



Applying the Method of Different Cumulative Bin Local Binary Pattern (DCBLBP) to A Small Iris Region for Features in Iris Classification

Ahmad N. ALI*

*School of Electrical and Electronic Engineering, University Science Malaysia, Engineering Campus, 14300 Nibong Tebal, Penang, Malaysia.

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Abstract

This paper presents an extended variant of the local binary pattern (LBP) method to extract the iris feature for iris classification system. The method is called Different Cumulative Bin Local Binary Pattern (DCBLBP) in which the local iris information will be projected into the binary bit and applies global characteristic for features according to the ratio of bit transition along the horizontal axis. The proposed DCBLBP scheme employs the majority bit decision for assigning the bit to the reference elements where the assigned bit is unaffected by the predetermined index number of the pixel block. The results demonstrate a good classification score and show that the features extracted from the proposed DCB_LBP scheme are reliable for iris classification system.

1. INTRODUCTION

Iris classification is a method to classify the individuals using the richness tiny textures on iris. It is unique for each individual even for the identical twins. The iris has been accepted as one of the successful traits for individual classification. Firstly suggested by Daugman[1-4], iris recognition or classification have achieved a great development from Daugman's time up to the current years. With the advances in image processing and pattern recognition methods, the iris classification or recognition has been researched by numerous scientific communities with different alternative methods and comparable with Daugman's work [5-10].

Feature extraction is one of the key elements in the classification system for achieving a high score. Finding reliable features using the latest image processing method requires complicated mathematical processes, and sometimes needs longer time to process. For the system that employs machine learning based classifiers such as Neural Network and Support Vector Machine, enough templates are likely obligatory, especially during the training session. For the features that comprise large vector size, it will increase the computation overhead for completing the classification process. Finding the fine-scale characteristic using local image descriptors have been extensively used in various image processing applications including iris recognition [11]. It should be implemented onto the richness textures region so that the descriptors are sufficient to represent personal statistical characteristic. A potential approach to obtain the local information is by using local binary pattern (LBP) method, which is a convincing and proving in many image classification systems. Local binary pattern (LBP) is an approach that considers local information which has been widely used in various application areas including face, texture and iris processing field [12-15].

Besides that, to ensure only the iris information is computed for the features, the unwanted information due to eyelid and eyelashes that frequently exist in eye images need to be masked before features extraction but

requires the additional algorithm to perform it. Noises due to the eyelid and eyelashes are the common unwanted attributes that may cause to the unsatisfied classification rate. Noise removal algorithm is the method that has been proposed for overcoming the problem, but it requires additional computation overhead due to the complexity of the algorithm. Having the problem and purposely to reduce the overhead computation from the usage of noise removal algorithms, an extended LBP approach called difference cumulative bin local binary pattern (DCBLBP) is proposed in this paper. The method will use the local fine-scale characteristic from a small patch of iris images for extracting the features. The designated piece is selected at the area where the presence of the noises is none or minimum but contains sufficient iris attributes. The main idea for the proposed LBP is to project each neighbouring pixels with either bit 1 or 0 based on its different to the reference and then using the majority cumulative binary bin to replace the intensity value of the reference into binary bit value. The algorithm of the proposed LBP is simple to implement where the features are computed based on the global bit transition ratio which is unaffected to any index of the pixels of the selected image blocks.

The remainder of this paper is subdivided into the following sections: Section 2 summarizes the related works of the local binary pattern in texture and iris classification. Section 3 and Section 4 describe the proposed DCBLBP method and the experimental results respectively. Then, Section 5 presents the discussion and followed by Section 6 for the conclusion.

2. RELATED WORKS

Several extended LBPs have been introduced to overcome some shortcomings such as due to scaling, rotation and so on. For current development, Reza et al. [16] have proposed an improved LBP by using blob-like formation to resolve the circular neighbouring set of every central pixel. They assigned the dominant orientation to each pixel to guarantee the rotation invariance. A weighted LBP feature is also proposed to discard the magnitude difference between the center and neighbouring pixel. In different extended LBP [17], an improved robust descriptor called Joint Local Binary Pattern with Weber like responses (JLBPW) has been introduced to overcome the problem due to local intensity differences and correlation of patterns when scaled at a different level which is always ignored in current LBP.

Nanni et al. [18] have presented several variants of local binary pattern considering different shapes for the neighbourhood calculation and different encoding for evaluating the local grey-scale different. They used five values encoding instead of 2 values as in conventional LBP to produce robust descriptor. In another work, Nanni et al. [19] have combined several different LBP variants purposely to improve the classification performance. They have proposed the method to produce the features from the histogram of uniform patterns using the Fourier Transform and different definition of uniform patterns.

Due to the LBP method is simple; it has been further explored for iris processing field. For recent development, Gragnaniello et al. [20] have suggested the work of using LBP descriptor to detect between the printed-iris and liveness iris images for mobile devices. Gragnaniello and colleagues have limited the LBP computation either 4 or 8-connected neighbours to avoid complexity constraints which are necessarily required by mobile devices. He et al. [21] have also implemented the LBP approach to distinguish between counterfeit and live iris images in iris recognition system. They have adopted multi-resolution LBPs with a different value of R and P to the sub-region of iris images for texture representation. Inspired by LBP approach, Hamouchene and Aouat [22] have suggested the neighbourhood based binary pattern for iris feature descriptors. The process to extract the binary pattern is similar to the LBP approach at the beginning of the process (finding different between neighbouring pixels with the central pixel) but they used an encoding method for finalizing the LBP descriptor rather than considering the histogram value for feature vectors.

LBP has also been used to overcome the spoofing attack in iris recognition. It has been proposed by Malathy et al. [23] in which the multi scale LBP (MLBP) is realized to produce the valuable features. The algorithm has employed Gabor wavelet and LBP descriptor where the feature is extracted from the real part of Gabor wavelets. Fusion of histograms from different variants of uniform LBP has also been proposed specifically for predicting the gender based on left and right iris images [24]. Fusion LBP

histogram with others scheme such as from GLCM, Edge based features and Local Directional Pattern (LDP) has also been reported in the literature [25].

Conventional LBP is also adopted to characterize the local iris texture from different image blocks [26]. Utilizing the conventional LBP to half portion of the iris image instead of the whole image for extracting the feature has also been introduced, and it was reported that the outcome for recognition and verification is remarkable [27]. Though the histogram of uniform or non-uniform patterns is commonly computed for features vector, it sometimes inapplicable to a particular classifier or matching technique, and requires the pattern to be transformed using specific encoding method. It has been done by He et al. [21] where the LBP patterns are generalized to another encoding process purposely to reduce the number of features for matching using Hamming distance. In this approach, the iris image is chunked into an equal size rectangular block and performed the local and global relationship calculation between adjacent blocks.

3. THE PROPOSED METHOD

In this paper, a simple method called “Difference Cumulative Bin Local Binary Pattern” (DCBLBP) is proposed for extracting the features of iris. Rather than able to reduce computational complexity, the proposed method also able to lessen the number of features vector by applying the method to a small iris region for extracting the features. In this paper, the DCBLBP is combined with a modified histogram equalization method [28] as a package computation for feature extraction as illustrated in Fig.1.

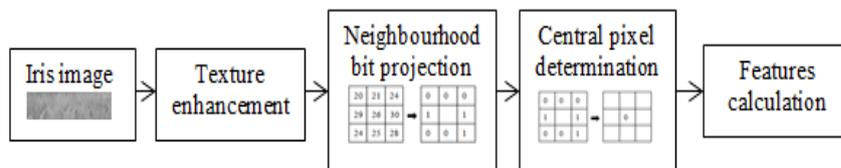


Figure 1. Feature extraction stage based on DCB_LBP

3.1. Modified Histogram Equalization

The histogram equalization (HE) becomes a very significant stage in this study as the method can improve the contrast of the iris textures. The enhanced iris texture appearance provides an appropriate viewpoint for the proposed DCBLBP for extracting the relevant features. The enhancement is performed using the Eq. (1) where $p[x]$ is the probability density function, and, C_x is the cumulative distribution function.

$$T_{he} = (C_x(i) - (0.5 \times p[x])) \times imax \quad (1)$$

where $imax$ is the maximum intensity in the input image while T_{he} is the value that will replace the previous corresponding element value, i .

3.2. Bit Projection

At the initial stage, the proposed method applies the similar rule as in conventional 2DLBP [29] for comparing the reference with its neighbouring elements. The implementation of the proposed method can be divided into two main stages: bit projection and descriptor computation. The intensity of the central pixel from a 3 by 3 neighbourhood block will be used to equate its adjacent elements for projecting the pixel into binary bit value. Fig. 2(a) shows an example of the progression for the proposed 2DDCBLBP while Fig. 2(b) is the conventional LBP descriptor computation for 3 by 3 pixels block. The proposed method applies similar projection calculation as practiced in conventional to encode each neighbouring pixels either 1 or 0.

However, to ascribe the central pixel, the proposed method employs dissimilar route where the bit that provides majority volume will be chosen for representing the central pixel. Conversely, in conventional, the central pixel is represented with one of 256 distinct values. For instance, in Fig. 2(b), the value 152 (LBP = 8+16+128=152) will be used as an operator representation for the central pixel in the conventional method where the computation is made according to the assigned decimal weight on each pixel. However, for the proposed method, bit 0 will be projected to the central pixel due to this bit is the majority within the projected block after the first stage of the processing.

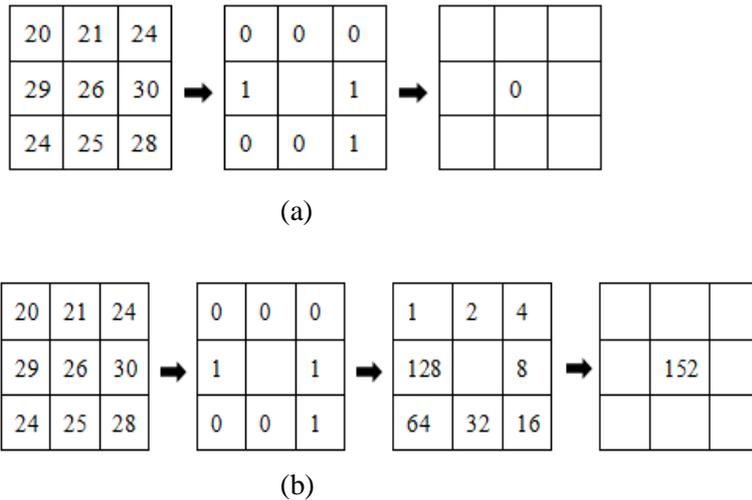


Figure 2. The central pixel descriptor computation for; a) The proposed DCB_LBP b) the conventional 2DLBP (the central pixel is assigned with the operator of LBP= 8+16+128=152)

Generally, the neighbourhood bit determination can be defined by Eq. (2) and Eq. (3) where P_i and P_c are the intensity at index i th and the central elements respectively for bit projection.

$$s_i = \begin{cases} 1 & \text{if } P_i > P_c \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

$$\text{where, } \begin{cases} 1 & \text{if } s_i \geq 0 \\ 0 & \text{Otherwise} \end{cases} \quad (3)$$

Meanwhile, Eq. (4) summarizes the advancement of the proposed method for the bit assignment to the central pixel with Z is the respective central pixel that needs to be projected.

$$CBE(z) = \max \begin{cases} 1 & \text{if } \sum_{i=0}^7 s_i = 1 \geq \sum_{i=0}^7 s_i = 0 \\ 0 & \text{if } \sum_{i=0}^7 s_i = 1 < \sum_{i=0}^7 s_i = 0 \end{cases} \quad (4)$$

Fig. 3 shows the bit projection process flow of the neighbourhood pixels and bit determination for the central pixel. One of the exceptional features of the proposed method is about the assigned bit for the central pixel which is unaffected by any index arrangement of the neighbourhood pixels. The assigned bit is also unchanged for either follows the circle in term of clockwise or counter-clockwise during bit determination. This feature is not reachable in the conventional or any variants of the LBP where the central values follow the number of the allocated indexes and also the direction of the indexes are read for the descriptors. For example, Fig. 4(a) and Fig. 4(b) shows how the pixels with 20 and 24 are set as the first index respectively. It clearly can be seen that in the proposed method, the bit 0 is still the majority bit and similar bit will also be assigned to the central element. However, the dissimilar consequence cannot be applied in the conventional LBP due to the reference (central pixel) will be assigned with two different values those are 152 and 98. A similar case happens when the descriptor is computed in counter-clockwise where the value is changed to 50 as illustrated in Fig. 5. Also, the projected bits are invariant though the neighbourhood pixels are rotated by any degrees as demonstrated in Fig. 6.

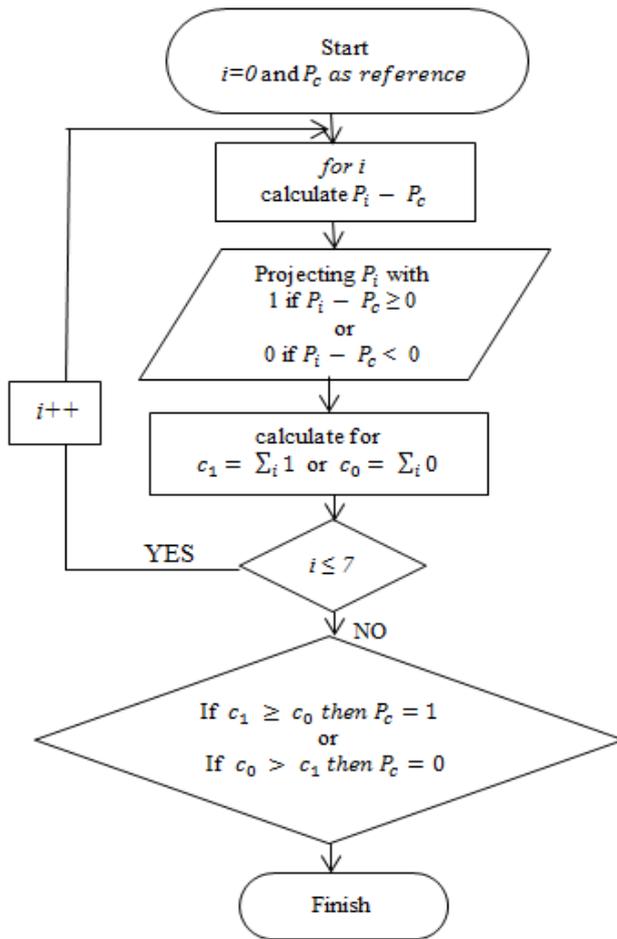
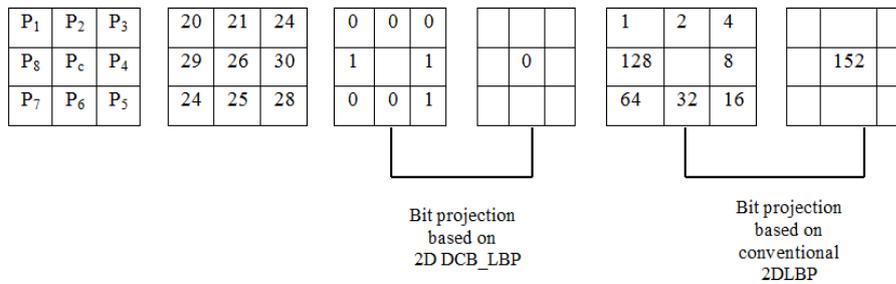
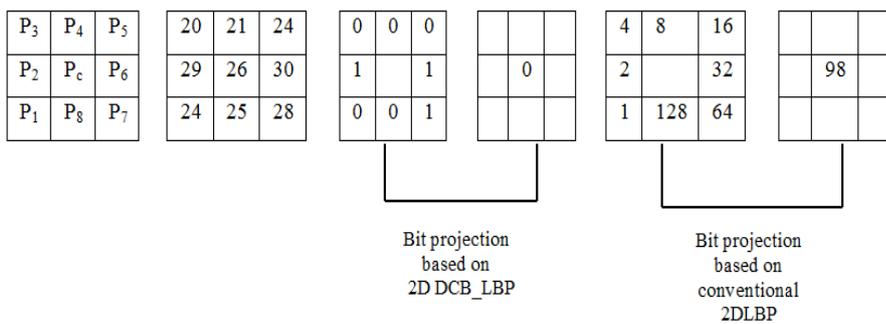


Figure 3. Process flow for bit projection and determination



(a)



(b)

Figure 4. Comparison between conventional and the proposed 2DLBP at two different index positions

0	0	0
1		1
0	0	1

1	128	64
2		32
4	8	16

	50	

Figure 5. The central descriptor value when calculated in counter-clockwise

24	29	20
25	26	21
28	30	24

0	1	0
0		0
1	1	0

	0	

28	25	24
30	26	29
24	21	20

1	0	0
1		1
0	0	0

	0	

Figure 6. The unaffected bit determination for the case when pixels are rotated to 90° and 180°

3.3. Features Generation

Another piece in the proposed method is the computation for descriptor (feature) where the value is based on the ratio of the bit transition from 1 to 0 along the horizontal axis rather than the histogram bin values. The principle for calculating the feature is defined by Eq. (5) and Eq. (6) where U is the total number of bit transition from bit 1 to bit 0, m is the total number of the binary bit in a row, and F is the feature vector for the respective row (horizontal axis). Generating the feature based on this method able to separate the overlook pattern between templates. Rather than that, it able to reduce the features vector size from 256 (histogram bin values) to less than half where the amount is identical to the vertical size of the selected iris region.

$$U = \sum_{i=0}^m B_i[1] \rightarrow B_{i+1}[0] \quad (5)$$

$$F_j = U_j/m \quad (6)$$

4. EXPERIMENTAL APPROACH AND RESULTS

In this study, a Naïve Bayes and the SVM classifier with four types of the kernel which are Linear, Polynomial, RBF and Sigmoid are used to classify the class (subject). C++ programming language based on Borland C++ Builder environment is preferred to perform all the proposed algorithms. For the classification, the LIBSVM library [30] is used to implement the SVM classifier whereas the executable version of the Naïve Bayes algorithm as suggested by Rui [31] is applied to evaluate the proposed method on Naïve Bayes classifiers.

One versus one and one versus all classification modes are considered to evaluate the proposed method for the balance and imbalance class learning environment respectively. Due to limited samples in each subject, only three samples from each subject are used for training, and the remaining samples are for testing. In one versus one, it requires $z(z-1)/2$ binary classifier in which each classifier is trained using six samples from two subjects and each of them is assigned either positive or negative class respectively. While for one versus all, three samples from one subject are designated as positive class, and some amount of negative class from different subjects are used for training and requires z binary classifiers.

Suitable training samples have been selected by employing leave one out cross validation to obtain satisfactory classification score. For the SVM classifier, appropriate penalty and kernel parameters have been appropriately chosen to achieve an acceptable classification rate. The performance of the proposed methods is assessed using the iris images from CASIA Version 1.0 (108 subjects), CASIA Version 3.0(249 subjects), and the IITD (224 subjects). In this paper, the selected region for extracting the features is the area where the amount of the unwanted noise due to eyelid or eyelashes are none or at least contains minimum traits. Fig. 7 shows the example where a specific region is allocated on different images, and it can be seen that the scheme is reasonable to minimize the presence of the above-mentioned unwanted traits so that the features are solely extracted from the iris textures with fewer attributes of the unwanted noises.

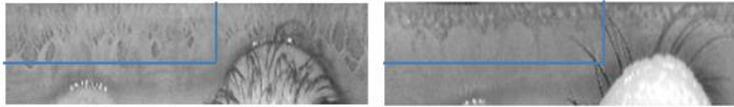


Figure 7. Region of interest of iris texture for features extraction on different images

Before the extraction, the non-normalized rectangular iris image will be histogram equalized (HE) for smoothing the texture contrast. Then, from the histogram equalized image, a patch of iris information is designated to perform the local iris texture extraction. The results of the assessment are shown as in Table 1 after performing the preliminary experiment to 25 subjects using the polynomial kernel.

Table 1. Classification rate with and without HE (polynomial kernel)

Database	Classification rate, %	
	With HE	Without HE
CASIA v1	91.83	9.18
CASIA v3	91.32	7.65
IITD	92.34	7.65

Having the results in Table 1, an evaluation of the proposed method has been further performed to the entire iris images in the database. In the assessment, texture operator is derived from the local 3 x 3 neighbourhood of a grey texture image. For an initial evaluation, the size of 120 x 26 is chosen with the assumption that enough iris information is covered with fewer traits of the unwanted noises. The results summarized in Table 2 shows the classification score of the proposed LBP for one to one classification mode for both SVM and Naïve Bayes classifiers. It is demonstrated that the proposed DCB_LBP performs well in SVM classifiers and has reached an exceptional performance in Naïve Bayes even with a small decrement compared to the SVM classifiers.

Table 2. Classification score in SVM and Naïve Bayes classifiers for one versus one classification for the image size of 120 x 26

		Classification score, %		
		CV1	CV3	IITD
SVM	Poly	94.85	93.45	93.92
	Linear	94.62	93.22	93.69
	RBF	94.15	93.92	93.45
	Sigmoid	93.92	93.45	93.69
NB		92.75	90.88	91.35

Using the same samples as in one versus one, the features are also trained and tested with one versus all classification where the results of the assessment are shown in Table 3. With the results, it is demonstrated that the evaluation mode unable to provide a proficient background for the samples to achieve a comparable score as in one versus one classification.

Table 3. Classification score in SVM and Naïve Bayes classifiers for one versus all classification for the image size of 120 x 26

		Classification score, %		
		CV1	CV3	IITD
SVM	Poly	86.44	86.68	86.91
	Linear	86.21	86.44	86.91
	RBF	86.91	86.44	86.21
	Sigmoid	86.91	86.21	85.98
NB		83.41	83.87	80.60

But, the performance can be figured as a tolerable performance rating due to the training process are performed with the unbalanced samples between two classes where the amount of the negative class samples are more than the positive class samples. Rather than the iris size as mentioned earlier, a different combination of the horizontal and vertical size of iris region is also evaluated to discover the best combination that able to convey a constructive performance score. To realize the outcome, an additional experiment with different combinations are set, and only one versus one classification using the SVM classifiers (polynomial kernel) is preferred due to its performance compared to one versus all. The performance for each combination is shown as in Fig. 8 and Fig. 9 for CASIA v1 and CASIA v3 respectively. It was revealed that there are limited combinations which are 120, 140 and 160 for the horizontal with 26 and 28 of the vertical that able to achieve an outstanding classification score.

Meanwhile, for the IITD database, the only difference is on the vertical where the usage of 24 until 34 with the horizontal size similar as in CASIA database can achieve the expected classification score. The result for the IITD database is shown in Fig. 10. It was also presented that the vertical with 28 can maintain the performance when the size of the horizontal is increased up to 200 even there is small drop at 160.

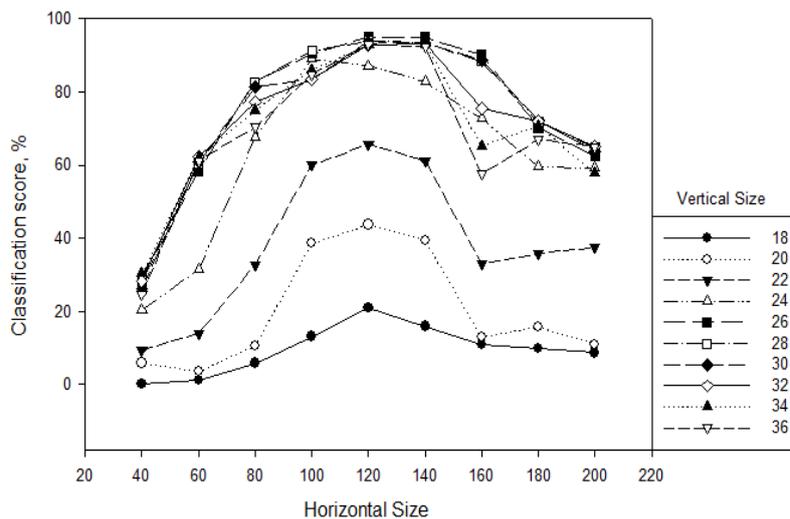


Figure 8. Classification scores for different combination of the horizontal and vertical sizes for CASIA v1

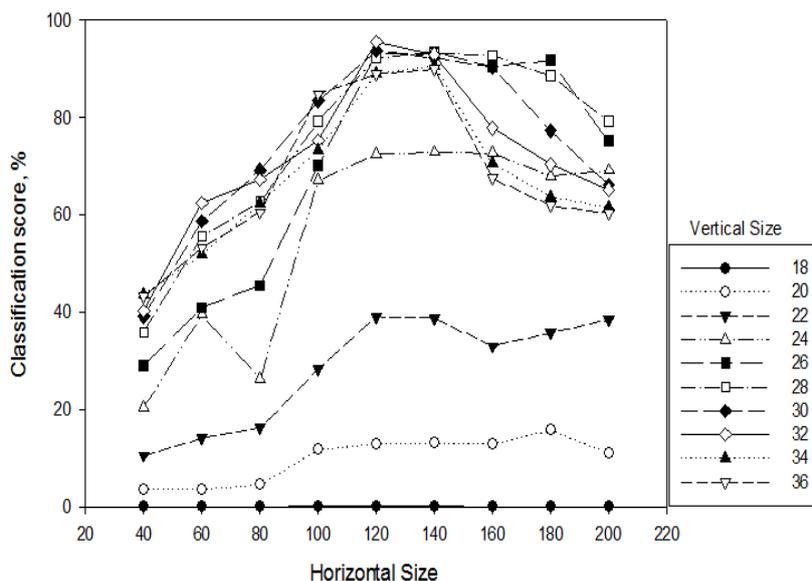


Figure 9. Classification scores for different combination of the horizontal and vertical sizes for CASIA v3

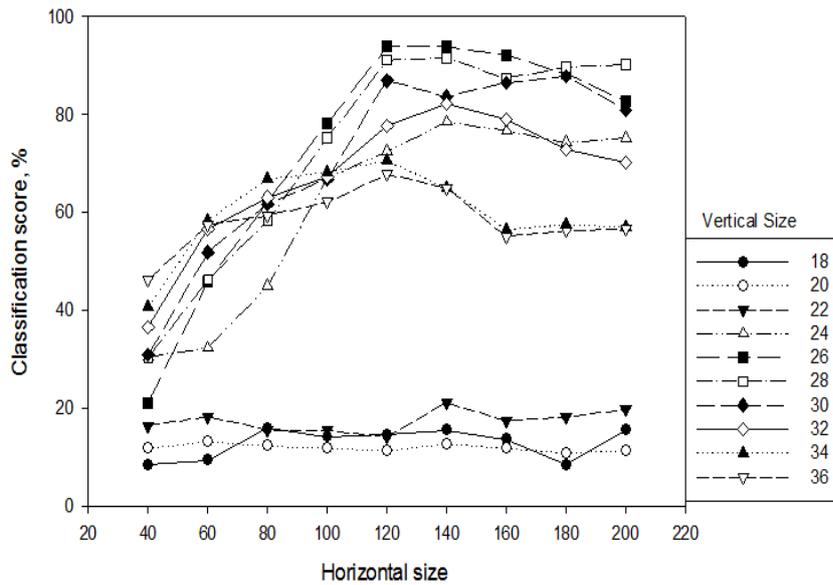


Figure 10. Classification scores for different combination of the horizontal and vertical sizes for IITD

To further validate the performance, an equal error rate (EER) is computed based on some points of the true positive rate (sensitivity) and false positive rate (1-specificity) when the amount of decision threshold is set. Several regions are selected for the assessment, and only the SVM classifiers with polynomial kernel are applied for the samples that are trained with one versus one classification. The results of the assessment are shown as in Table 4. It is shown that tolerable EER can be achieved on all the selected regions which are between 0.2 and 0.35. The best result of the EER that is 0.232 is achieved through the IITD database for the region of 120 x 28. Besides that, it was found that 5 out of 6 regions in CASIA V1 able to achieve the EER that less than 0.3 with the lowest rate is from the region of 140 x 26. The optimal EERs have been obtained through CASIA V3 database where all the regions able to achieve an average rate with only a small difference between regions.

Table 4. Equal error rate (EER) of the selected region on SVM classifiers

	Equal Error Rate (EER)					
	120 x 26	120 x 28	140 x 26	140 x 28	160 x 26	160 x 28
CV1	0.301	0.276	0.245	0.253	0.271	0.264
CV3	0.303	0.316	0.305	0.299	0.292	0.311
IITD	0.241	0.232	0.345	0.341	0.308	0.316

5. DISCUSSIONS

According to the above results, it can be concluded that the features generated from the proposed DCBLBP are suitable to be used in both SVM and Naïve Bayes classifiers. It can also be seen that there are several regions are favourable to achieve best classification rate. It is noticed that too challenging to find the exact size that may produce reliable features. But the analysis has shown an explicit observation where a particular range can be designated during extraction as the deviation of the score between regions is less than 2%.

The results obtained in the different combination demonstrate that the robust features are comparative when extracting from particular sizes of images and simply durable though the features are trained in imbalance learning environment. It is probable to justify that the outcome of the proposed method proportionally conforms to the size of the iris image for acceptable performance score and it is found that the generated features for this outstanding results are located in the region with high abundant iris textures but contains less the unwanted noises due to eyelid or eyelashes. As tabulated in Table 5, it is verified that

the performance of the proposed method is very close to the previous works if the judgment is made according to the LBP method with different matching approaches.

The only exceptional result is from Chengcheng and colleagues [34] where the performance is 5% higher than from the achievement of the proposed method. The mentioned result as shown in Table 5 is obtained when the average LBP (as proposed by Chengcheng et al.) with several partitions are applied by using of 40 comparative trials. Also, the better results can only be achieved when the radius used is more than 3. Without partitioning the image, the results of the method as proposed by them are identical and comparable with the proposed DCBLBP method. Although their method has achieved a good recognition rate, they have a problem to determine the most suitable radius automatically and also the exact partition to be used. Therefore, if the performance is considered regarding the methodology employed, the proposed DCBLBP is more efficient compared to the ALBP as the DCBLBP only requires a single radius computation and uses a small patch of iris region which is less processing complexity. It makes the proposed method applicable for iris classification where the classification speed is important due to a small usage of the reliable features vector.

Table 5. Performance comparison

	Feature Extraction Method	Performance rate, %	Matching Approach
O'Connor et al[32]	2-D LBP (Modified)	88.34	Manhattan Distance
Tian et al[33]	2D-LBP (Original)	87.00	Vector Similarity
Chengcheng et al [34]	Average LBP	99.91	Nearest Neighbor and SVM Classifier
Proposed method	DCB_LBP	94.85	SVM Classifier

6. CONCLUSION

A new technique for extracting the iris features based on a new variant of the LBP is presented in this paper. The assessment is strengthened by examining the effect of several combinations of horizontal and vertical size to the performance. The study has achieved two primary objectives. First, a new iris feature extraction technique is implemented with a new variant of the LBP which less computational time to produce a small size of the features vector. Second, the DCBLBP is realized from different sizes of the unwrapped iris regions with less unwanted attributes to find the best region that produces more reliable iris features. Therefore, the proposed method provides additional benefit to iris classification system by reducing the need for eyelid or eyelashes removal algorithm and simplifying the number of features.

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CONFLICT OF INTEREST

No conflict of interest was declared by the author.

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