Analysis utilizing Square-Box ROI extraction approach with Convolution Neural Network Classifier ($CFDCNN_{Net}$) is suggested to achieve a high authentication recognized accuracy in PRS. That can be achieved uniquely with 98.66% correct authentication accuracy of different palm hand images from various datasets, which is shown in Fig.10. And Table.3 exposes the performance analysis of various approaches used in PRS with the proposed approach ($CFDCNN_{Net}$) and divulges the achievement of best with 98.66% of authentication recognized accuracy in this research.

Table 3. Performance Analysis of Various Approaches along with the Proposed Approach

S.No.	Approaches	Accuracy Rate	Year
1.	Box Counting +Mass Radius+ Cumulative intersection+KNN+ SVM classifier[18]	96.35% for CASIA-Palmprint dataset and 95.98% for IITD-Touchless-Palmprint dataset.	2016
2.	TAFD-BC[19]	96% of PolyU 2D Palmprint database	2017
3.	The Multi-fractal dimension features using the Canonical Correlation Analysis (CCA) incorporating the Linear Discriminant Analysis (LDA) [20]	96.02% for PolyU-Palmprint database and 97.00% for CASIA-Palmprint database.	2017
4	DSL+DCFPR[21]	98% of authentication accuracy.	2022
5	DSL+RCFD[22]	98% of authentication accuracy.	2022
6	Proposed System	98.66%of accuracy	---

5. Conclusion

This research explores the authentication control of PRS using the novel system $CFDCNN_{Net}$ with different dataset images. This research experienced on five different datasets, on each 300 palm hand images are taken and make it as 2D-PROI using the Square-Box ROI extraction approach and formed the CP^I image using the Canny edge detection algorithm. A distinctive feature vector of CP^I *is* created as testing and training templates using the estimation of Fractal Dimension (FD) values using the Box-Counting algorithm. At ultimate, identification and authentication process can be performed and achieved 98.66% accuracy of authentication rate using $CFDCNN_{Net}$ classifier approach. Although, this research does not obtain the 100% accuracy of authentication recognized rate due to the presence of similarity in the FD values in several dataset images. In the future work, it will be carry out by applying the hybrid approach of model based feature extraction approach in PRS that tends to make more distinctive feature values without similarity values.

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