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Original Research Article

Effect of Particle Swarm Optimization Convolutional Neural Network in An Iris Recognition System

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Abstract: An iris recognition system based on Convolutional Neural Network with Particle Swarm Optimization (CNN-PSO) was developed to improve the identified hitches in the existing systems. Iris images of 150 and 108 persons were acquired from LAUIRIS (Nigeria) and CASIA (China) respectively. The images were resized and cropped after which Hough transform was used for effective localization of the iris region and normalised using Daugman's rubber sheet model, while an efficient Cumulative Sum-based analysis method was used to extract discriminative features from the normalised iris images after which the iris code was generated. The iris code generated in a vector form was optimised with PSO after which they are fed into Convolutional neural network; the same procedure was engaged during enrolment and authentication to generate the iris template. Euclidean distance was used for decision making on test sample template and stored template. The system was implemented with MATLAB R2013a. The performance of the developed system was evaluated on LAURIS and CASIA, and compared with the existing systems (CNN, BPNN-PSO and BPNN) using False Acceptance Rate (FAR), False Rejection Rate (FRR) and Recognition Rate (RR). CNN-PSO has the highest recognition rate of 98.67% and 97.22% for LAUIRIS and CASIA respectively among the systems which showed an improvement over other three recognition technique. The developed CNN-PSO has not only produced an improved Iris recognition system over the others, with the highest recognition rate for both datasets but it also provides a significant recognition rate of black Iris images despite the limitations identified with black Iris images in separating Iris image from other part of the eyes. The developed technique can be applied to various field of life like security, surveillance systems.

Keywords: Iris images, CNN-PSO, Neural Network, eyes.

1.0 INTRODUCTION

1.1 Background of the Study

Today, accurate security of lives and properties is one of the most challenging issues facing the society. It is important to certify the identity of individuals in place of preventing illegitimate users from intruding into various systems and such identification method should be efficient. Compromising of systems has transform to a norm where people profess to be who they are not or claim what does not belong to them. This and many more necessitated authentication so as to save sensitive systems from intruders. Conventional methods of recognizing individual's identity which are 'something you know' such as password, personal identification number (PIN), and 'something you have' such as cards or token are not always dependable (Sarhan, 2009) and can be compromised by persons handling it. Passwords are renowned for being frail and can be cracked easily due to human nature and the liability to make passwords easy to remember by penning them down somewhere easily accessible. Cards and tokens can be presented by anybody, although the card or token can be recognized no means of confirming if the personality of the individual presenting the card is the actual owner (Khaw, 2002). Biometric solutions 'something you are', such as identification systems using fingerprint, Iris, face, and palm print, have an edge over the traditional authentication techniques (Sun *et al.,* 2005), which cannot be compromised easily.

Iris recognition is one of the important and most reliable biometrically based recognition, a method of identifying individuals on the basis of their Iris patterns. This is because Iris texture traits of individuals provide uniquely high dimensional data that yields the lowest false acceptance rates among all forms of biometric verification systems, even the Iris of the left and right eye of an individual are unique. Hence Iris recognition is becoming much secured way of identifying an individual (Balaji *et al.,* 2011; Bastys *et al.,* 2011). Compared with other biometrics, Iris is quite resistant to aging, and the wearing of glasses. Other technologies such as fingerprint may be damaged by burning or by taking some drugs and voice can be altered by colds. Consequently, Iris recognition is a biometric system that can be relied upon in generating accurate results (Sibai *et al.,* 2011).

One of the recent techniques for developing biometric system is deep learning. A type of machine learning that allows computers to learn from occurence and comprehend the world in terms of a hierarchy of concepts. It is expected that human input will not be required in operating the computer; inputting the information needed by the computer, as the computer accumulates knowledge from experience. The hierarchy of concepts enables the computer to study most complex concepts by fabricating them out of simpler ones. It includes regularization, deep feedforward networks, optimization algorithms, sequence modelling, convolutional neural networks (CNN or ConvNet), and practical methodology; these have already proven useful in various disciplines such as online recommendation systems, natural language processing, speech and audio processing, computer vision, speech recognition, bioinformatics, robotics, and videogames (Goodfellow *et al.,* 2016). CNN is one of the most popular types of deep neural networks. The efficacy of deep learning became more prominent and popular in image recognition on the account of the efficacy of convolutional nets. They are powering major advances in computer vision (CV), CNNs are simply neural networks that employs convolution, a mathematical operation instead of general matrix multiplication in one or more of their layers (Karen and Andrew, 2015).

CNNs are cognate to traditional ANNs in that they consist neurons that self-optimise through learning. In CNNs, the fully connected layer employed for identification are fixed during the training process as well as the weights of the convolutional layer engaed for feature extraction while feature extractors are manually designed in traditional models for pattern recognition. CNNs allow encoding of specific image features into architecture which makes the network more desirable for image focused tasks - while minimizing the parameters required to set up the model. CNNs improved network structures reduces memory requirements, lower computation complexity and, simultaneously give preferable performance for applications whither the input has local correlation (for example speech and image) (Samer *et al.,* 2015). These are notable reasons why convolutional neural networks are seemingly significant. CNNs have been explored in differs areas such as video analysis, and natural language processing, speech recognition, image and pattern recognition.

Optimization techniques are methods used for finding the optimal result from all feasible results in optimization problem. There are numerous optimization techniques employed in optimization problems which include Particle Swarm Optimization (PSO) and Cuckoo Search (CS). PSO is a stochastic population-based global search methods and most often used natural optimization algorithms inspired in nature, owing to its simplicity of implementation and fast convergence speed (Chen *et al.,* 2015). CS was introduced by (Yang and Deb, 2009, 2010), an algorithm motivated by the unique life of cuckoo species where each egg in a nest amount to a solution and a new cuckoo egg means a new solution. The intention of CS is to extend the survival rate of eggs, employed the recently better results (cuckoos) to suceed a worse result in the nests.

Deep learning has been explored for some biometrics system including face recognition but very few consideration has been given to exploring Iris recognition using deep learning, hence this research employed the Convolution Neural Network (CNN) a type of deep learning optimised with particle swarm optimization (PSO) technique for Iris recognition system. Iris recognition system is applicable in many fields like Immigration system, airports, military, secure access of bank accounts, secure financial transaction, network security, security of sensitive areas, and permission to examination hall and so on.The developments in technology and increasing emphasis on security have resulted in more attention towards biometric based personal verification and identification methods (Rai and Yadav, 2014).

The main challenge of human Iris recognition system is the difficulty in detecting apparent feature points in the image and to keep their representability effectively high and also the capability to establish the identification or verification process suitable for Iris patterns that is capable of producing infallible accuracy (Lim *et al.,* 2001). The identification or verification process is meant to provide absolute accuracy, as high as 100% so that no illegitimate person is wrongly accepted and no legitimate person is wrongly rejected. So any research effort towards constantly increasing the recognition accuracy of Iris recognition system is worthwhile.

Most Iris recognition systems are limited with high error rates (FAR, FRR) and reduced recognition accuracy. Therefore, in this research, PSO was combined with CNN to develop an improved Iris recognition system with enhance recognition rate for efficient identification process.

2.0 LITERATURE REVIEW

2.1 Related Works

Wildes in year 1997 represented the Iris texture with a Laplacian pyramid constructed with four different resolution levels and used the normalized correlation to determine whether the input image and the model image are from the same class having as a principal disadvantage the dependence of threshold values on the edge-map construction (Wildes, 1997).

Boles and Boashash (1998) calculated a zero-crossing representation of one-dimensional (1D) wavelet transform at several resolution levels of a concentric circle on an Iris image to characterize the texture of the Iris. Iris matching was hinged on two dissimilarity functions. The algorithm for extracting unique traits from Iris images and representing these traits using the wavelet transform (WT) zero crossings was proposed. This representation is then used to recognise individuals from the Iris images of their eyes. A wavelet function that is the first derivative of a cubic spline is used to construct the representation. The proposed technique is translation, scale, and invariant rotation,. It is also largely unaffected by variations in illumination and noise levels in the images, a recognition rates of 93.23 was achieved.

Lim *et al.,* (2001) proposed a method of making feature vector efficient and compact mechanisms for a competitive learning technique such as weight vector initializations and the winner selection. Edge detection method was utilised to identify the inner boundary and apply the bisection method to detect the centre of the inner boundary. After it, they determine the inner and outer boundary using virtual circle. Gabor wavelet transform and wavelet transform which are widely used for extracting features–were evaluated. From this evaluation, they found that Haar wavelet transform had better performance compare to Gabor transform. Secondly, optimization of the dimension of feature vectors was done using Haar wavelet in order to minimise processing space and time. They present an Iris pattern with 87 bits code without any negative influence on the system performance. Lastly, a modified competitive learning neural network (LVQ) was adopted for classification, they improved the accuracy of the classifier by proposing an initialization method of the weight vectors and a new winner selection method designed for Iris recognition. With these methods, the highest Iris recognition performance that could be obtained is 98.4%.

Kong and Zhang (2001) developed variance of intensity and Gabor filter approaches for detection of eyelash. The eyelashes were divided into multiple eyelashes and separable. Separable eyelashes are identified using 1D Gabor filters while multiple eyelashes were identified using intensity variance. Connective criterion was used in their model. Convolution of the separable eyelashes using Gabor filter produced a low output value. For multiple eyelashes, the variance of intensity in a window is smaller compare to threshold, the centre of the window was taken as eyelashes.

Tisse *et al.,* (2002) analyzed the Iris features through the analytic image constructed by the original image and its Hilbert transform. They developed a segmentation process hinged on integro-differential operators and Hough Transform. This minimised the computation time and removed potential centres exterior to the eye image, however the pupil noises Eyelash were also not considered.

Huang *et al.,* (2002) developed a recognition method which constructs basic functions for training set by Independent Component Analysis, which determines the centre of every class by competitive learning mechanism and finally recognizes the pattern based on Euclidean Distance. The algorithm utilizes all patterns of all the classes to determine ICA basic function and when a new class is joined all the patterns must be retrained. They obtain 81.3% for blurred images, 93.8% for variant illumination and 62.5% for noise interference images.

Daugman (2003) used Multiscale Gabor filters to demodulate texture phase structure information of the Iris. Filtering an Iris image with a family of filters returned 1024 complex valued phasors which indicate the phase structure of the Iris at different scales. Each phasor was then estimated to one of the four quadrants in the complex plane. The following 2048-component Iris code was used to represent an Iris. The difference between a pair of Iris codes was measured by their Hamming distance.

Krichen *et al.,* (2004) used a hybrid procedure for Iris segmentation, Hough transform for outer Iris boundary and Integro-differential operator for inner Iris boundary. The Iris code was produced using wavelet packets. This method obtains 2% FAR and 11.5% FRR which is improved to Daugman method.

Sun *et al.,* (2005) observed that recognition methods using local features have better performance than the texture analysis-based methods because the texture features are unable to accurately capture fine spatial changes of the Iris. The global feature is presumed to overcome the limitations of local feature based classifiers (LFC) since it is sensitive to photometric and geometric distortions. Consequently, it is required to complement the local features with global features to attain the best possible recognition accuracy. Thus Cascaded classifiers was proposed for Iris recognition system. The basic design of the approach is to construct a two-stage classification method with a reject option. The LFC is first implemented and global feature based classifier (GFC) is rarely utilised except the LFC is unsure of its outcome, which is set by the matching score betwix the input Iris and the stored template. When the score is near the decision boundary of LFC and the input is assumed as genuine, noisy Iris images are usually involved in matching. Compared with LFC, the GFC is capable of recognizing noisy Iris images. So the integrated LFC-GFC system is more accurate than the single classifier.

Poursaberi and Araabi (2005) computed binary code representation of the Iris and utilised Euclidian distance for matching. This Iris recognition method contain six main steps: (1) pre-processing including image capturing, (2) image filtering and enhancement, (3) image Iris localization and Iris normalization,(4) Iris de-noising and enhancement, (5) Iris feature extraction, and (6) Iris feature classification. The algorithm was evaluated with CHUK Iris database and a considerable success rate was achieved. Binary coding in feature extraction stage enhance the matching process.

Schmid *et al.,* (2006) developed an algorithm to estimate the performance of Iris biometrics system on a large dataset using Gaussian Model constructed from a smaller dataset. It uses a sequence of *K* Iris codes in the matching stage to represent an Iris subject. The distance between a pair of Iris subjects is defined as a *K*-dimensional Hamming Distance, modelled as Gaussian distribution.

In Nabti and Bouridane (2008), an approach based on multiscale edge detection was employed at pre-processing stage to localize the Iris with combination of some Multiscale feature extraction techniques: special Gabor filters and wavelet maxima components. Also, a feature vector representation based on moment invariants and a fast matching scheme based on exclusive OR operation to compute bits similarity was developed. They used statistical features (mean and variances) and moment invariants. Moment invariants is seen to perform more than statistical features, but this method is developed for identification phase.

Sarhan (2009) presented an Iris recognition method using discrete cosine transform (DCT), the method used 2-D DCT and Artificial neural network (ANN). The DCT was used to extricate distinct traits from the Iris image. These features are then applied to ANN for classification. Maximum number of DCT coefficients and ANN structure (number of layers and number of neurons in each layer) were investigated, their simulation results showed the best recognition accuracy rates of 96% when the ANN used is a 3-layer structure, using 49 DCT coefficients, trained with 74 epochs.

Gawande *et al.,* (2010) presented Iris recognition with score based fusion method; it is an approach that fuses multiple algorithms for Iris recognition. The technique combines three algorithms namely Zero crossing based 1D wavelet, Genetic algorithm and Euler No., for feature extraction. The result of the algorithms is normalized and their score are fused to determine whether the user is imposter or genuine. Due to their advantages the combined approach would cover up the flaws in feature extraction process using single method and would increase the Iris recognition performance.

Balaji *et al.,* (2011) presented an Iris recognition system involving effective edge detection method was presented. They used canny edge detection and Hough transform for localizing the Iris and pupil regions to attain automatic segmentation. Next, normalized Iris is decomposed using Haar wavelet decomposition and statistical features were computed and matching was done using hamming distance method. The algorithm was not effective in analysis of the requirements for the physical implementation of the non-cooperative prototype system, simultaneous adapting and improving of algorithms for the real time must be carried out.

Sibai *et al.,* (2011) presented an Iris recognition using a simple feedforward artificial neural network trained with the Backpropagation algorithm. The output of their pre-processing stage serve as input to the neural network. The approach possess the ability to produce a no match or match output while in others' work, the neural network generates an Iris code which will be later subjected to a matching algorithm such as Hamming distance computation to recognise a match. Only 20 brown coloured Iris images was used to test the system and optimum accuracy of 93.33% was achieved when the number of neurons in the hidden layer was 60.

Si *et al.,* (2012) presented an eyelash detection algorithm based on directional filters. A Multiscale and multidirectional data fusion method is introduced to reduce the edge effect of wavelet transformation produced by complex segmentation algorithms. Th approach achieves a low rate of eyelash misclassification.

An indexing mechanism was developed by Dey and Samanta (2012) to extract Iris templates through Gabor energy features. The Gabor energy features are calculated from the preprocessed Iris texture in different scales and orientations to produce a 12-dimensional index key for an Iris template. An index space is created based on the values of index keys of all individuals.

Falohun (2013) developed a feature extraction for Iris recognition based on Enhanced inverse analytical Fourier-Mellin Transforms. Two-level segmentation technique combining circular Hough transform and integro-differential operator coupled with some morphological was developed which helped in proper segmentation of the newly introduced Iris from black people's faces while a modification of Bourennane's inverse analytical Fourier-Mellin Transforms was used to extract the isolated Iris texture. The system was evaluated using black Iris images captured in Nigeria and Iris images from Chinese Academy of Sciences Institute of Automation (CASIA), a typical white Iris database. For CASIA data the optimum recognition rate of 97.22% was achieved at hamming distance of 0.39 where no enrolee was falsely accepted and 2.78% were falsely rejected i.e. legitimate users were rejected. Optimum recognition accuracy of 96.10% for the black Iris images was achieved at hamming distance of 0.45 where FAR is 0.57% and FRR is 3.33%.

Neural networks model biological neural networks in the brain and have proven their efficiency in a number of applications such as organization and categorization, prediction, pattern recognition and control. Shaikh and Doye (2013) developed an Iris recognition system using local histogram and optimized with Feed forward back propagation neural network optimized with particle swarm optimization (FFBNN-PSO). The input eye images were pre-processed using adaptive median filter to remove the salt and pepper noise. Then, the features generated from the pre-processed image are fed into FFBNN for training and testing, to obtain accurate results the FFBNN parameters were optimized using PSO. Accuracy of 80% was obtained with the optimized FFBNN-PSO which is an advancement over standard FFBNN with accuracy of 72%.

Nguyen *et al.,* (2013) developed a novel feature-domain super-resolution approach using 2D Gabor wavelets for Iris recognition. The proposed approach is meant to overcome the non-linearity of 2D Gabor wavelet features and it outperforms the unenhanced features, the pixel domain super-resolution equivalent, as well as other existing feature domain super-resolution and fusion techniques though the computational cost of the approach was not estimated. It capitalizes on both the feature fusion using maximum posteriori and the enhanced performance against other fusion approaches; an equal error rate (EER) of 0.5% was obtained.

An Iris recognition system based on combination of support vector machine and Hamming distance was developed . They selected the zigzag collarette area of the Iris for feature extraction, it was believed that it captures the most rich areas of Iris complex pattern. The approach employed trimmed median filter and parabola detection for detection of eyelash and eyelid detection and removal. Iris feature was extracted using HAAR wavelet of decomposition level 3 and 1D Log Gabor filter. Support vector machine was the major classifier and Hamming distance served as the secondary classifier (Rai and Yadav, 2014).

Falohun *et al.,* (2015) developed an Iris recognition system using Artificial Neural Network (ANN) with two Segmentation techniques (Quadtree and Hough transform). ANN was engaged for training the database using endcoded segmented Iris. It also accounts for the final stage which is matching the tested Iris to its corresponding encoded version, in other words, recognition. The research focus is on the segmentation stage of recognition system, evaluating the segmentation time and recognition time of the two segmentation methods. Quadtree segmentation technique was seen to outperform Hough transform.

Karen and Zisserman (2015) observed the result of the depth of convolutional neural network on accuracy with large-scale image recognition setting. They simulated very deep convolutional networks (up to 19 weight layers) for largescale image classification and deduce that the representation depth is useful for the classification accuracy, which established the usefulness of depth in visual representations. Their model generalize well to a wide range of tasks and datasets, matching or exceeding more complex recognition pipelines built around less deep image representations.

Amol *et al.,* (2016) developed an Iris recognition using gray level Co-occurrence matrix and hausdorff dimension. The segmentation of the Iris uses intensity, location information and shape of pupil or Iris localization and performs normalization of the Iris region by un-wrapping the circular region into a rectangular region. The feature extraction of Iris was done by GLCM (Gray Scale Co-occurrence Matrix) and HD (Hausdorff Dimension. The Biometric Graph Matching (BGM) algorithm was utilised for matching the graphs of the test image with the training image of the Iris biometric. The BGM algorithm utilize topology of graph to define various traits values of the Iris templates. A Support Vector Machine (SVM) classifier was employed to differentiate between imposter and genuine. Only 10 persons Iris image were employed to test the system, reasonable conclusions cannot be made with such small amount of Iris image and efficiency of 97.5% was achieved.

Long *et al.,* (2016) developed a highly optimized and unified deep learning architecture (UniNet), for both Iris region masking and feature extraction, using fully convolutional networks (FCN). The unified network contain two sub-networks; MaskNet and FeatNet was originally designed for semantic segmentation. Their fully convolutional network obtained improved segmentation of PASCAL VOC (30% relative improvements to 67.2% mean IU on 2012).

Liu *et al.,* (2016) deployed CNN for Iris segmentation. Hierarchical CNNs (HCNNs) and multiscale FCNs (MFCNs) were utilised to automatically locate Iris boundary in non-cooperative environments. Full Iris image was used without stating the ROI (region of interest) into the CNN which made the hairs, eyelids, glasses frames and eyebrows have a similar look to Iris image which could be recognised as Iris points by the CNN model. This work shows a better performance than the preceding methods but Iris segmentation error can be potentially reduced further.

Muhammad *et al.,* (2017) proposed a two-stage Iris segmentation method using CNN to locate the actual boundary in noisy Iris images in a non-cooperative environment. The technique correctly locate the actual boundary even in intense cases such as rotated eyes, glasses, side view, off-angle eyes, and partially opened eyes. Modified circular HT was utilised in the early stage to recognise the rough Iris boundary which defines the ROI by small increase in the Iris radius. While CNN was used by VGG-face fine-tuning to the data achieved from the ROI in the second stage, which can produce the actual Iris boundary with the aid of learned features, the CNN output layer provides two output features. Therefore, the non-Iris and Iris points are classified to locate the real Iris boundary based on these features. The method achieved considerable segmentation, However it is essential to minimise the processing time for CNN-based segmentation.

Zhao and Ajay (2017) developed a generalizable deep learning frame work for Iris recognition system using fully convolutional network (FCN), which is capable of reducing parameter space significantly and produce spatial corresponding Iris trait descriptors. The system does not only produce considerable matching accuracy but also possess exceptional generalization capability for Iris recognition on various databases. However, there is a need to learn more robust Iris mask information through the deep networks, anticipated to explore further the spatially fit characteristics for increased Iris recognition accuracy.

Adegoke *et al.,* (2018) developed a feature level fusion algorithm for Iris recognition system evaluated with Black Iris images. Integro-differential was employed for segmentation, PCA was utilised to isolate principal features to form Iris template and KNN was used for classification. Features extracted using FFT (Fast Fourier Transform) and HWT (Haar Wavelet Transform) were fused at feature level using weighted sum technique to produce composite feature developed into EIRS (Enhanced Iris recognition system). Three systems were developed FFT based IRS (FIRS), HWT driven IRS (HIRS) and EIRS with recognition rate of 83.83% and 89.87%, and 94.16% respectively.

Muthanah and Samah (2018) implemented Iris recognition system for reconizing human identity using two feature extraction methods; Fourier descriptor (FD) and principle component analysis (PCA). FD was based on transmuting the individual Iris quality to the frequency domain and represented by Iris signature graph. The low spectrums define the usual illustration of Iris pattern while traits of the Iris is represented as high spectrum coefficients. The PCA is a relative method to minimize the trait dimensionality. Each of the system was tested with three classifiers (Cosine, Euclidean, and Manhattan) using Iris images of fifty(50) individuals. The recognition results for FD on the three classifiers gives 86, 94, and 96%, versus 80, 92, and 94% for PCA when Cosine, Euclidean, and Manhattan classifiers were used respectively. The results shows that FD outperform PCA as feature extractor.

While other researchers have engaged state of the techniques for development of Iris recognition with high error rates(FAR, FRR) and low recognition rate, this research engaged the lightweight structure of Convolutional neural network optimized with particle swarm optimization to develop a deep Iris recognition system. Employed over indigenous black Iris images of Ladoke Akintola University of Technology multimodal database and very popular CASIA Iris images which achieved a considerably high recognition rate.

3.0 METHODOLOGY

3.1 Development of Iris Recognition System

The Iris recognition system consist of four (4) stages: Image acquisition, Pre-processing stage, Feature extraction and pattern recognition stage as shown in Figure 3.1. The Iris images used were acquired from two publicly available databases (CASIA and LAUIRIS). The input images were pre-processed to efficiently detect the Iris region, isolation of the actual Iris region to reflect the exact features of the Iris. The extracted features were subjected to normalization because of variation in Iris size, pupil position which differs for different individuals and environmental conditions during capturing of Iris image such as the intensity of light. This is necessary to have a uniform representation in dimension. Next stage was to extract unique features from the normalized images which were encoded and stored as template for each individual. The recognition stage is the last stage and the major focus of this research which involves training and verification, the extracted features served as input to the Convolutional neural network to generate template for the Iris and stored in the database. Euclidean distance metrics was employed to take decision on the authentication of individuals (whom to accept and whom to reject), the stored templates and template generated were compared according to the threshold set and the template being considered.

3.2 Image Acquisition

Images used for the recognition process were acquired from two of the databases reviewed which are:

i. Chinese Academy of Science's Institute of Automation (CASIA): a publicly available Iris image databases for research purposes, CASIA version 1 containing 108 subjects. Three (3) samples per subject was used, a total of 324 images.

ii. LAUIRIS: black Iris image database captured in Nigeria containing 150 subjects. 3 samples per subject was used, a total of 450 images.

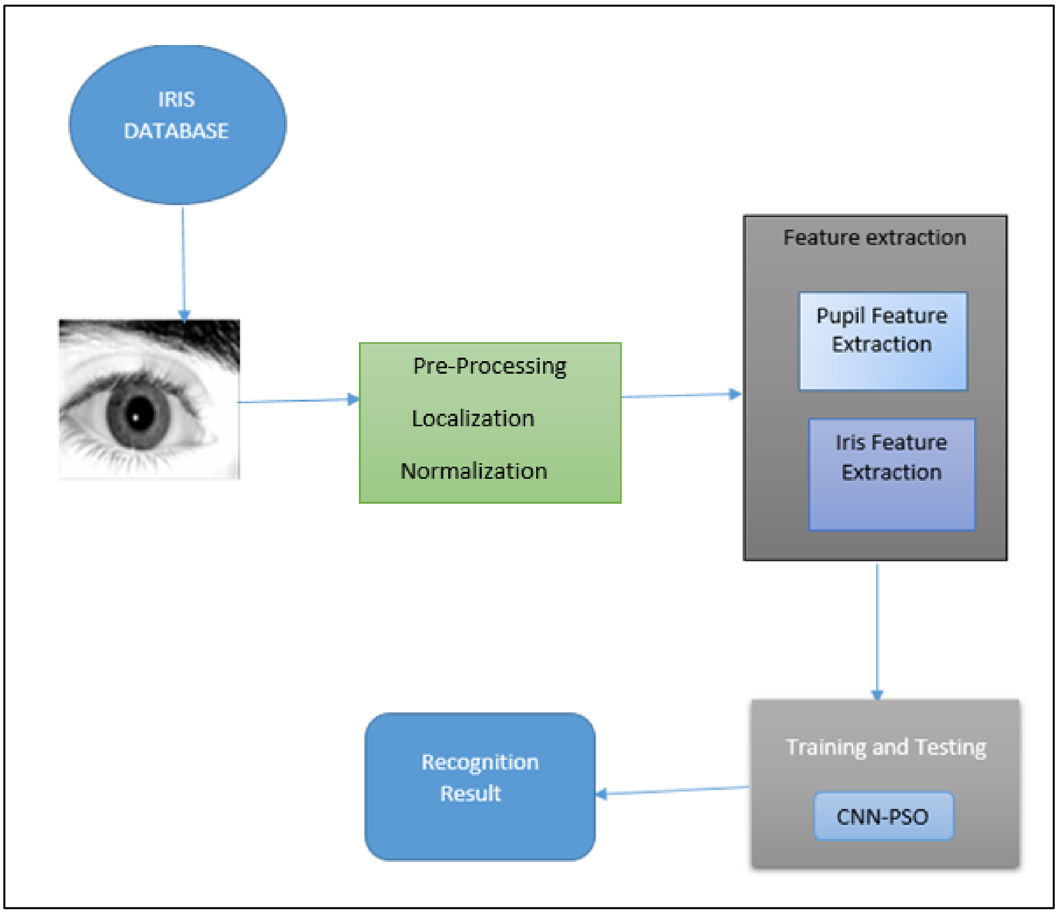

Figure 3.1: Architecture of the Iris recognition system

3.3 Iris Image Pre-processing stage

Iris images captured in bitmap format and pixels of 320 x 280 for CASIA and 640 x 480 for LAUIRIS as shown in Figure 3.2a and 3.2b respectively were converted to JPEG format for ease of processing; they were also cropped and resized to 200 x 150 pixels as shown in Figure 3.3a and 3.3b for CASIA and LAUIRIS. This is to decrease unwanted segment of the images and increase the chances and ease of detecting the Iris region. The images were converted to gray scale using 'rgb2grayscale' in MATLAB after which histogram equalization method was employed to enhanced the contrast by transforming intensity of the images for actual segmentation process.

3.3.1 Iris localization (Segmentation)

Segmentation was carried out to localize Iris region from the eye image and isolate noisy areas such as occluding eyelashes and eyelids for accurate segmentation result which is highly essential to the performance and recognition accuracy of the system. Integro-differential operator was employed for segmentation. The center coordinate and radius of the pupil and Iris region were deduced using the center coordinates parameters X_c, Y_c and r Equation 3.1.

$$x_c^2 + y_c^2 = r^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

x_c is x coordinate of the iris center
y_c is y coordinate of the iris center and r is radius of the Iris

The integro-differential operator was performed to locates the Iris centre around the pupil center and the Iris radius as shown in equation 3.2.

$$\text{Max } (x_o, y_o, r)|G_\sigma(r) * \frac{\partial}{\partial r} \oint x_o, y_o,\ r \frac{I(x,y)}{2\pi r} ds \ldots\ldots (3.2)$$

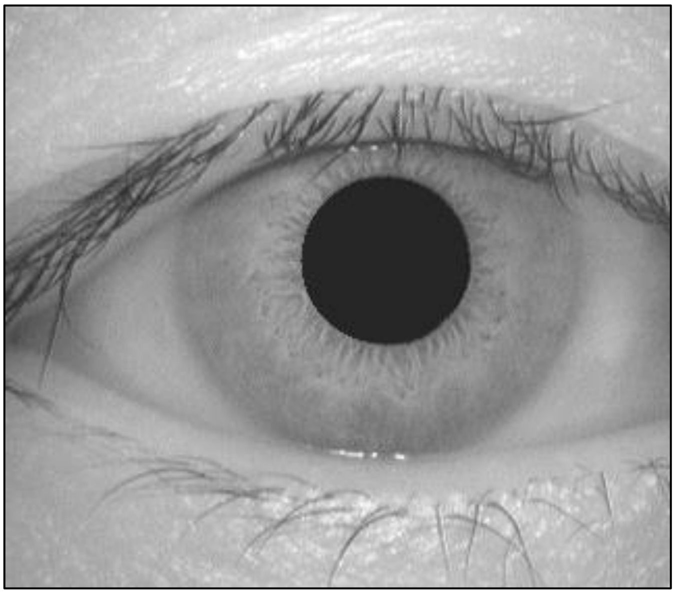

Figure 3.2a: Sample CASIA IRIS

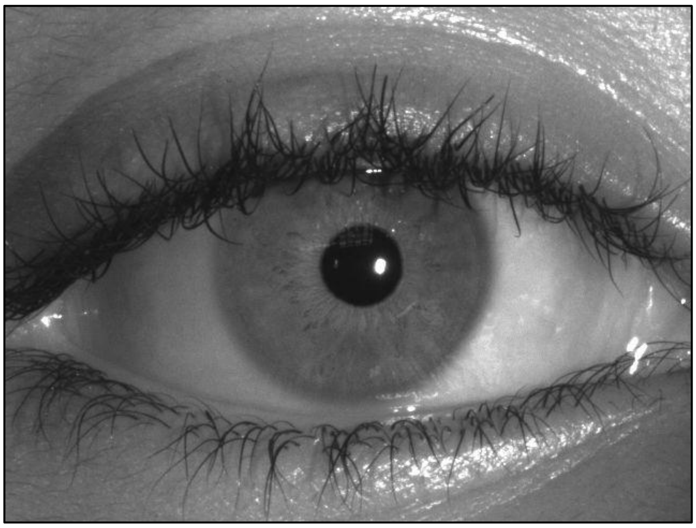

Figure 3.2b: Sample LAUIRIS image

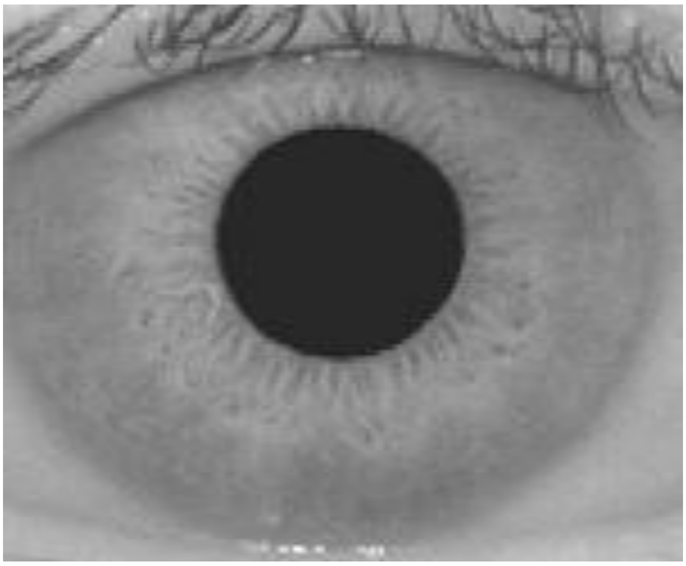

Figure 3.3a: Image resizing and cropping CASIA

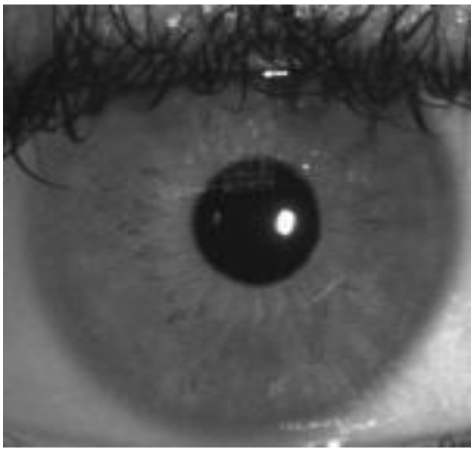

Figure 3.3b: Image resizing and cropping LAUIRIS

I(x, y) represent eye image, r is the radius to search for, Gσ(r) is Gausian smoothing function, such as a Gaussian of scale σ and s is contour of the circle given by r, x_o, y_o. The operator searched for circular Iris and the arcs of the lower and upper eyelids, it searches for the circular path with the maximum change in pixel values by varying the centre x and y and radius position of the circular contour to arrive at accurate location of the eyelids. Sample of segmented image of CASIA and LAUIRIS are shown in Figure 3.4a and Figure 3.4b respectively.

3.3.2 Iris normalization

In the normalization process, Iris is unwrapped and converted into its polar equivalent. Daugman's Rubber sheet model was explored for normalization of the segmented Iris images. It allows easy transformation of the circular region to a rectangular shape, the center of the radial circle across the Iris region is considered as the refrence point. Each pixel of the iris in the Cartesian domain is assigned a correspondent in the pseudo-polar domain according to the distance of the pixel from the centers of the circles and the angle that it makes with these centers as shown in Figure 2.9. The normalized Iris strip for CASIA and LAUIRIS are shown in Figures 3.5a and 3.5b respectively.

3.4 Iris feature extraction

Discriminative traits of the Iris were extracted from the normalized Iris image using Cumulative sum-based change analysis. The extracted features during the enrollment are encoded and stored in the database while during verification the system compares the extracted features of the presented Iris against the database to verify the identity of an individual. The Iris codes is generated by the algorithm through the analyzes of changes in grey values of the Iris pattern. The algorithm is as shown in section 2.9.3.2. After feature extraction Iris images were represented as a feature vector. The feature vectors are basically features stored in vector form and referred as feature vector.

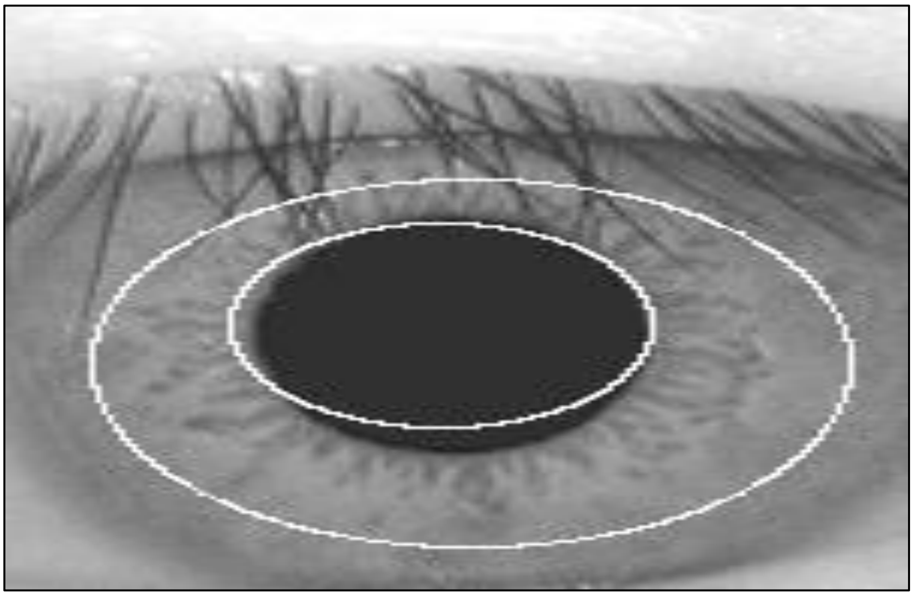

Figure 3.4a: Sample segmented image (CASIA)

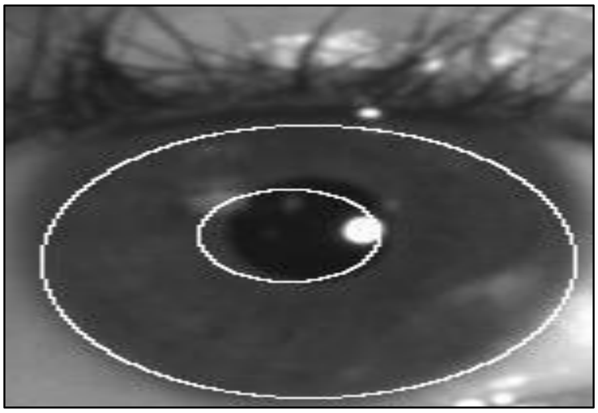

Figure 3.4b: Sample segmented image (LAUIRIS)

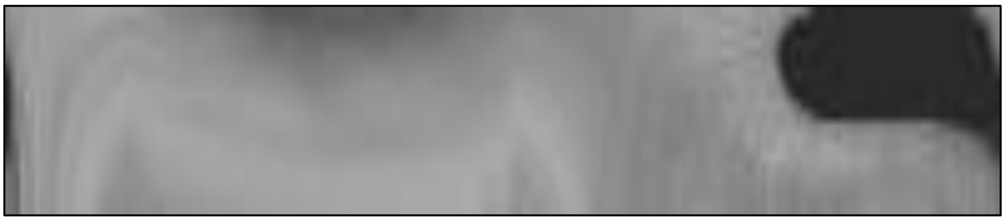

Figure 3.5a: Sample of normalized CASIA Iris

Figure 3.5b: Sample of normalized LAUIRIS Iris

3.5 Recognition Stage

The feature vector obtained from the feature extraction process was optimized using PSO to obtain optimal solution, and they are being fed into the neural network during training and testing phase. During the training process, optimal parameters for training CNN were automatically sought and pinpointed using PSO, which result into reduced training time as the process of parameter tuning for training the network has been cut off. Thereby reducing the Computational cost by using PSO optimized parameters.

PSO starts with initial solutions and finds the best global optimum; each particle has a randomly initialized position. PSO utilizes several searching points and the searching points gradually get close to the global optimal point using its pbest and gbest. At initialization the fitness value calculated for each particle is set as pbest p^b value of each particle, the optimal pbest is selected as the global best (g^b). The calculation of the fitness value is repeated and the p^b were updated, the best p^b is then selected to update the value of g^b if the value is greater than the previous g^b and if not the value of g^b remains the same, the process continues until the solution is good enough or maximum iteration is reached. The algorithm is as shown figure 3.6, where ω is the inertia weight, $c1$ and $c2$ are acceleration constants while $R1$ and $R2$ are random numbers generated from a uniform distribution.

The architecture and parameters of CNN were selected according to the implementation of the stochastic method of PSO on both the training and testing data. The CNN is fine-tuned and trained after the optimized parameters has been obtained in order to secure an improved network convergence and classification performance. The convolution operation extracts hierarchical features of the input. The first convolution layer extracts low-level features like edges, lines and corners. The discrete convolution between the two functions j and k is as shown in equation.

$$(j* k)(x) = \sum_t f(t)g(x+t). \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

Initialization for each of the particles R

Initialize the position of $yk\ (0)\forall k \in 1{:}R$

Initialize the particle's best position to its initial

Position $p_k(0) = y_k$

Calculate the fitness of each particle

If $f(y_i\ (0)) \leq f\big(yk(0)\big)\forall k \neq i$, initialize global

Best as g=$y_i(0)$

Repeat the following steps until the maximum iteration is met:

Update the particle velocity

$$v_k(t+1) = \omega(t+1)v_k(t) + c1R_1\big(P_K - x_k(t)\big) + c2R_2\ (g - y_k(t))$$

Update the particle position (p_k) $p_k\ (t+1) = p_k\ (t) + v_k\ (t+1)$

Evaluate the fitness of the particle $f(y_k\ (t+1))$

If $f\big(y_k\ (t+1)\big) \leq f(p_i)$, update personal best: $p_k = y_k(t+1)$

If $f\big(y_k\ (t+1)\big) \leq f(g)$, update global best: $g = y_k(t+1)$

Obtain the best solution, g for CNN
end function

Figure 3.6: PSO parameter optimization for CNN

In a two-dimensional signals, 2D-convolutions is represented as
$(f * g)(a,b) = \sum_{c,d} f(c,d)g(a+c, b+d)$. ….. (3.4)

F is the convolution filter on the 2D image g.

Each of the convolutional layers incorporated is followed by the ReLu activation function are convolved with convolutional kernels also known as filters with a stride of one to output feature maps. Pooling/subsampling layers used kernels with individual stride. This reduced resolution of the features and makes the features robust against noise and distortion. In the Fully connected layer, the network concatenated high-level features learned by the convolutional layers. Finally, a single neuron is computed as the final output of the network.

The fully connected layer produces class scores from the activations, to be used for classification. During enrolment stage, the feature vector produced is stored in the database, while in authentication mode, the resultant feature vector of the Iris image presented are compared against the database to verify the identity of the individual. In the last layer of CNN, individual Iris image is categorised with its feature vector using Euclidean distance classifier. The performance of the Iris recognition system was evaluated with two databases and the flow diagram for the training and testing phase is as depicted in Figure 3.7.

3.6 Classification

Euclidean Classification was done by calculating distance between the new instance and all training point. The feature vectors from the test images were compared with the feature vectors stored in the database to measure the distance between these feature vectors.

ED = d(a, b) $\sqrt{\sum_{j=1}^{k}(a_j - b_j)^2}$ …………..…. (3.5)

K represents the dimension of the feature vector
a_j is stored feature vector while b_j is the test feature vector

The minimum distance is considered and compared with the threshold.

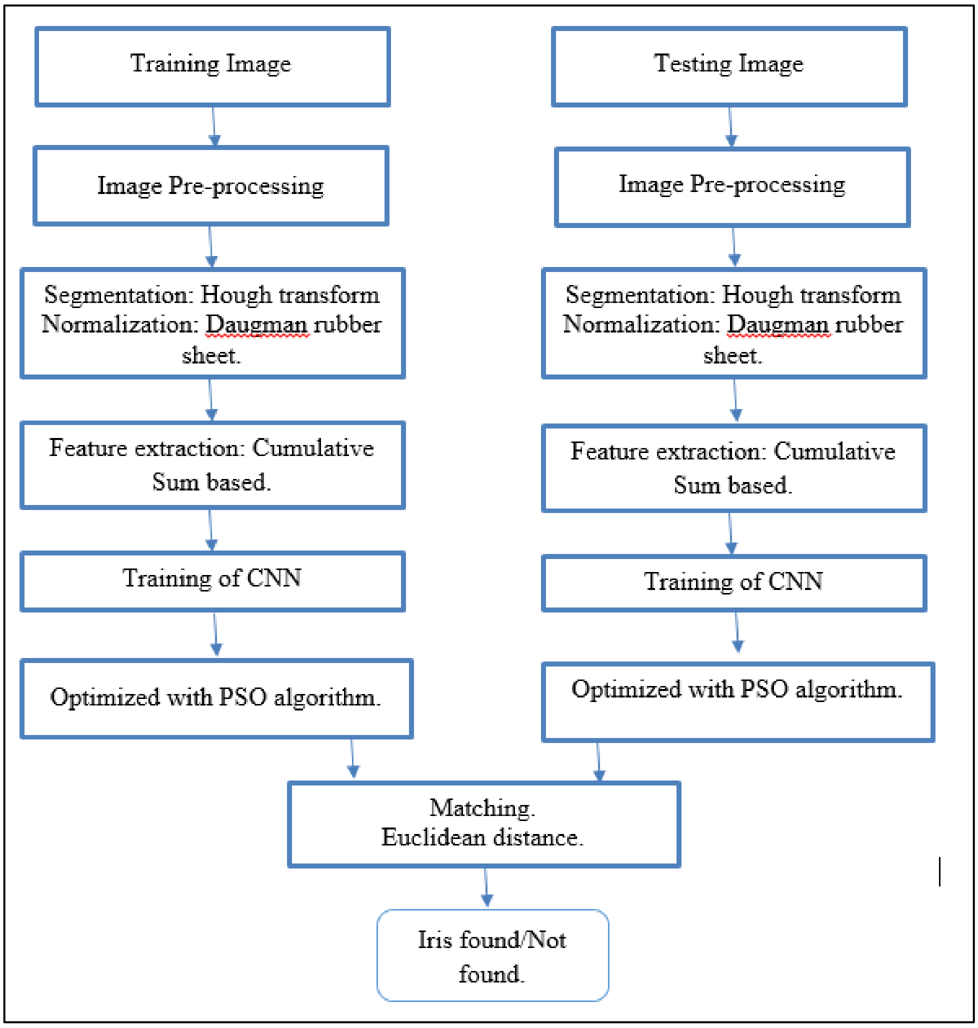

Figure 3.7: Iris Recognition System

3.7 Implementation of the Developed Iris Recognition System

The research was implemented with MATLAB 13 (R2013a) on windows 10 64-bit operating system, Hewlett Packard(HP) with Intel ® Dual Core (TM) i3 Central Processing Unit (CPU) with a speed of 2.10GHz, 8GB Random Access Memory (RAM) and 905 GB hard disk drive (HDD). Two data sets were used for this research CASIA (white Iris database) and LAUIRIS (Black Iris database). 108 individuals were used with 3 images per person, a total of 324 images for CASIA database while 150 individuals were used with 3 images person, a total of 450 images were used for LAUIRIS database. Two (2) images of individuals were used for training the developed recognition system; a total of 300,216 images used for CASIA and LAUIRIS respectively while 1 image of individuals were used for testing; a total of 108,150 images used for CASIA and LAUIRIS respectively.

3.8 Performance Evaluation of the Developed System.

The performance of the system was evaluated using FAR (False Accept Rate), FRR (False Reject Rate) and Recognition Rate (RR) at different thresholds.

FAR is the probability of recognizing an illegitimate user as authentic user while FRR is the probability of denying an authentic user access, as if he is an outsider (Malik *et al.*, 2014). The reasons for false Iris rejects are environmental or user error, i.e. presenting or not clearly opening eye (obscured Iris), reflection from glasses i.e. glare in the image, user difficulty (non-dominant eye) etc. The performance of Iris recognition can be improved if FRR and FAR are reduced. The performance of the developed system was evaluated on LAUIRIS and CASIA, and compared with the existing systems (CNN, BPNN-PSO and BPNN) using False Acceptance Rate (FAR), False Rejection Rate (FRR) and Recognition Rate (RR). The equations for FAR, FRR and RR are shown below:

$$\text{FAR (\%)} = \frac{\text{No.of false accepted}}{\text{total No.of imposter attempts}} \times 100 = \frac{\text{FP}}{\text{FP+TP}} \times 100 \ldots\ldots \text{(3.6)}$$

$$\text{FRR (\%)} = \frac{\text{No.of false rejected}}{\text{total No.of authentic attempts}} \times 100 = \frac{\text{FN}}{\text{FN+TN}} \times 100 \ldots\ldots \text{(3.7)}$$

$$\text{Accuracy (\%)} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \times 100 \text{ OR } \ldots\ldots \text{(3.8)}$$

$$\text{Accuracy (\%)} = 100 - \left(\frac{\text{FAR+FRR}}{2}\right) \times 100 \ldots\ldots \text{(3.9)}$$

Where,

FP represent number of imposters identified as legitimate users,
TP is the number of legitimate users identified correctly,
FN is the number of legitimate users identified as imposters and
TN is the number of imposters of correctly identified as imposters.

4.0 RESULTS AND DISCUSSION

4.1 RESULTS

The results obtained from the Iris recognition system for the two data sets; LAUIRIS and CASIA were presented in Tables 4.1a and 4.2a respectively. Tables 4.1b-d showed the result of Iris recognition system with CNN (Convolutional neural network), BPNN (Back propagation neural network) and BBPNN-PSO (Back propagation neural network optimized with particle swarm optimization) for LAUIRIS while the results for CASIA data set were presented in Tables 4.2b-d. Tables 4.3a and 4.3b showed the comparison between the developed system and existing system when LAUIRIS and CASIA data set were employed respectively.

Tables 4.1a, 4.1b, 4.1c and 4.1d showed the result of different performance metrics of the systems at different thresholds for LAUIRIS while Tables 4.2a, 4.2b, 4.3c and 4.2d showed the result of different performance metrics of the systems at different thresholds for CASIA. Table 4.3a showed comparison of the optimum metrics of the systems for LAUIRIS while that of CASIA is as shown in Table 4.3b. Figure 4.1 shows the graphical representation of the RR for the two datasets. Appendix showed the MATLAB graphical user interface of the developed Iris recognition system.

For LAUIRIS, minimum FAR values of 0.00, 2.67, 0.00 and 1.33% at thresholds of 0.5 to 0.8 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively, and highest FAR values of 5.33% at 0.4 threshold, 5.33% at threshold of 0.3, 6.67% at 0.1 to 0.2 thresholds, and 8.00% at thresholds of 0.1 to 0.2 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively. Similarly, least FRR values of 1.33% at thresholds 0.1 to 0.3, 1.33% at thresholds 0.1 to 0.2, 2.67% at thresholds 0.1 to 0.2, and 2.67% at thresholds 0.1 to 0.3 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively, and highest.

Table 4.1a: Recognition Technique CNN-PSO LAUIRIS

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	5.33	1.33	96.67	1976.73
0.2	5.33	1.33	96.67	1853.49
0.3	4.00	1.33	97.33	2670.70
0.4	1.33	2.67	98.00	1726.00
0.5	0.00	2.67	98.67	1963.88
0.6	0.00	2.67	98.67	1910.62
0.7	0.00	2.67	98.67	1804.38
0.8	0.00	2.67	98.67	1661.39

Table 4.1b: Recognition Technique CNN LAUIRIS

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	4.00	1.33	97.33	1442.90
0.2	4.00	1.33	97.33	1881.40
0.3	5.33	2.67	96.00	2117.33
0.4	2.67	4.00	96.67	7354.54
0.5	2.67	5.33	96.00	1443.68
0.6	2.67	5.33	96.00	1714.47
0.7	2.67	5.33	96.00	1887.48
0.8	2.67	5.33	96.00	1902.12

Table 4.1c: Recognition Technique BPNN-PSO LAUIRIS

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	6.67	2.67	95.33	2034.01
0.2	6.67	2.67	95.33	1935.77
0.3	4.00	4.00	96.00	1834.21
0.4	1.33	5.33	96.67	2640.23
0.5	0.00	5.33	97.33	1994.61
0.6	0.00	5.33	97.33	2663.65
0.7	0.00	5.33	97.33	1689.07
0.8	0.00	5.33	97.33	2247.73

Table 4.1d: Recognition Technique BPNN LAUIRIS

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	8.00	2.67	94.67	1457.26
0.2	8.00	2.67	94.67	1470.50
0.3	6.67	2.67	95.33	1448.74
0.4	4.00	4.00	96.00	1439.29
0.5	1.33	5.33	96.67	6688.87
0.6	1.33	5.33	96.67	1688.32
0.7	1.33	5.33	96.67	2812.99
0.8	1.33	5.33	96.67	1951.82

Table 4.2a: Recognition Technique CNN-PSO CASIA

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	3.70	1.85	97.22	3469.88
0.2	3.70	1.85	97.22	2697.41
0.3	5.56	3.70	95.37	2296.10
0.4	1.85	5.56	96.30	2673.73
0.5	1.85	3.70	97.22	3896.50
0.6	1.85	3.70	97.22	1008.14
0.7	1.85	3.70	97.22	1103.64
0.8	1.85	3.70	97.22	1951.82

Table 4.2b: Recognition Technique CNN CASIA

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	9.26	3.70	93.52	1225.99
0.2	9.26	3.70	93.52	2718.51
0.3	7.41	5.56	93.52	1775.69
0.4	3.70	7.41	94.44	2293.06
0.5	5.56	9.26	92.59	1711.27
0.6	5.56	9.26	92.59	2559.55
0.7	5.56	9.26	92.59	1541.53
0.8	5.56	9.26	92.59	2457.51

Table 4.2c: Recognition Technique BPNN-PSO CASIA

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	11.11	3.70	92.59	1486.40
0.2	11.11	3.70	92.59	3529.10
0.3	7.41	5.56	93.52	2157.00
0.4	3.70	7.41	94.44	2109.70
0.5	1.85	7.41	95.37	2855.60
0.6	1.85	7.41	95.37	2325.00
0.7	1.85	7.41	95.37	2084.90
0.8	1.85	7.41	95.37	1916.41

Table 4.2d: Recognition Technique BPNN CASIA

Threshold value	FAR(%)	FRR(%)	RR(%)	Rt(secs)
0.1	12.96	3.70	91.67	1219.12
0.2	12.96	3.70	91.67	1229.02
0.3	11.11	3.70	92.59	1452.30
0.4	5.55	7.41	93.52	1804.69
0.5	1.85	9.26	94.44	1575.56
0.6	1.85	9.26	94.44	2256.26
0.7	1.85	9.26	94.44	1737.19
0.8	1.85	9.26	94.44	1916.41

FAR values of 5.33% at 0.4 threshold, 5.33% at threshold of 0.3, 6.67% at 0.1 to 0.2 thresholds, and 8.00% at thresholds of 0.1 to 0.2 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively. Similarly, least FRR values of 1.33% at thresholds 0.1 to 0.3, 1.33% at thresholds 0.1 to 0.2, 2.67% at thresholds

0.1 to 0.2, and 2.67% at thresholds 0.1 to 0.3 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively, and highest FRR values of 2.67% at thresholds 0.4 to 0.8, 5.33% at thresholds of 0.5 to 0.8, 5.33% at thresholds of 0.4 to 0.8, and 5.33% at thresholds of 0.5 to 0.8 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively as shown in Table 4.1a to 4.1d.

For CASIA, least FAR values of 1.33%, 5.56%, 1.85% and 1.85% at thresholds of 0.5 to 0.8 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively, and optimum FAR values of 3.70%, 9.26%, 11.11%, and 12.96% at thresholds of 0.1 to 0.2 was achieved for CNN-PSO, CNN, BPNN-PSO and BPNN respectively. Consequently, lowest FRR values of 1.85%, 3.70%, 3.70%, at thresholds 0.1 to 0.2 and 2.67% at thresholds 0.1 to 0.3 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively, and highest FRR values of 5.33% at thresholds 0.5 to 0.8, 9.26% at thresholds of 0.5 to 0.8, 7.41% at thresholds of 0.4 to 0.8, and 9.26% at thresholds of 0.5 to 0.8 was obtained for CNN-PSO, CNN, BPNN-PSO and BPNN respectively as shown in Table 4.2a to 4.2d. For LAURIS RR of CNN-PSO ranges from 96.67% to 98.67%, 96.00% to 97.33% for CNN, 95.00% to 97.33% for BPNN-PSO, and 94% to 96.67% for BPNN. While for CASIA the RR differs from 95.37% to 97.22% using CNN-PSO, 92.59% to 94.44% for CNN, 92.59% to 95.37% for BPNN-PSO and 91.67% to 94.44% for BPNN.

4.2 DISCUSSION OF RESULTS

According to tables 4.1a to 4.2d, CNN-PSO has the minimum value of FAR for LAUIRIS and CASIA in comparison to CNN, BPNN-PSO, BPNN which means that the system is highly sensitive to illegitimate users, the probability of imposters being accepted as genuine user is minimal as against the other systems. Also, it has a minimal value of FRR for LAUIRIS and CASIA, which implies that the rate at which legitimate users are regarded as imposters and denied access is least as against other systems. It also means that the developed system has low tolerance for imposters and is less receptive to illegitimate users in relative to other systems. CNN-PSO has a considerably high RR compared to other systems.

Table 4.3a: Optimal Recognition Rate of the systems LAUIRIS dataset

Recognition Technique	FAR (%)	FRR (%)	Threshold	RR (%)
CNN-PSO	0.00	2.67	0.5	98.67
CNN	4.00	1.33	0.2	97.33
BPNN-PSO	0.00	5.33	0.5	97.33
BPNN	1.33	5.33	0.5	96.67

Table 4.3b: Optimal Recognition Rate of the systems CASIA dataset

Recognition Technique	FAR (%)	FRR (%)	Threshold	RR (%)
CNN-PSO	3.70	1.85	0.5	97.22
CNN	3.70	7.41	0.4	94.44
BPNN-PSO	1.85	7.41	0.5	95.37
BPNN	1.85	9.26	0.5	94.44

In addition, Tables 4.3a and 4.3b showed that CNN-PSO has the highest RR of the four systems, with RR of 98.67 and 97.22% for LAUIRIS and CASIA respectively. In view of the significantly high authentication capacity, it can be deduced that the system is the best recognition system and that PSO has a significant effect on the result of the recognition system. Also, when compared with earlier work of Falohun *et al.*, (2013) where an accuracy of 96.10, at FAR of 0.57 and FRR of 3.33% was obtained For LAUIRIS and RR of 97.22, at FAR of 0.00, FRR of 2.78% for CASIA, the system outperforms the state of the art method.

Ordinarily, CNN has higher RR which shows that CNN outperform BPNN for both datasets due to CNN's ability to encode specific image features and reduction in system complexity thereby giving rise to a better performance (higher recognition rate) in image recognition. The evaluation of the systems showed that PSO has a significant effect on CNN for CASIA (white Iris) and LAUIRIS (black Iris), by combining PSO's strong ability regarding convergence rate and simultaneous sampling of multiple search space region with CNN's image-specific encoding features, modelling of very complex data distributions and nonlinear data changes capability in achieving a more robust recognition system with the highest recognition rate. The developed system result into more recognition accuracy, hence it is more preferred and reliable for authentication and identification purposes. This also implies that CNN-PSO based Iris recognition system is highly efficient for black Iris images despite the difficulties in separating Iris image from other part of the eyes.

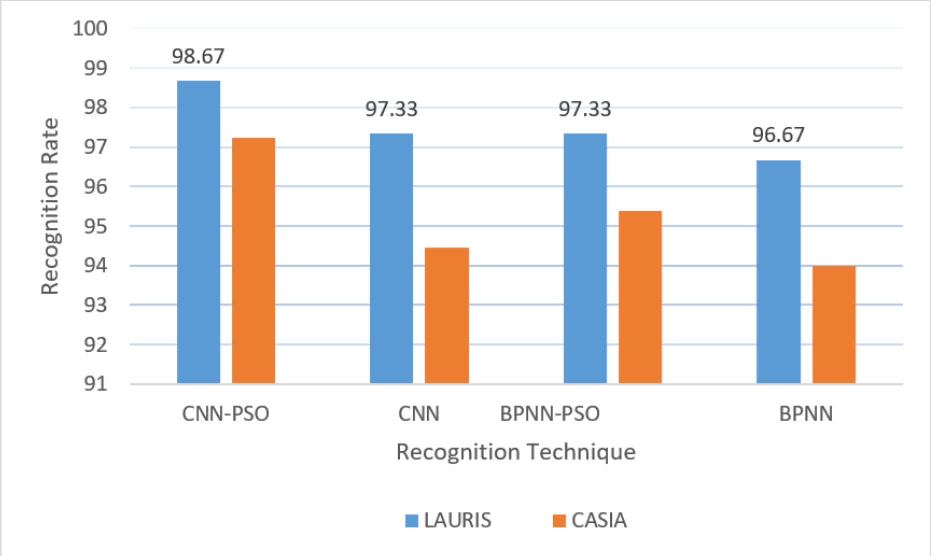

Figure 4.1: Recognition Rate of LAUIRIS and CASIA

APPENDIX

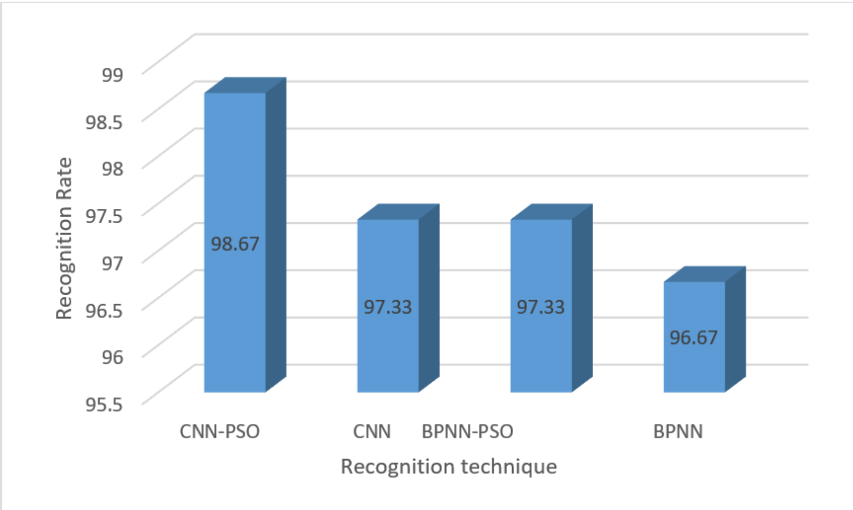

Figure A1: Recognition Rate of LAUIRIS

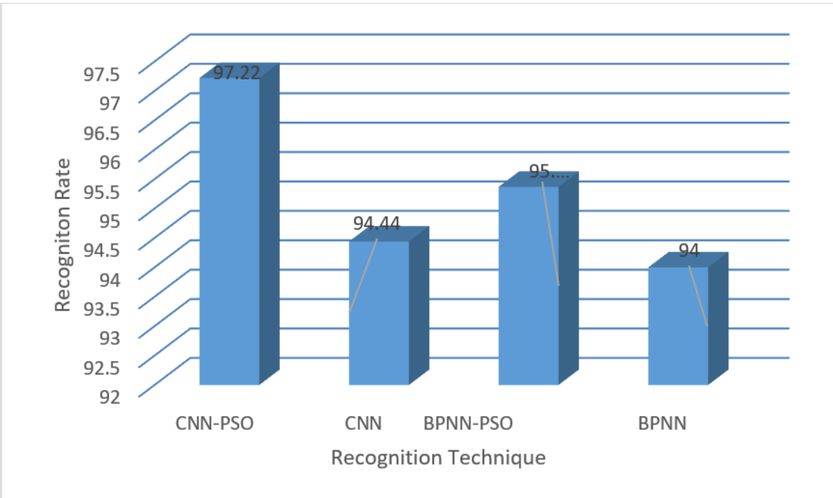

Figure A2: Recognition Rate of CASIA

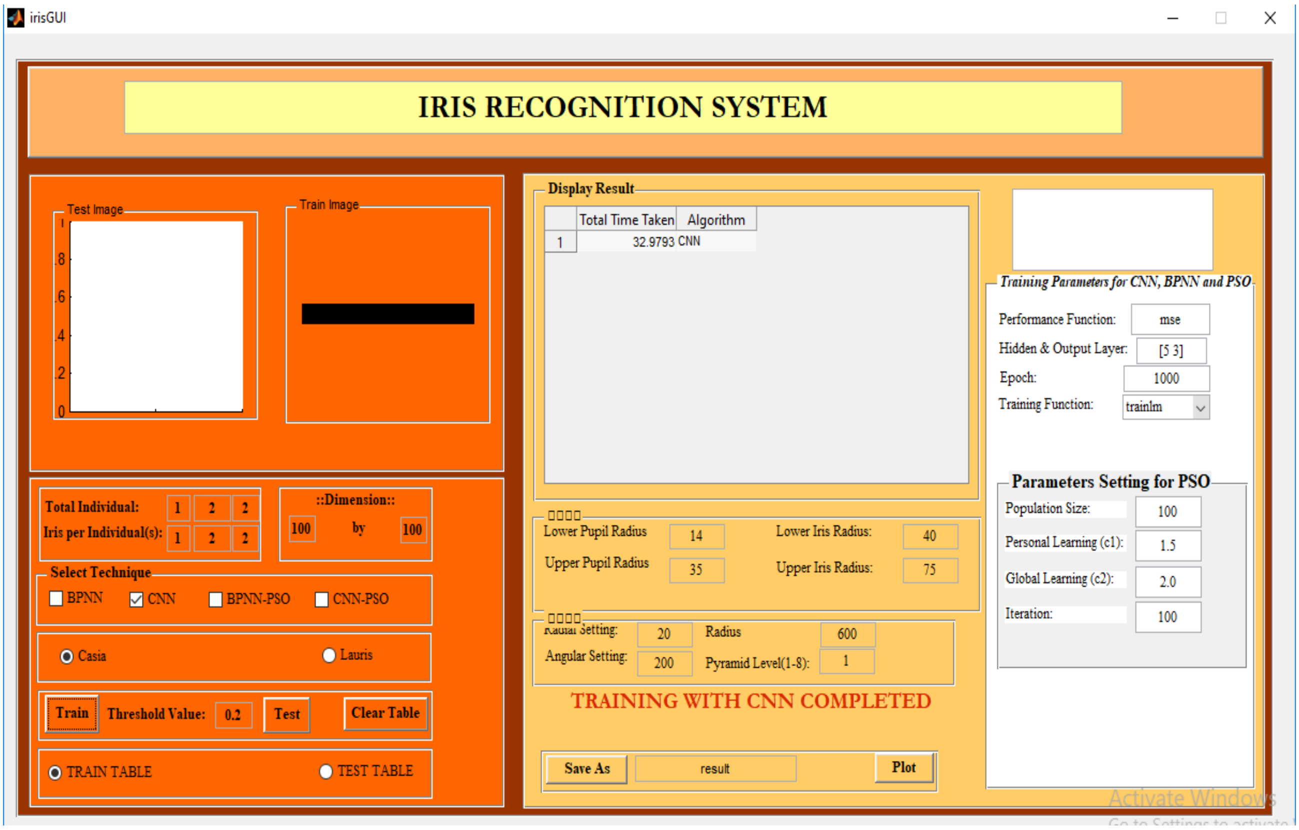

Figure A3: Graphical user interface of the Iris Recognition System

5.0 CONCLUSION AND RECOMMENDATION

5.1 CONCLUSIONS

An Iris recognition system based on Convolutional Neural Network-Particle Swarm optimization (CNN-PSO) was developed in this work. CNN-PSO has the highest recognition rate of 98.67% and 97.22% for LAUIRIS and CASIA respectively among the systems which showed an improvement over other three recognition technique.

The developed CNN-PSO has not only produced an improved Iris recognition system over the others, with the highest recognition rate for both datasets but it also provides a significant recognition rate of black Iris images despite the limitations identified with black Iris images in separating Iris image from other part of the eyes. The developed technique can be applied to various field of life like security, surveillance systems.

5.2 RECOMMENDATIONS

Further research on the system will include evaluation of the computational complexity to ensure the recognition time meet up real time requirement. The performance of the system can be evaluated with larger Iris dataset to test the robustness of the system. Other forms of deep learning can be explored for simulating the developmemt of Iris recognition system.

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