

Explore the Hybrid Approach of Texture Analysis with Deep Supervised Learning Classifiers on Palmprint Recognition System

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Abstract. Emerging cyber-environments emphasize the criticality of remaining aligned with authentic security systems to safeguard the exchange and storage of unique private and public confidential digital information. The Biometric Authentication and Identification System (BAIS) is a dependable application designed to mitigate the risks of unauthorized access to valuable electronic information in the digital realm. Among various BAIS implementations, the palmprint recognition system (PRS) stands out as one of the most widely adopted systems, attributed to its ease of access, high durability, distinctiveness, and accuracy in identifying legitimate individuals while maintaining a cost-effective approach. This proposed study explores a hybrid methodology in texture feature extraction techniques alongside supervised deep learning classifiers. This can be achieved by independently and collectively assessing the fractal dimension and lacunarity texture values utilizing the Box-Counting and Gliding-Box algorithms, then integrating these with two Supervised Deep Learning algorithms known as the Deep Backpropagation Learning classifier (DBL_{Net}) and the Convolutional Neural Network (CNN_{Net}) classifier, to achieve an advanced BAIS with enhanced accuracy. The 2DPROI image datasets are sourced from a multispectral 2D-palmprint image database at Hong Kong Polytechnic University in Hong Kong. The entire task is programmed using MATLAB R2020a Update 4 (9. 8. 0. 1417392) 64-bit (win64). Ultimately, the benchmarks of this proposed system are tabulated and analyzed to substantiate the assertion of improved recognition and identification accuracy through the hybrid feature extraction process, yielding an Authentication Recognition Rate (ARR) of 99.50% and 99.75% when employing the DBL_{Net} and CNN_{Net} classifiers, respectively.

Keywords: Biometric Authentication and Identification System (BAIS), Palmprint recognition system (PRS), Box-Counting, Gliding-Box, Fractal Dimension, Lacunarity Feature Value and Deep Backpropagation Learning classifier and Convolution Neural Network Classifier – Authentication Recognition Rate (ARR).

1. Introduction

Biometric Authentication and Identification Systems (BAIS) are generally essential for safeguarding the evolving digital landscapes within the IoT domain by collecting and analyzing data values through the statistical examination of human biometric characteristics. [1-3] BAIS involves the comparison of human characteristic data against a predefined template to verify the identity of the individual. Figure.1 depicts the block diagram of BAIS.

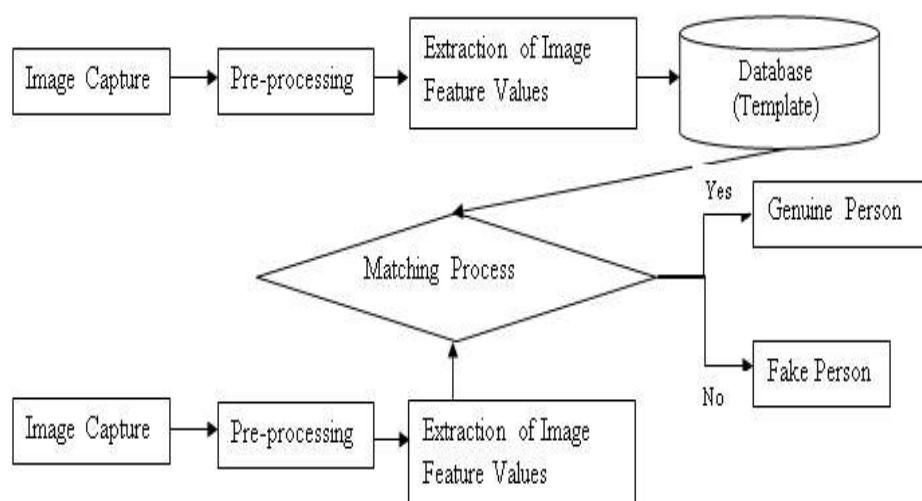


Figure 1. Block Diagram of BAIS

Researchers systematically investigate various biometric characteristics to obtain distinct BAISs. Recently, numerous scholars have directed their inquiries toward PRS, primarily due to their efficiency, robustness, and uniquely distinctive capabilities for authenticating access control. [6][7]. The PRS comprises four principal components: palmprint image acquisition, pre-processing, feature value extraction, and the classification process. Among these components, the feature extraction and classification processes are deemed essential, as they involve minimizing the 2DPROI (Two-Dimensional Palmprint Region of Interest) image size by preserving unique non-redundant data that encapsulates color, shape, texture, or contextual information. This data is retained as a genuine template of the individual, facilitating the classification of subjects in one-to-many or one-to-one scenarios. [8] Each 2DPROI image can be distinguished as a unique identifier based on variations in size, shape, density, and the organization of principal lines, creases, ridges, and minutiae, reflecting the diverse structural composition of the palmprint surface to accommodate versatile arrangements of texture information. Consequently, texture information within a 2DPROI image is critical for identifying the legitimate authorized individual. Texture is characterized by the spatial variation of image tones. [9][10] One effective technique for extracting texture features is the application of model-based texture methods, owing to their reduced computational time in comparison to alternative approaches.[11][12] Model-based methods are fundamentally designed to extract the foundational qualitative properties of the texture. [11] In 1970, Mandelbrot introduced a novel area of mathematics known as fractals to illustrate coarseness, roughness, and self-similarity within a texture image. [13][14] Model-based texture methods provide a consistent representation of fractals, revealing textural information across different dimensions despite identical fractal characteristics. [15][16] The Box-Counting algorithm, developed by Gangepain and Roques-Carmes, has proven to be a preferred approach for estimating approximate fractal dimensions. It is noted that divergent fractal sets might possess equivalent fractal dimension values yet display contrasting appearances or textures. To enhance the understanding of fractal dimension textures, the concept of Lacunarity was introduced to characterize varying texture appearance patterns that share the same dimensional values by delineating distinct variances or mean values, leading to differing lacunarity texture values. [17][18][19] Since 1983, Mandelbrot has devised algorithms for calculating lacunarity. Additionally, Allian & Cloitre (1991) and Dong (2000) initiated a straightforward "gliding box" algorithm for lacunarity computation, aimed at recognizing the geometric characteristics of specific and arbitrary sets of patterns as textured properties. [22][23][24][25] Evidence suggests that combining fractal dimension features related to shape with lacunarity features of texture achieves superior accuracy in recognition compared to the utilization of each feature in isolation.

Machine Learning (ML) and Deep Learning (DL) methodologies represent subsets within the realm of Artificial Intelligence (AI) technology, utilized to implicitly encode prior knowledge of content to forecast outcomes derived from analyzed data. However, substantial datasets often do not undergo adequate training within ML algorithms, leading to deficiencies in transparency and interpretability during the decision-making process. [26] To mitigate the limitations associated with ML algorithms, researchers broaden their perspective to a higher level, which is the domain of deep learning algorithms. [27] DL serves as an enhancement of neural networks, incorporating multiple layers to facilitate the learning of more abstract features utilizing pertinent data to accurately predict the final classification. [18] DL represents the evolution of a neural network characterized by multiple layers designed for processing large datasets, with vital data aimed at ensuring accurate forecasting of final classifications. [20] The architecture of deep learning is comprised of a Deep Neural Network (DNN), which contains an input layer, an output layer, and various hidden layers.

In the proposed system, a rapid and optimized method for feature extraction is introduced by utilizing a hybrid approach that combines fractal dimension and lacunarity algorithms to create a feature vector set that serves as a template for both training and testing datasets. During the classification phase, template datasets are aligned in a one-to-one or one-to-many manner with the features of an authenticated individual to facilitate the recognition and validation of an authentic person. To enhance the speed and accuracy of recognition, the classification phase employs deep learning algorithms. This proposed system utilized and evaluated two classification algorithms: the DBL_{Net} Classifier and the CNN_{Net} Classifier, aimed at improving the efficiency of the training and testing processes on 2DPROI image datasets. Consequently, this proposed system implemented advanced deep supervised learning classifier algorithms to attain a higher accuracy rate in PRS.

2. Methodology

This study utilized the multispectral 2DPROI palmprint grayscale image database from the Biometric Research Centre (UGC/CRC), POLYU, Hong Kong [37]. The database consists of 8000 samples gathered from the palms (left and right) of 400 volunteers, with the data collected and stored across two distinct sessions. During each session, participants were requested to provide 10 images for each palm. Each sample, which includes the corresponding 2DPROI images, was saved in bitmap format, as illustrated in Figure.2. To

gather the rich and unique feature information of 2DPROI image, the following preprocessed processes are performed and formed pre-processed 2DPROI image(PI). Preprocessed processes are: 1. grey-scale image conversion, 2. Reducing noises, and 3. increased the contrast level of image. Semantic representation of recognition and identification process of the proposed system is illustrated in Figure.3.a and 3.b. The process of gathering texture information is significant in the realm of image classification. Model-based texture approaches apply parameters associated with the model design of image composition to articulate the fundamental qualitative characteristics of the texture. The most prevalent applications of model-based texture methodologies include fractal and lacunarity techniques. [13] Fractal is advantageous for modeling casual textures across various scales and for its self-similar nature. [20] Lacunarity characterizes the intricate interplay of shapes and the distribution of voids within the image pattern. [32] In this paper, the quantitative texture attributes of a PI image $f(\alpha_i, E)$ can be derived by executing the Box-Counting algorithm and the Gliding-Box algorithm to determine the Box or Minkowski dimension $f(\alpha_{BD}, E)$ of the image. The Box or Minkowski dimension $f(\alpha_{BD}, E)$ enhances the visual quality of the image by highlighting the point-wise singularity, which aids in accurately retrieving the fractal dimension values (FD_ϵ) and lacunarity values (L_r).

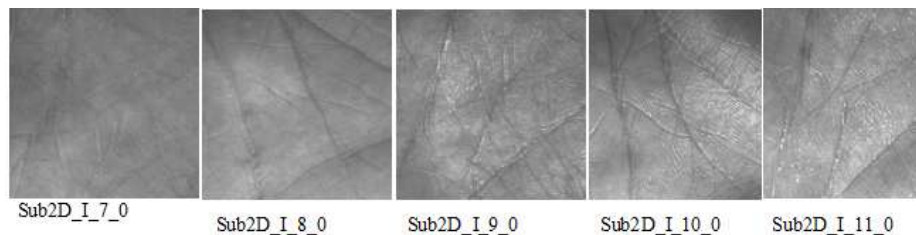


Figure 2. Original 2DPROI of size 128×128 bitmap images from HongKong POLY University.

At first, substitute the Box or Minkowski dimension values $f(\alpha_{BD}, E)$ to the entire original 2DPROI image E with the gray-scale intensities $f(\alpha_i)$, that caused the creation of another image MBI with homogeneity intensity values $f(\alpha_{BD})$. 2DPROI input image, preprocessed image (PI), and Minkowski dimension image (MBI) are illustrated in Figure. 4. After that, calculate the fractal dimension (FD_ϵ) and lacunarity(L_r) feature values using the fractal dimension and lacunarity procedures on Box or Minkowski dimension image ($f(\alpha_{BD}, E)$).

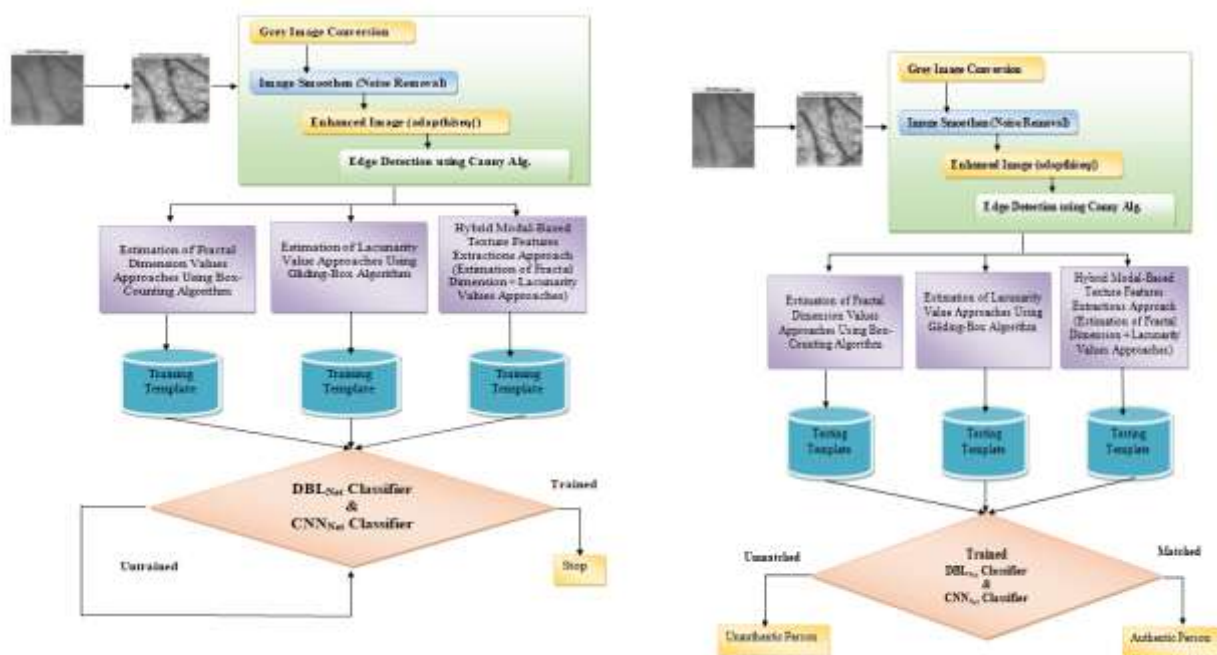


Figure 3. a. Semantic Description of Recognition Process and 3.b. Semantic Description of Identification Process

2.1. Estimation of Fractal Dimension (FD) Values Using Box-Counting Algorithm

[34] The Box-Counting algorithm represents the most advanced method for assessing the fractal dimension (FD) of an image. The box-counting approach involves segmenting the image space $f(\alpha_{BD}, E)$ of size $\eta \times \eta$ into uniformly sized square boxes of dimensions $\Phi \times \Phi$, which are contingent upon the resolution, dimensions, and configuration of the scanned image. The proposed system identifies the appropriate box

sizes Φ at intervals of size $\varepsilon = 1, 2, \dots, \log_2(\eta/2)$ for overlaying boxes on the image. For each box size Φ , the number of boxes N_Φ is calculated at each diameter ε across the entire image set $f(\alpha_{BD}, E)$. The intensity values of each pixel are assigned to the sets N_Φ of boxes at various sizes ε , resulting in a frequency distribution of box masses $N(f(\alpha_{BD}, E), \varepsilon)$. The cumulative gray-scale fractal pixels (p) within each box of size Φ (commonly referred to as box-mass) are utilized to derive a characteristic mass distribution $D(p, \varepsilon)$ through Equation (1). Subsequently, the probability distribution $PD(p, \varepsilon)$ is derived by dividing the frequency (mass) distribution $N(p, \varepsilon)$ by the total number of boxes N_Φ , as expressed in Equation (2).

$$D(p, \varepsilon) = \sum_{i=0}^{\varepsilon} \sum_{j=0}^{\varepsilon} N_{\Phi}(p_{ij}, \varepsilon) \mid \Phi = 1, \dots, \frac{\eta}{\varepsilon} \mid \varepsilon = 1, 2, \dots, \log_2(\eta/2) \quad (1)$$

$$PD(p, \varepsilon) = \frac{D(p, \varepsilon)}{N_\Phi} \mid \Phi = 1, \dots, \frac{\eta}{\varepsilon} \mid \varepsilon = 1, 2, \dots, \log_2(\eta/2) \quad (2)$$

FD_ε , the fractal dimensions, can be estimated from the least square linear fit by the Equation (3)

$$FD_\varepsilon = \frac{\log(PD(p, \varepsilon))}{\log(1/2^\varepsilon)} \mid \varepsilon = 1, \dots, \log_2(\eta/2) \quad (3)$$

The process is repeated in different box sizes (ε) to find the fractal dimension (FD_ε) values on an image.

2.2. Lacunarity in Gliding-Box algorithm

[21] [35] Certain images do not exhibit true self-similarity and possess comparable fractal dimensions, yet display differing texture values (Mandelbrot, 1982; Lin and Yang, 1986), which can be utilized to differentiate spatial patterns via the pixel gap distribution at specific intervals that are intrinsically associated with scale, density, voids, variation, and multi-scalar metrics (Plotnick et al, 1996).

In the proposed framework, lacunarity is computed from the normalized Box or Minkowski dimension $f(\alpha_{BD}, E)$ image through the application of the Gliding-Box algorithm on a dataset of dimensions $\Phi \times \Phi$ of set μ , where $\Phi = \eta / \mu$ at various box scale intervals μ , ($\mu = 2, 4, 8, 16$, and 32). Within the Gliding-Box algorithm, a gliding box of dimension $\mu (\leq \Phi)$ is positioned at the origin of the dataset and is moved one pixel at a time by adding one pixel at the leading edge hyper-plane while simultaneously removing the trailing edge hyper-plane of base box dimension $\mu \times \mu$ from the upper left corner of the image $\Phi \times \Phi$. [45], [46] The number of boxes N_Φ with dimension μ containing filled gray-scale pixels (p) across the image $\Phi \times \Phi$ for each of the overlapping boxes is determined through the frequency distribution, and the aggregate of occupied gray-scale fractal pixels (p) within every box of dimension μ (referred to as box-mass) is employed to calculate a characteristic mass distribution $D(p, \mu)$ using Equation (4). Subsequently, the probability distribution $PD(p, \mu)$ is derived using Equation (5), where $PD(p, \mu)$ is obtained by dividing the total mass frequency distribution $M(p, \mu)$ by the overall count of boxes N_μ .

$$D(p, \mu) = \sum_{i=0}^{\Phi} \sum_{j=0}^{\Phi} N(p_{ij}, \mu) \mid \mu = 2, 4, 8, 16, 32, 64, 128 \mid \Phi = 1, 2, \dots, \frac{\eta}{\mu} \quad (4)$$

$$PD(p, \mu) = \frac{D(p, \mu)}{N_\Phi} \mid \mu = 2, 4, 8, 16, 32, 64, 128 \mid \Phi = 1, 2, \dots, \frac{\eta}{\mu} \quad (5)$$

Lacunarity is estimated as the ratio of second order moment (variance) to the first order moment (average) determined from the box mass. For a gray-scale image, the mass is the sum of gray-scale intensities. Then, calculate the first and second moments ($f^1(\mu)$ and $s^2(\mu)$) of the box-mass probability distribution by using the Equation (6) and (7).

$$f^1(\mu) = \sum_{i=0}^{\Phi} \sum_{j=0}^{\Phi} p_{ij} \times PD(p_{ij}, \mu) \mid \mu = 2, 4, 8, 16, 32, 64, 128 \mid \Phi = 1, 2, \dots, \frac{\eta}{\mu} \quad (6)$$

$$s^2(\mu) = \sum_{i=0}^{\Phi} \sum_{j=0}^{\Phi} p_{ij}^2 \times PD(p_{ij}, \mu) \mid \mu = 2, 4, 8, 16, 32, 64, 128 \mid \Phi = 1, 2, \dots, \frac{\eta}{\mu} \quad (7)$$

Gliding-box lacunarity can be defined by Equation (8)

$$L_\mu = \frac{f^1(\mu)}{s^2(\mu)^2} \mid \mu = 2, 4, 8, 16, 32, 64, 128 \quad (8)$$

Where L_μ denotes the lacunarity value at a specified box size μ , p signifies the mass or pixels of interest, and $PD(p_{ij}, \mu)$ indicates the probability of frequency distribution at box size μ . Consequently, the lacunarity value is attributed to the central pixel of the window by deriving it from various box sizes, each associated with its own lacunarity values. Utilizing differing window dimensions μ (i.e., 2×2 , 4×4 , 8×8 , 16×16 , 32×32 , 64×64 , 128×128), the aforementioned lacunarity and fractal dimension methodologies are employed to obtain the fractal dimension and lacunarity values, which form a set of unique feature i-vector templates for the training and testing datasets intended for the classification task. Thus, seven distinct feature i-vector templates are generated by separately storing and combining estimates from two approaches: FD and lacunarity values.

3. Classification Phase

This proposed system incorporates two supervised DNN classifiers: the DBL_{Net} classifier and the CNN_{Net} classifier. These two classifiers are evaluated against appropriate benchmark measurement methods to ascertain their performance regarding ARR. The descriptions of the DBL_{Net} and CNN_{Net} classifiers are provided in the forthcoming sections 1. 4. 1 and 1. 4. 2.

3.1 DBL_{Net} Classifier

[36][37] A deep supervised learning algorithm is utilized for classifying one-to-many or one-to-one individuals for the purposes of 2DPROI image recognition and identification. In constructing the DBL_{Net}

configuration, this study employs a five-layer architecture for DBL_{Net} throughout all training and testing phases. The initial layer consists of an input layer containing input nodes that fluctuate at each template level based on the feature i-vectors, while the final layer serves as the output layer encompassing ten output nodes, determined by the equation $\lceil \log_2(n) \rceil + 1$, where n represents the number of features within a feature vector. Throughout all training phases, the hidden layers maintain consistency; however, adjustments are made to the hidden nodes, learning rate, and epoch values until the DBL_{Net} architecture achieves the appropriate learning necessary to accurately identify all training templates. Table.1 presents the hyper-parameter values utilized in this experiment across three templates for 400 2DPROI images. The optimized DBL_{Net} architecture is established by implementing the back-propagation supervised algorithm alongside the ReLU activation function at each hidden layer node and the Sigmoid function at each output layer node, thereby facilitating effective learning of the correct templates for authorized personnel during training phases. The same trained DBL_{Net} architecture is subsequently employed during the testing phase to recognize the distinct authorized individual.

3.2. CNN_{Net} Classifier

In this research endeavour, the CNN_{Net} classifier is developed utilizing the Matlab Deep Learning ToolBox to accurately assimilate the training templates within the recognition framework of the proposed system. Following the establishment of all appropriate parameter values in the CNN_{Net} configuration as outlined in Table.2, an array of layer and training option values is generated to facilitate the learning of three distinct training templates. The learning process of CNN_{Net} commences with the application of the proposed array of layers and training options to the trainNetwork() function. The output from the trainNetwork() illustrates the training progress chart. This learning process is concluded when a 100% accuracy and a 0% loss are attained at specific epoch iterations as depicted in the training progress chart.

4. Experimental Analysis

This investigation employs 400 2DPROI images sourced from 20 workers in the PolyU dataset. Of this dataset, 80% is designated for training, while 20% is allocated for testing within the context of palmprint identification. To utilize the proposed system, the PolyU 2DPROI bitmap image, sized at 128×128 , is transformed into a contrast gray-level image through the application of the built-in Matlab functions mat2gray() and adapthisteq() to enhance the interpretative quality of the image information. The extraction of unique texture feature values is accomplished by employing both separate and fusion methodologies utilizing the Box-counting algorithm and the Gliding-box algorithm to ascertain the FD and L values on the 2DPROI images. 2DPROI input image, preprocessed image, and Minkowski dimension image are illustrated in Figure. 4.

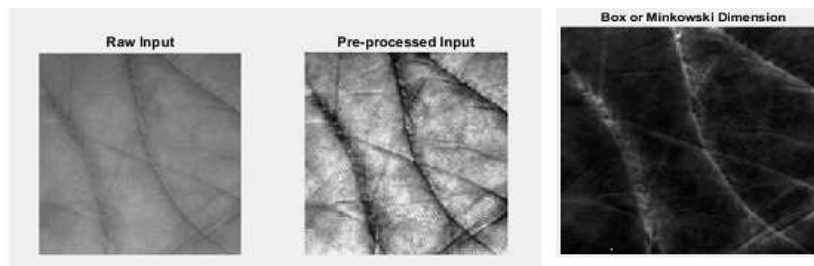
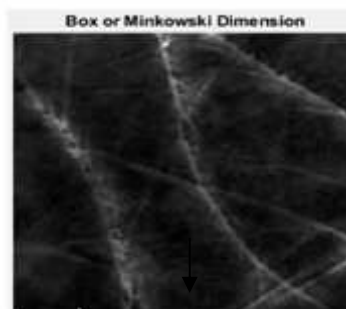


Figure3.Original POLYU 2D-ROI Palmprint image, Pre-processed Image and Box or Minkowski dimension Image

4.1. Fractal Dimension (FD) in Box-Counting Algorithm

This experiment utilizes seven distinct boxes with uniform dimensions of $\epsilon \times \epsilon$, applying the power law with $\epsilon = 1, 2, 3, \dots, \log_2(1/2)$ to derive the fractal values of an image by inserting the values corresponding to the number of boxes and the probability of fractal pixel values within each box of size ϵ into Equation (3). Figure.5 displays the results of the fractal measurement values for the seven diverse boxes of equal dimensions $\epsilon \times \epsilon$.



ε	$\Phi \times \Phi$ Each Box Size	N_Φ	$PD(p, \varepsilon)$	$1/2^\varepsilon$	$\text{Log}(1/2^\varepsilon)$	$\text{Log}(PD(p, \varepsilon))$	FD_ε
1	2×2	4	7.8454	0.5	-0.3010	0.8946	-2.9720
2	4×4	16	4.5895	0.25	-0.6020	0.6617	-1.0991
3	8×8	64	1.7856	0.1250	-0.9030	0.2517	-0.2787
4	16×16	256	0.4521	0.0625	-1.2041	-0.3447	0.2862
5	32×32	1024	0.1478	0.0313	-1.5043	-0.8303	0.5519
6	64×64	4096	0.0365	0.0156	-1.8068	-1.4377	0.7957
7	128×128	16384	0.0114	0.0078	-2.1075	-1.9430	0.9219

Figure 4. Result of a Test Image's Fractal Measurement Values in Seven Various Boxes with Equal Dimension $\varepsilon \times \varepsilon$

Finally FD is 1.6246 obtained from the slope of the points FD_ε of various seven dimension boxes, which means more uniform spatial distribution of the mass $PD(p, \varepsilon)$ in a test image is close to the number 2 that reveals the degree of gray tones concentration in an image. Figure.6.Lacunarity values of seven different dimension Gliding-Boxes of a Test Image

4.2. Lacunarity in Gliding-Box algorithm

Test image of the 2DPROI with a size η (128×128) is a power of 2, which facilitates the construction of the Gliding-Box with dimension μ , where $\mu = 1, 2, \dots, \Phi$. This experiment accomplished seven distinct dimension Gliding-Boxes sliding over an image to calculate the lacunarity values utilizing Equation (8), as illustrated in Figure.6.



Iteration	$\Phi \times \Phi$ Each Box Size	$P(\mu)$	$s^2(\mu)$	L_μ
1	127×127	-0.0245	0.0125	-1.1964
2	125×125	0.0785	0.0245	3.2040
3	121×121	0.6587	0.1578	4.1742
4	113×113	2.4578	1.2165	2.0203
5	97×97	9.1245	1.5452	5.9050
6	65×65	10.124	2.5455	3.9772
7	1×1	12.154	2.8989	4.1926

Figure6.Lacunarity Values of Seven Different Dimension Gliding-Boxes of a Test Image

Three templates for training and testing are employed during the training and testing procedures. These templates are developed using distinct and hybrid approaches to FD and L estimation values. In forming these templates, a singular FD value for 400 2DPROI datasets is preserved in one training and testing template, while seven lacunarity values for 400 2DPROI datasets are contained as a collection of feature i-vectors in the second training and testing template. Furthermore, eight values derived from the combined approach of FD and lacunarity values for 400 2DPROI datasets are retained as a set of feature i-vectors in the third training and testing template. The proposed DBL_{Net} and CNN_{Net} classifiers are utilized to train and assess these three types of training and testing templates. Table.1 presents the hyper-parameters utilized in the optimized DBL_{Net} classifier for the three training and testing templates, employing separate and combined FD and lacunarity values. Table.2 outlines the essential parameters used in the optimized CNN_{Net} classifier for these three training and testing templates, applying separate and combined FD and lacunarity values.

Table 1.Hyper-parameters value of DBL_{Net} classifier for Recognizing the 400 Training Images

Feature extraction approaches	Number of Input Nodes	Number of Output Nodes	Epochs	Number of Hidden Layers	Number of Hidden Nodes	Learning Rate
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Table 2. Salient Parameters of CNN_{Net} for Recognizing the 400 Training Images

Feature extraction approaches	Num. Features	Num. Filters	Filter Size	Num. Hidden Units	Num. Classes	Max Epochs	Mini Batch Size	Learning Rate
Box-counting fractal dimension method	1×1×1	7	[2 2]	35	400	100	8	0.0001
Gliding-box lacunarity method	1×7×1	10	[3 3]	45	400	100	9	0.0001
Proposed Method	1×8×1	15	[5 5]	60	400	100	10	0.0001
Box-counting fractal dimension method	1	10	7000	3	45	0.00001		
Gliding-box lacunarity method	7	10	5500	3	35	0.000001		
Proposed Method	8	10	3500	3	40	0.000001		

4.3. Performance Discussion

The performance of the proposed system is evaluated by assessing the benchmark values (i.e., Sensitivity, Accuracy, Precision, and Specificity) within the confusion matrix, based on comparative parameter results of individual and combined approaches of fractal dimension and lacunarity feature values of 2DPROI images. The parameters include True Positive (identifying the condition when true), True Negative (failing to identify the condition when false), False Positive (identifying the condition when false), and False Negative (failing to identify the condition when true). During the training phase, an appropriate segment of the feature dataset from the training template is compared against a compilation of learning outcomes from the trained DBL_{Net} and CNN_{Net} within the training template dataset. This comparison indicates that the training procedure has been completed with a recognition rate of 100% accuracy. Benchmark values are derived from the comparative parameter values generated by tallying the number of True Positives, False Positives, False Negatives, and True Negatives throughout the testing phase. These values can be enumerated by contrasting the outcomes matched between the training and testing template feature sets. The estimated values are then inserted into the confusion matrix benchmarks utilizing Equations (9), (10), (11), and (12) to evaluate the efficacy of the proposed system.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (9)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

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

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

The confusion matrix's benchmark are shown in Table.3 and Figure.7, which shows the benchmark values for three kinds of testing templates using separate and hybrid proposed feature extraction approaches of DBL_{Net} classifier. And it divulges that proposed hybrid feature extraction approaches achieved better percentage of accuracy value (99.50%) compare than individual feature extraction approach with DBL_{Net} classifier. This shows that how precisely and effectively the proposed system handles the huge datasets in a precious manner. Table.2, Table.3, Figure.7, and Figure. 8 show that how the suggested DBL_{Net}, CNN_{Net} and hybrid texture feature extraction approaches effectively carry out the proposed system.

The evaluation metrics of the confusion matrix are presented in Table.4 and Figure.8, illustrating benchmark values for three distinct testing templates employing both separate and hybrid feature extraction methodologies CNN_{Net} classifier. It is evident that the proposed hybrid feature extraction techniques outperform the individual feature extraction method in terms of accuracy, achieving rates of

99.75%, respectively with CNN_{Net} classifier. This finding highlights the capability of the proposed system to efficiently and effectively manage large datasets with a high degree of precision.

Table.3. Result of DBL_{Net} classifier performance for 400 2DPROI Testing Template

Feature extraction approaches	TP	TN	FP	FN	Accuracy	Precision	Sensitivity	Specificity
Box-Counting Fractal Dimension Approach	354	34	5	5	97.49%	1.39%	98.61%	87.18%
Gliding-Box Lacunarity Approach	358	35	3	4	98.25%	1.10%	98.90%	92.11%
Proposed Approach	343	55	1	1	99.50%	0.29%	99.71%	98.21%

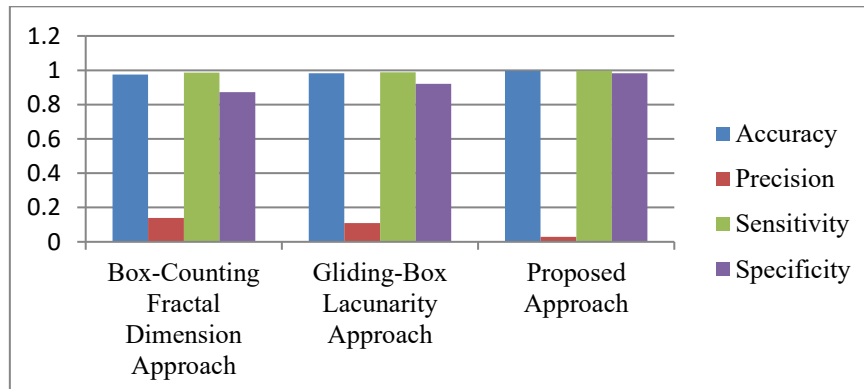


Figure7. Comparison chart of recognition accuracy with separable and inseparable model-based feature extraction approaches with DBL_{Net} classifier

Table.4. Result of CNN_{Net} classifier performance for 400 2DPROI Testing Template

Feature extraction approaches	TP	TN	FP	FN	Accuracy	Precision	Sensitivity	Specificity
Box-Counting Fractal Dimension Approach	355	38	5	2	98.25%	0.56%	99.44%	88.37%
Gliding-Box Lacunarity Approach	360	35	3	2	98.75%	0.55%	99.45%	92.11%
Proposed Approach	392	6	1	0	99.75%	0.00%	100%	85.71%

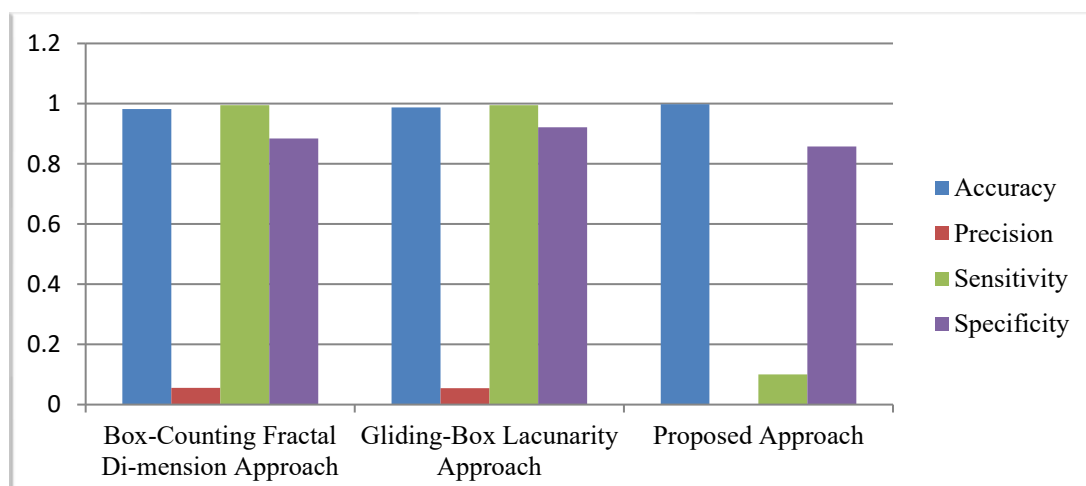


Figure8. Comparison chart of recognition accuracy with separable and inseparable model-based feature extraction approaches with CNN_{Net} classifier

5. Discussion

In this study, Figure.7 and Figure.8 provide a comprehensive assessment of accuracy, precision, specificity, and sensitivity concerning both the separable and hybrid models of texture feature extraction applied to 400 2DPROI images and reveals hybrid model of texture analysis approach got better accuracy percentage than individual texture analysis approaches. Figure.9 exposes that the proposed system significantly attained high accuracy rates of 99.50% and 99.75% through the hybrid texture feature extraction techniques utilizing DBL_{Net} and CNN_{Net} classifiers.

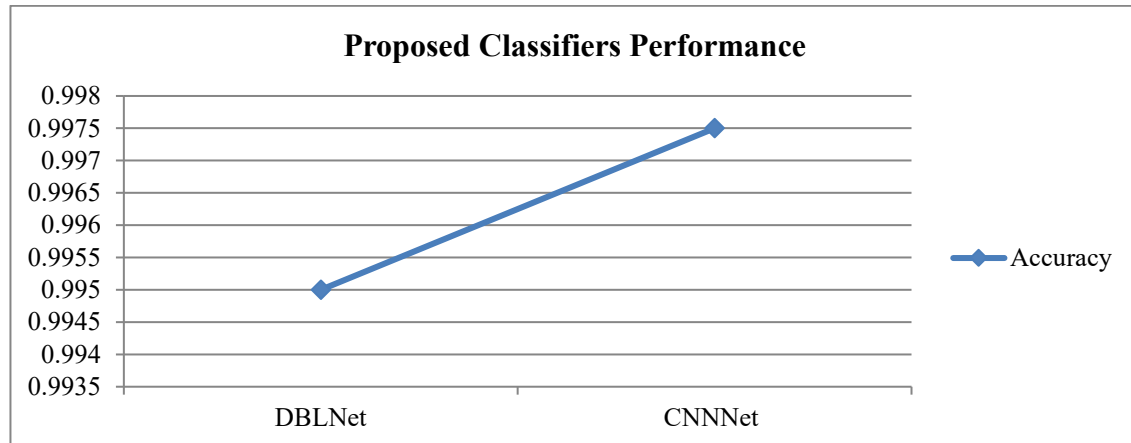


Figure9. Chart representation of Proposed Classifiers Performance (DBL_{Net} and CNN_{Net} classifiers)

6. Conclusion

This research introduces a distinctive BAIS, formulated through a hybrid model-based texture feature extraction approach combined with a Deep Supervised Learning classifier algorithm. The analysis is divided into three phases: the extraction of Fractal Dimension (FD) texture feature values using the Box-counting algorithm, the extraction of Lacunarity texture feature values employing the Gliding-Box algorithm, and the integration of both techniques. The accuracy percentages for the proposed hybrid approach are recorded as 99.50% for the DBL_{Net} classifier, while the CNN_{Net} classifier achieved as 99.75%. It is concluded that the amalgamation of fractal dimension and lacunarity texture feature extraction techniques, in conjunction with deep supervised learning classifiers applied to the 400 2DPROI image dataset, yields superior results when compared to existing methodologies from recent decades. Future research may involve the application of hybrid techniques with varied or additional levels of fusion to enhance the system's recognition capabilities. The findings corroborate that the features extracted within the proposed system yield superior accuracy outcomes compared to the separate implementation of the two feature extraction methods, establishing it as a reliable approach for authentication purposes.

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