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A NOVEL IRIS BASED SECURITY POLICY USING LDP AND ENSEMBLE CLASSIFICATION

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Abstract:

Iris is one of important biometrics, which remains static and cannot be altered all-through the life of mankind. Iris is the most powerful biometric among all the other biological measures such as voice, fingerprint, palm print, signature and so on. Understanding the merit of iris, this paper presents an iris based security policy that grants access to the users by matching the iris of the individual with the trained iris sample. The main objective of this article is to attain maximum recognition accuracy. The objective is attained by segmenting the iris region and the extracted iris region is normalized. The Local Directional Pattern (LDP) features of the normalized iris images are extracted and the decision about user access grant or denial is made by the ensemble classifier. This work utilizes k-Nearest Neighbour (k-NN), Support Vector Machine (SVM) and Extreme Learning Machine (ELM) as ensemble classifier. The performance of the proposed approach is evaluated by varying the segmentation, feature extraction and classification techniques. On analysis, it is found that the performance of the proposed morphological operation based segmentation algorithm works better than the comparative segmentation algorithms. The idea of ensemble classification maximizes the recognition accuracy, as the final decision is made by considering the decisions of three efficient classifiers. The performance of the proposed approach is tested in terms of recognition accuracy, sensitivity and specificity. The proposed approach outperforms the existing approaches with better results.

Key Words: Iris Recognition, Biometrics & Segmentation

1. Introduction:

Biometric based security applications intend to provide security to any sort of application by extracting the biological traits from the human. The biometric based applications are popular and promising, as the biological traits of a human being cannot be duplicated and they remain the same throughout the lifetime of the individual. Additionally, it is easy to acquire the biological identity of a person without more hassles. Some of the popular biometrics are fingerprint, palm print, voice, iris and so on. This article utilizes iris images as the biometric, owing to several positive points. For instance, the iris of the human eye remains permanent and cannot be altered by any means. On the other hand, the human voice may change with respect to illness and situations. Finger prints and palm prints may fade off, due to excessive work and illness. Taking these points into account, this work proposes to exploit human iris for enforcing security to the application. However processing the iris images is not simple, as the structure of human eyes is intricate and delicate. The iris based security enforcement scheme can accomplish its goal, only when the iris is processed and matched accurately. This is highly complex and has to be attained with utmost care. Understanding the technical complexity of the system, this work segregates the complete work into image acquisition, iris segmentation, post-processing, feature extraction, and iris recognition. The human eye images are acquired from standard datasets and the iris regions are segmented from the human eye images by means of circular hough transform. The segmented iris images are normalized by Dougman's rubber sheet model and the Local Directional Pattern (LDP) features are extracted.

Finally, the ensemble classification is imposed, which is attained by the classifiers k-Nearest Neigbour (k-NN), Support Vector Machine (SVM) and Extreme Learning Machine (ELM). The ensemble classifier recognizes the iris of the human eyes and grants access with respect to the match. The performance of the proposed approach is validated in terms of recognition accuracy, sensitivity, specificity and computation time. The noteworthy points of this work are listed below.

- ✓ The iris region from human eyes are segmented for better efficiency.
- ✓ The LDP takes the edge information of multiple directions into account. Hence, the LDP features are crisp enough to differentiate between different samples.
- ✓ The iris is recognized by employing ensemble classification, which does not rely on the performance of a single classifier but three different classifiers. This increases the accuracy rates, as it is the milestone of every security based application.

The remainder of this paper is organized as follows. Section 2 presents the related review of literature with respect to iris recognition and the proposed iris recognition approach is elaborated in section 3. The performance of the proposed approach is evaluated in section 4 and the experimental results are presented. The conclusions are presented in section 5.

2. Review of Literature:

The related literature with respect to iris recognition is reviewed and discussed as follows.

A remote based boosting framework is proposed to recognize iris in [1]. This work explores the characteristics of the iris in a remote fashion and the adaboost learning process is adjusted in line with the issue. The iris is detected by Haar features and is recognized by Gaussian model. In [2], an iris recognition system is proposed by means of class-specific dictionaries. This work is based on least square regression and the final decision is made by considering the class with clear estimation. This algorithm is compared against Sparse Representation Classification (SRC) and Bayesian fusion techniques. A multi-sensor scheme is proposed for simultaneous video and iris image recognition in [3]. As this scheme is applicable for both images and videos, fusion techniques are utilized at segmentation level by means of modified laplacian pyramid-based fusion technique. The performance of the proposed approach is tested upon four datasets in terms of recognition accuracy. In [4], the iris images are recognized by reducing the feature keypoints. This work proposes a density based spatial clustering and the keypoints are minimized by applying Phase Intensive Local Pattern (PILP) on the extracted set of features. However, the keypoint minimization should not affect the accuracy of the iris recognition system.

A survey on iris recognition system by means of machine learning techniques is presented in [5]. The scope of this survey considers only the iris recognition problem and not in the aspects of iris detection and feature extraction techniques. The taxonomy of several machine learning techniques right from neural networks and deep learning is presented. In [6], a technique to localize and recognize iris is presented. The iris is localized by converting the gray image to binary image via adaptive threshold computed from the histogram of the image intensity. The centre point of the eye is extracted by morphological processing and the results are refined by integro-differential operator. An approach to recognize iris in noisy environment based on neural network is proposed in [7]. Initially, the noise is removed from the image and the texture features are extracted from Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM). An iris recognition system based on multiscale morphological features is proposed in [8]. This work segments the iris region from the eye image by means of Restricted Circular Hough Transformation (RCHT). The multiscale morphological operator is applied over the normalized iris image. The classification process is carried out by dichotomy method and the performance of this approach is carried out in four different databases.

An iris recognition approach namely Random Sample Consensus (RANSAC) is proposed in [9]. This work considers the iris with non-circular boundaries and the Daugman's rubber sheet model is utilized for iris normalization. The templates are matched by means of Peak Side Lobe Ratio (PSR). In [10], an iris recognition approach is proposed for bovine iris images. This work utilizes Scale Invariant Feature Transform (SIFT) and bag-of-features. Initially, the region based active contour is utilized for detecting the inner boundary. The keypoints of the iris image are identified by SIFT technique and the feature dictionary is built. Finally, the histogram distance is computed to check for the match. A super resolution based iris recognition technique is presented in [11]. The super resolution of the iris images is transformed from the intensity to the feature domain. A 2D gabor phase quadrant features are extracted from the image and the iris is recognized. In [12], an iris recognition system is proposed for noisy iris images. This work differentiates between the left and right eyes and the next step takes the colour information into account by means of Euclidean, chi square and hamming distances in various colour models. The third step takes the texture information into account and is achieved by 1D gabor filter. The results are combined and the final decision is made by weighted sum rule.

An iris recognition system that relies on keypoint based feature extraction technique is presented in [13]. The keypoints of the images are detected by means of Harris-Laplace, Hessian-Laplace and Fast-Hessian. All these keypoints are represented by SIFT and are combined in terms of weights. Motivated by these existing works, this paper intends to propose a promising and efficient iris recognition system based on LDP features and ensemble classification. This results in better accuracy, sensitivity and specificity rates. The proposed approach is described in section 3.

3. Proposed Iris Recognition Approach:

This section presents all the details about the proposed iris recognition approach with the overview of the proposed work.

3.1 Overall Flow of the Proposed Approach:

The goal of this work is to present an iris recognition system based on LDP features and ensemble classifier that can prove better accuracy with reasonable time consumption. For this sake, the working policy of the proposed approach is divided into five key stages and each stage is concerned with attaining a goal. Initially, the human eye images are acquired from the standard benchmark databases. As this work performs iris recognition, the iris region has alone to be processed and hence, the iris of human eye is extracted by the process of segmentation. The eye image is segmented by circular hough transform. The segmented regions are normalized to have a standard form, which is accomplished by applying Daugman's rubber sheet model. The normalized iris images are treated with the process of feature extraction, which aims to extract crispy and better features from the iris images. The ensemble classifier makes the final decision to recognize the iris by matching test sample with the trained samples. The process of feature selection reduces the overall time complexity however, this time is compensated with the ensemble classification.

3.2 Image Acquisition:

The iris images are acquired from the standard datasets such as CASIA V1, V2, V3, Ubiris V2 datasets. The CASIA V1 dataset contains 756 images of iris extracted from 108 eyes. Seven different images are captured for every eye and the image resolution is about 320×280. The CASIA V2 dataset is comprised of about 2400 iris images with resolution 640×480. The CASIA V3 dataset possesses three subclasses such as Iris-interval, Iris-lamp and Iris-twins. The proposed work is tested on Iris-interval and Iris-lamp versions of the dataset. The iris-interval images and iris-lamp images are captured by a short distance camera and hand-held iris sensor respectively. All these datasets are downloaded from the link [14]. The Ubiris V2 dataset can be downloaded from [15], which contains about 522 iris images.

3.3 Iris Segmentation:

The iris region is segmented from the eye image by incorporating Wilde's approach that detects the inner and outer boundaries of iris [16]. This approach transforms the image intensity information into an edge map, which is binary. The points being present in the edge vote for fixing the contour values. The edge map takes the centre coordinates (x_i, y_i) and the radius rad are taken into account. The hough transform with circular edges with (x_p, y_p) as edge points is represented by

$$HT(x_i, y_i, rad) = \sum_{p=1}^{n} h(x_k, y_k, x_i, y_i, rad) \quad (1)$$

$$h(x_k, y_k, x_i, y_i, rad) = \begin{cases} 1 & if\ g(x_k, y_k, x_i, y_i, rad) = 0 \\ 0 & Otherwise \end{cases} \quad (2)$$

$$g(x_k, y_k, x_i, y_i, rad) = (x_p - x_i)^2 + (y_p - y_i)^2 - rad^2 \quad (3)$$

The border of iris is detected by computing the gradients horizontally, such that the influence of eyelash and eyelids are reduced. The border of pupil is found out by calculating the gradients vertically. By this way, the iris region is segmented and the segmented region is normalized, as discussed in the following subsection.

3.4 Iris Normalization and Enhancement:

The contrast of the segmented iris images is enhanced by histogram equalization technique. This process results in the improvisation of the final results. When the image contrast is enhanced, several minute details of the images can be observed easily. The image contrast is enhanced by means of adjusting the gray levels of the pixels, such that uniformity is attained. When this process is repeated for all pixels, the image contrast is increased. The histogram is computed by considering different gray level intensities of an image from 0 and 255. Each and every pixel is treated for enhancing the contrast and is achieved by

$$HE = \sum_{pi=1}^{l} \frac{s_p}{T_p} \quad (4)$$

In the above equation, s_p is the total number of pixels with the intensity kp_i and T_p is the total count of pixels in an image. This operation uniformly distributes the gray level and enhances the image contrast. These contrast enhanced iris images are then normalized by Daugman's rubber sheet model [17,18].

3.5 LDP Feature Extraction on Iris Images:

LDP is proposed by Jabid T., Kabir M.H. and Chae O. in the year 2010, which is an improvisation of Local Binary Pattern (LBP) [19]. The LBP is based on the intensity of the pixels, whereas the LDP depends on the gradients of the image, which is more stable. LDP processes the images in various directions and each pixel is represented by eight bit binary code. For instance, consider an image Img with pixels (x_i, y_i). The Kirsch compass edge detector is utilized to find eight directional outcomes (dir_{op}) as denoted by

$$dir_{op_i} = \sum_{a=-1}^{1} \sum_{b=-1}^{1} Mk_{dir}(a+1, b+1) \times Img(x+a, y+b) \quad (5)$$

The dir_{op_i} $(i = 1,2,\ldots,7)$ is computed for all the eight directions. All the eight directional outcomes are represented by codes. This code assigns the value 1 to the corresponding bit and the rest of the bits are assigned to 0. This assignment is carried out for k count of directional outcomes and the corresponding bit is set to 1 and $8 - k$ bits are set to 0. At last, all the directional outcomes of a pixel are denoted by

$$LDP_{x,y}(op_1, op_2, \ldots, op_8) = \sum_{i=1}^{8} q(op_i - op_k) \times 2^i \quad (6)$$

$$q(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (7)$$

In the above equation, op_k is the k^{th} significant directional outcome. In this work, the value of k is varied from 1 to 5 and the optimal results are observed when the value of k is 3. When all the LDP codes are built for all the pixels of an image, LDP histogram is constructed as follows.

$$LDP_{his} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} P(LDP_{(x,y)}, LDP_{p_i}) \quad (8)$$

In equation 8, LDP_{p_i} is the i^{th} pattern value of LDP and it varies with respect to the value of k. P is set to 1 when the value of x is 0 and 0 otherwise. By this way, the features are extracted and the classifiers are trained. The process of classification is presented in the following section.

3.6 Iris Classification and Matching:

In order to distinguish between different iris of humans and to provide security to the application, this work extracts the potential features from the iris and matches it against the trained samples. The final decision about 'access grant or deny' is made by considering the decisions of all the three different classifiers. The most dominating result being shown by the classifiers is declared as the final. This way of decision making results in better accuracy rates, which is the main ingredient of any security based application. This work has built ensemble classifier with k-NN, SVM and ELM classifiers. All these classifiers work independently to differentiate between the iris and results of all the classifiers are collected from the classifiers. The maximal occurring decision is declared as the final. The working principles of the classifiers are summarized as follows.

3.6.1 k-NN Classifier:

k-NN is the most simple classifier and it strongly depend on the value of k. The performance of this classifier strongly relies on the value of k and hence, optimal value has to be chosen. Yet, choosing the value of k is challenging, as the knowledge about the dataset is required. In addition to this, it consumes more time and computation. Taking this into account, this work employs k fold cross validation to automate the choice of k. k-NN classifier calculates the Euclidean distance between the train and test samples by

$$Dis_m = \sum_{i=1}^{N} \sqrt{x_i^2 - y_i^2} \tag{9}$$

The k fold cross validation scheme divides the training sample images into k divisions and each division is treated as the testing and the remaining images are treated as training samples. This operation continues until all the images are processed as test samples. Finally, the mean value is calculated for all the k results and is assigned as k. This method overthrows the need of manual choice of the value k and makes the process effective.

3.6.2 SVM Classifier:

SVM is a famous classifier that is trained with the features of the iris images. Let {1,2,3,…N} be the iris images, which are to be granted or denied access by matching the test iris image and the trained samples. The classification process is carried out by a hyperplane, that separates between the classes based on a classification. The efficiency of classification depends on the hyperplane and the separation is done by

$$f(x) = \sum_{i=1}^{N} LM_i \psi_i(B, M) \tag{10}$$

In equation 10, LM_i is the lagrange multiplier that separates the hyperplane of the classifying area $\psi_i(B, M)$. The classification of iris is made by comparing the test iris image with the trained samples for granting or denying access.

3.6.3 ELM Classification: ELM is one of the promising classifiers with quicker learning capability [20]. The classifier can perform its function, when it undergoes two significant phases such as training and testing. The training phase involves the process of learning and knowledge gaining through feature vectors. With the gained knowledge, the classifier is equipped to differentiate between the iris images in the testing phase. Let there be A_{TS} training samples as denoted by (s_i, t_i), where $s_i = [s_{i1}, s_{i2}, s_{i3}, \dots, s_{in}]^T \in D^n$, where s_i is the i^{th} training entity having n dimensions. $tk_i = [tk_{i1}, tk_{i2}, tk_{i3}, \dots, tk_{im}]^T \in D^m$. that represents the i^{th} training label with m dimensions. Here, 'm' is the number of classes. This is followed by the construction of a Single hidden Layer Feed-Forward Neural Network (SLFN) with an activation function $act(x)$ having NR neurons. The following equation represents the same by

$$\sum_{i=1}^{NR} \mu_i (wt_i . s_i + c) = r_j; j = 1,2, \dots, n \tag{11}$$

In the above equation, wt_i is the weights as given by $wt_i = [wt_{i1}, wt_{i2}, \dots, wt_{in}]^T$ and it interconnects the i^{th} hidden neuron with the input neurons and i ranges from $[i1, i2, \dots, im]^T$. The weight vector is responsible for linking the i^{th} hidden neuron to the output neurons through the bias $(bias_i)$ of the i^{th} hidden neuron. The following equation represents the SLFN.

$$\sum_{i=1}^{NR} \mu_i act(wt_i . s_i + bias_i) = tk_i; i = 1,2, \dots, n \tag{12}$$

Consider HDL as the hidden layer output matrix of the classifier, so the i^{th} column of HDL contains the i^{th} hidden neurons output vector with respect to the input $s_{i1}, s_{i2}, \dots, s_{in}$.

$$HDL = \begin{bmatrix} act(wt_1 . s_1 + bias_i) & \dots & act(wt_{NR} . s_1 + bias_G) \\ \vdots & \vdots & \vdots \\ act(wt_1 . s_n + bias_i) & \dots & act(wt_{NR} . s_n + bias_G) \end{bmatrix} \tag{13}$$

$$\mu = \begin{bmatrix} \mu_1^T \\ \vdots \\ \mu_{NR}^T \end{bmatrix} \tag{14}$$

$$TK = \begin{bmatrix} tk_1^T \\ \vdots \\ tk_n^T \end{bmatrix} \tag{15}$$

This can be written in matrix format as

$$HDL\mu = TK \quad (16)$$

The output weights are calculated by the norm least-square solution by

$$\mu = HDL^{\dagger}TK \quad (17)$$

In the above equation, the Moore-Penrose generalized inverse of HDL is represented by $HDL^{\dagger}$. The pre-requirements of ELM training includes class count m, activation function $act(x)$, NR hidden neurons. During the knowledge gaining phase, the ELM is provided with a training set $Tr_{set} = \{(s_i, t_i) | s_i \in D^n, t_i \in D^m; i = 1,2, \dots, N\}$. The training process is done by performing the operation as in equation 15. During the process of testing, the test image is carried out with all the preliminary processes, as discussed earlier. The feature vector of the test image is matched against the templates stored in the train set and based on the similarity, the user is provided or denied with the service. The ensemble classification is achieved by collecting the decisions of all the classifiers followed by the application of maxvote policy. This policy selects the decision with maximum occurrence. As this work employs three classifiers, eight possible cases comes into picture and is represented in equation 18. Each column of the matrix represents the classifiers k-NN, SVM and ELM.

$$D_m = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix} \Rightarrow FD_m = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 0 \\ 1 \end{pmatrix} \quad (18)$$

Where, D_m and FD_m are the decision matrix and final decision matrix respectively. The D_m represents the decisions of the three classifiers and the FD_m is obtained after the application of maxvote strategy. Hence, the objective of the work is attained by incorporating rich features and thereby discriminating between the iris images. This work consumes lesser period of time, as there is no complex computations are involved in the entire process. However, the proposed approach ensures the reliability and accuracy and the performance of this work is analysed in the forthcoming section.

4. Results and Discussion:

The performance of the proposed iris recognition system is evaluated over four different datasets and the proposed approach works in a consistent fashion on all datasets. Hence, this work is claimed to be promising and reliable. The experimental procedure is carried out in MATLAB environment on a standalone computer with 8 GB RAM and i7 Processor. The performance of the proposed approach is tested in terms of recognition accuracy, sensitivity and specificity.

$$Seg_{acc} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (19)$$

The sensitivity and the specificity of the proposed segmentation algorithm are measured by

$$Seg_{sen} = \frac{T_p}{T_p+F_n} \times 100 \quad (20)$$

$$Seg_{spe} = \frac{T_n}{F_p+T_n} \times 100 \quad (21)$$

The greater the sensitivity rate, the lesser is the false negatives. Similarly, the greater the specificity rate, the lesser is the false positives. Attaining maximum accuracy rates is a bit easier than to achieve greater sensitivity and specificity rates. The sample results of this work are presented in figure 1 and figure 2 presents the sample final decisions made by the ensemble classifier.

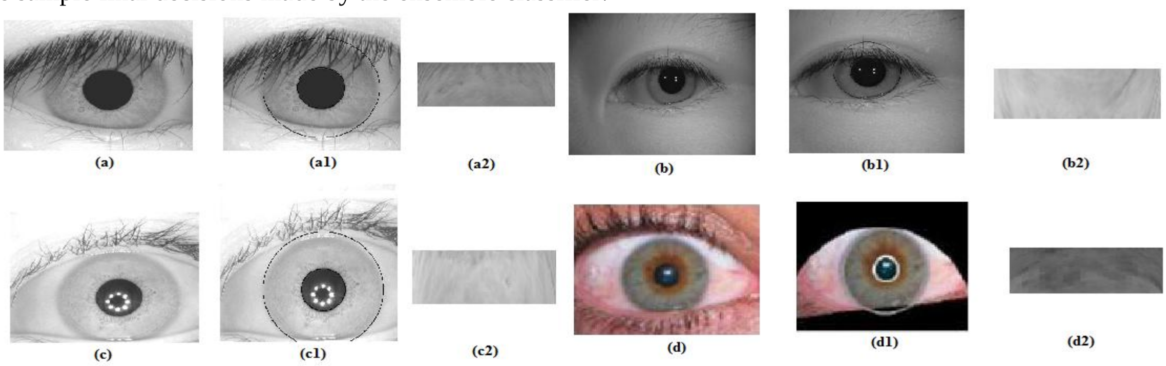

Figure 1: (a-d) Original iris images from CASIA V1, V2, V3, Ubiris V2, (a1-d1) Iris segmented images (a2-d2) Normalized iris

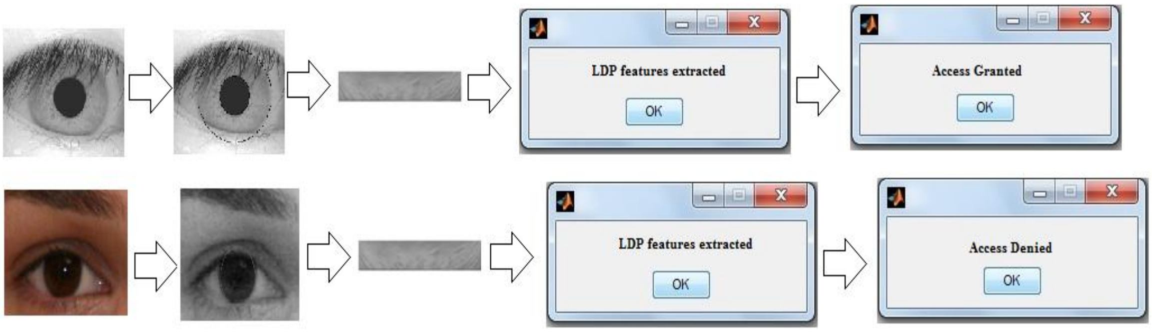

Figure 2: Sample decision making screens of ensemble classifier

When an iris recognition algorithm proves maximum sensitivity and specificity rates, then that algorithm is proven to be reliable. The experimental procedure of this work is carried out in three different aspects. The segmentation, feature extraction and classification techniques are varied and the performance of the proposed approach is tested. Additionally, the performance of the proposed iris recognition system is compared against the existing techniques.

4.1 Performance Evaluation by Varying Segmentation Techniques:

Initially, the iris is segmented from the eye images which are extracted from four iris databases. The segmentation is the most crucial phase of any recognition algorithm, as the accuracy of the iris recognition system relies on the efficiency of the segmentation results. The process of segmentation reduces the computational time and complexity by performing operations only on the segmented region. Taking this into account, this work segments the eye images by employing the segmentation technique proposed in [21], Integro Differential Operator (IDO) and circular hough transform. The experimental results of the segmentation techniques with the incorporation of LDP features and ensemble classification are presented in the following table.

Table 1: Comparative analysis by varying segmentation algorithms

Image category	Accuracy (%)			Sensitivity (%)			Specificity (%)			Time (ms)		
	IDO	Wildes	[21]	IDO	Wildes	[21]	IDO	Wildes	[21]	IDO	Wildes	[21]
CASIA Iris V1	97.2	98.8	99.2	96.2	97.9	98.1	93.8	95.3	97.6	2689	2463	2348
CASIA Iris V2	95.6	96.3	98.8	93.4	95.2	97.8	91.6	92.7	96.2	2868	2634	2486
CASIA Iris V3	97.3	98.7	99.4	92.7	95.9	98.4	90.7	92.8	96.9	2589	2389	2215
Ubiris V2	94.8	96.9	98.6	93.2	94.8	97.2	90.6	92.8	97.3	2479	2443	2186
Average	**96.2**	**97.6**	**99**	**93.87**	**95.9**	**97.87**	**91.6**	**93.4**	**97**	**2656**	**2482**	**2308**

On analysis, it is observed that the performance of previously proposed segmentation technique is better than circular hough transform based wilde's approach and IDO. The reason for the maximum time consumption is the ensemble classification, as the final decision depends on the decisions of three different classifiers. However, the accuracy, sensitivity and specificity rates are considerably improved. The following section evaluates the performance of the proposed approach by varying the feature extraction techniques.

4.2 Performance Evaluation by Varying Feature Extraction Techniques:

Feature extraction is the second important phase that decides the efficiency of the iris recognition technique. This work utilizes LDP features for performing the recognition task. The performance of LDP is tested against Local Binary Pattern (LBP) features. The LBP and LDP features are extracted after segmenting the iris by means of the previously proposed morphological operation based segmentation algorithm [21] and the extracted features are utilized for training the ensemble classifier. The experimental results are tabulated as follows.

Table 2: Comparative analysis by varying feature extraction techniques

Image Database	Accuracy (%)		Sensitivity (%)		Specificity (%)		Time (ms)	
	LBP	LDP	LBP	LDP	LBP	LDP	LBP	LDP
CASIA Iris V1	94.3	99.2	90.6	98.1	87.3	97.6	2186	2348
CASIA Iris V2	93.8	98.8	87.6	97.8	86.1	96.2	2246	2486
CASIA Iris V3	94.6	99.4	88.9	98.4	84.6	96.9	2039	2215
Ubiris V2	96.3	98.6	89.2	97.2	87.2	97.3	1986	2186
Average	94.75	99	89.07	97.87	86.3	97	2114	2308

From the experimental results, it is observed that the performance of LDP is better than LBP features. The main reason is that the LDP features are more descriptive than the LBP features. However, the iris recognition technique with LDP consumes more time than LBP features. The performance of the proposed approach is again tested to justify the choice of ensemble classification and is presented in the following section.

4.3 Performance Evaluation by Varying Classification Techniques:

This section analyses the performance of the proposed work that encapsulates the morphological operation based segmentation algorithm [21], LDP features by varying the classifiers. The performance of ensemble classifier is tested against individual classifiers such as k-Nearest Neighbour (k-NN), Support Vector Machine (SVM) and Extreme Learning Machine (ELM). The experimental results are presented as follows.

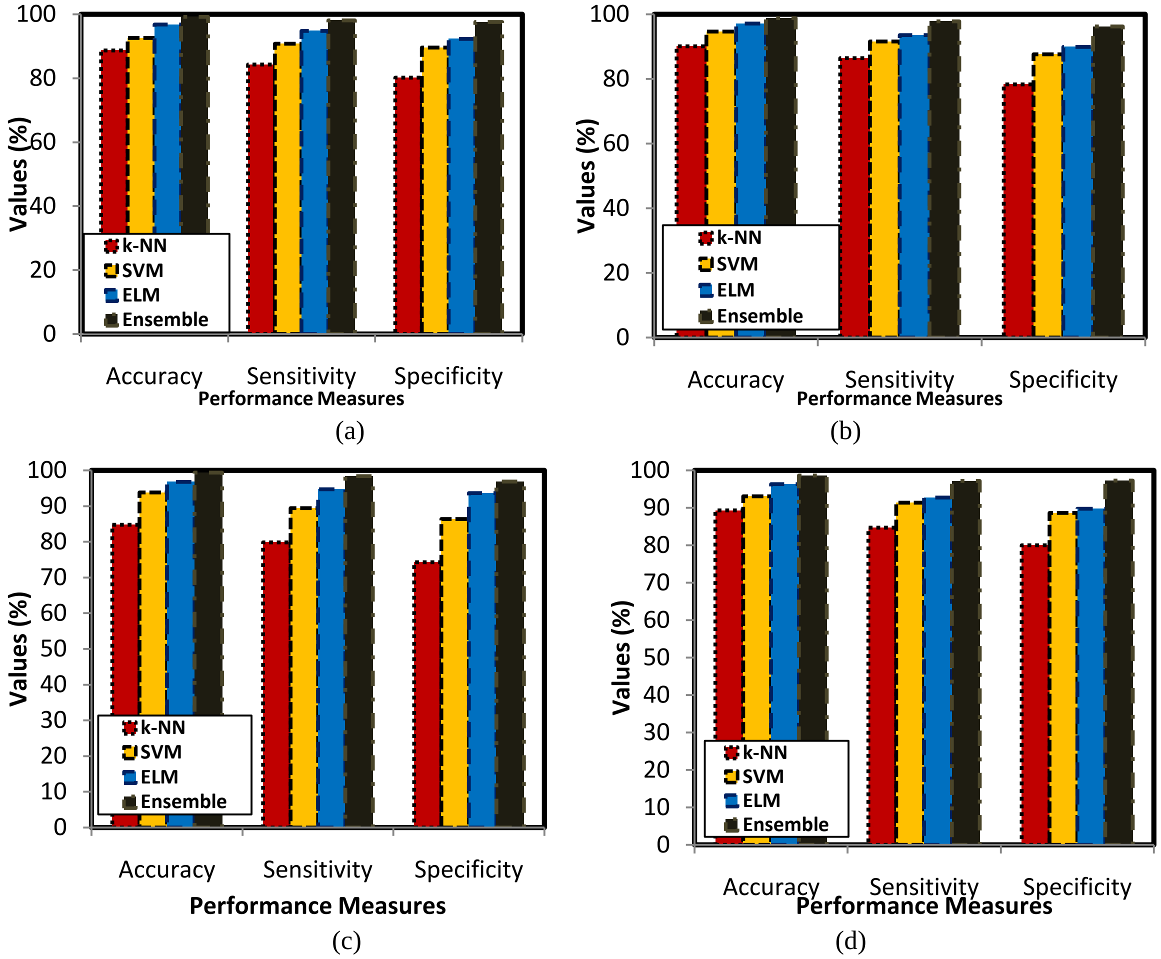

Figure 3: Performance evaluation on (a) CASIA IRIS V1, (b) CASIA IRIS V2, (c) CASIA IRIS V3, (d) UBIRIS V2

On observing the results, it is found that the performance of ensemble classification is better than individual classifiers. The main reason for the ensemble classifier to achieve better accuracy, sensitivity and specificity rates is that the final decision is made by three different classifiers. However, the ensemble classification involves time complexity and the time consumption results are shown below.

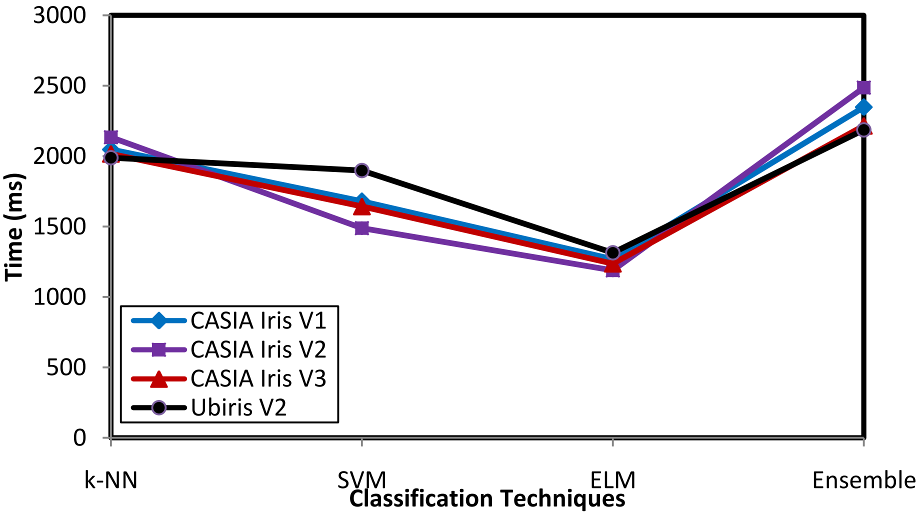

Figure 4: Time consumption analysis by varying classification techniques

The ensemble classifier achieves maximum accuracy, sensitivity and specificity rates at the cost of time consumption. However, the time consumption is tolerable and acceptable for the better performance. The following subsection presents the experimental results by comparing the proposed approach with the existing techniques.

4.4 Performance Evaluation with the State-of-the-Art Iris Recognition Techniques:

The performance of the proposed approach is tested against the related state-of-the-art iris recognition techniques proposed in [6, 7, 22]. The iris recognition technique proposed in [6] is based on adaptive threshold based segmentation. The neural network based approach is presented for iris recognition in [7]. The experimental results and the comparative analysis of the proposed approach are presented as follows.

Table 3: Comparative analysis with the existing approaches

Image Category	Accuracy (%)				Sensitivity (%)			
	[6]	[7]	[22]	Prop	[6]	[7]	[22]	Prop
CASIA Iris V1	89.1	94.7	96.3	99.2	83.6	87.8	94.8	98.1
CASIA Iris V2	90.3	94.9	94.4	98.8	84.2	87.3	91.2	97.8
CASIA Iris V3	91.6	96.5	96.1	99.4	84.8	87.9	90.2	98.4
Ubiris V2	93.4	96.3	93.8	98.6	87.9	90.2	90.4	97.2
Average	**91.1**	**95.6**	**95.15**	**99**	**85.12**	**88.3**	**91.65**	**97.87**

Image Category	Specificity (%)				Time (ms)			
	[6]	[7]	[22]	Prop	[6]	[7]	[22]	Prop
CASIA Iris V1	80.7	84.3	92.3	97.6	1836	1798	1298	2348
CASIA Iris V2	80.9	83.1	89.6	96.2	1896	1867	1876	2486
CASIA Iris V3	80.7	86.2	89.9	96.9	1962	1733	1767	2215
Ubiris V2	87.2	91.3	88.7	97.3	1983	1680	1683	2186
Average	**82.37**	**86.22**	**90.12**	**97**	**1919**	**1769**	**1656**	**2308**

From the experimental results, it is evident that the proposed approach outperforms the existing techniques in terms of accuracy, sensitivity and specificity rates. However, the better results are achieved by sparing time yet, the time consumption is acceptable for the attainment of good results.

5. Conclusion:

This article proposed a novel iris recognition system that relies on LDP features and ensemble classification. Initially, the images are acquired and the iris part of the human eye image is segmented by means of Wilde's approach. The segmented iris region is normalized and the contrast is enhanced. The features of the normalized iris region are extracted by means of LDP features. Finally, when a test iris image is passed on to the system, the iris based security application grants access to the users, whose iris matches the train sample. This decision is made by the ensemble classifier and the performance of the proposed approach is evaluated with respect to recognition accuracy, sensitivity and specificity rates. Additionally, the performance of the proposed morphological operation based segmentation algorithm is better than the Wilde's approach. The performance of the proposed approach is satisfactory with greater accuracy rates. In future, the potential features can be selected by means of feature selection techniques, which reduce the memory and time consumption. Additionally, a real time iris recognition system is planned to be proposed.

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