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Descriptor feature based on local binary pattern for face classification

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ABSTRACT

Local Binary Patterns (LBP) is a non-parametric descriptor whose purpose is to effectively summarize local image configurations. It has generated increasing interest in many aspects including facial image analysis, vision detection, facial expression analysis, demographic classification, etc. in recent years and has proven useful in various applications. This paper presents a local binary pattern based face recognition (LBP) technology using a Vector Support Machine (SVM). Combine the local characteristics of LBP with universal characteristics so that the general picture characteristics are more robust. To reduce dimension and maximize discrimination, super vector machines (SVM) are used. Screened and Evaluated (FAR), FARR and Accuracy Score (Acc), not only on the Yale Face database but also on the expanded Yale Face Database B datasets, the test results indicate that the approach is accurate and practical, and gives a recognition rate of 98 %.

Keywords: Face Classifaction, False Reject Rate ,Local Binary Pattern, False Accept Rate ,Support Vector Machine.

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1. Introduction

Faces are significant in our social lives since they allow us to learn about people's personalities, genders, ages, familiarity, and emotions. Humans recognize known faces more quickly and reliably than new faces, which is especially obvious in difficult viewing conditions where novel face classification frequently fails [1]. The development of biometric applications such as facial recognition has recently been a major priority in smart cities. Furthermore, numerous physicists and engineers all over the world have worked to design highly effective and powerful algorithms and procedures for these systems, which they now utilize in their daily lives. All types of security systems must secure personal data. The most frequent type of identification is a password. Many applications have begun to use a variety of biometric variables for the identification role because of the development of information technology and authentication algorithms [1,2,3,4]. People can be identified based on physiological or behavioral features thanks to these crucial variables. It also has several benefits, such as requiring only one person to stand in front of the sensor and removing the need for multiple keys or secret codes. Many biometric recognition systems, such as iris, fingerprint [5, and speech [6], are based on this principle, and the face to this effect has recently been published. Human identification systems that are biologically oriented are appealing because they are simple to use. The human face is made up of a variety of structures and features. It has become one of the most extensively used biometric identification technologies in recent years [7,8,9] due to its capabilities in a variety of applications and domains (surveillance, home security, border control, and so on). Consumers can already use face recognition as a recognition (identifier) outside of their phones, for example, at airports, sports stadiums, and concerts. Furthermore, because this technology does not require human contact to operate, people can be identified merely based on the photos captured by the camera. Furthermore, numerous biometric technologies developed for various types of investigations have great identification accuracy. However, it will be interesting to develop new biometric facial recognition solutions to satisfy the real-time restrictions. [9] Feature extraction and classification are the two primary stages of a face recognition system. Feature extraction reduces the computational uncertainty of the classifier, allowing it to recognize facial images. As a result, expanding the recognition range of a face recognition device requires discovering an effective feature extractor and a good classifier [10]. Several approaches for extracting the most useful features from (pre-processed) facial photos have been identified to enable face recognition. One such feature is label extraction (LBP). LBP can be used to show the texture and appearance of a digital image. This is accomplished by breaking the image into numerous blocks, each of which is then used to create a new image feature are extracted [11]. LBP accelerated the improvement of picture performance and computer vision. LBP uses a non-parametric approach to summarize the spatial foundation of effective images, comparing each pixel from side to side. LBP was developed expressly for tissue research, emphasizing how simple it is to categorize a local structure using a probable pathway [10]. While facial recognition is difficult, it has numerous uses. The Support Vector Machine (SVM) is a pattern recognition system that mainly relies on model selection. Face recognition using SVM has gotten a lot of press recently, and promising findings have been published. These results may be overstated because the details of SVM model selection are not revealed. [12].

2. Literature review

This paragraph will look at a few recent research that used different types of facial recognition. Face picture search, pre-processing, feature extraction, and six-emotion facial recognition are the four stages of the facial recognition system. A one-sided image was described as the initial step's entry. In a second phase, the image was transformed to HSV color space, and noise was reduced using medium filtering. The features were retrieved and represented in the third stage using two methods: principal component analysis (PCA) and linear discriminant analysis (LDA). A Supporting Vector Machine (SVM) and a Hidden Markov Model (HMM) were used in the fourth iteration to characterize the unique face on two separate data sets. Finally, by integrating two separate facial recognition vectors, the proposed device was able to distinguish six specific emotions. Joy, sorrow, anger, disgust, outrage, and fear are all emotions that people experience. An uncertainty and consistency ranking matrix is used to assess and current performance. For classifying and identifying facial expressions, the combination of features from PCA and LDA with SVM is efficient and useful that has been presented [13]. Meta Facial Recognition is a new approach to recognize faces using meta-learning (MFR). MFR synthesizes the source/target field transformation with the aim of meta-optimization, which necessitates the model learning functional representations not only for complex source domains but also for compound target domains. Specifically, we use a domain-level sampling approach to build domain transformation clusters, and we use multi-domain distribution optimization to achieve descriptive gradients/gradients that are then propagated on composite source/target scopes. To boost circularity, gradients and overlying gradients are further combined to refresh the pattern. Also, two standards for testing generalized facial recognition are proposed. Experiments of our criteria confirm that our approach is generalizable as compared to a variety of baselines and other cutting-edge technology [14].

A new face recognition descriptor is the orthogonally segmented local binary sequence descriptor (OD-LBP). Subtracting the two neighbors and nearest central pixels for each orthogonal site from the orthogonal value for each orthogonal locus yields three gray-level variations in OD-LBP (from the two groups in the pixel window). These gray standard transformations are then given the value gained through the new comparison process. Finally, a vector of the volume line is generated by joining the binary patterns of the two orthogonal groups. Finally, the 24-bit string vector is split into three 8-bit binary patterns, each of which produces three OD-LBP codes. Finally, at each pixel point, three OD-LBP images are converted using this term. The three photos used to extract the graph are then separated into sub-regions. The full features of the OD-LBP description are represented by the combined subregional plots of both interpreted images. The classification is then performed using SVM and the inline attribute representation derived from PCA. ORL, GT, JAFFE, MIT-CBCL, and Yale are five complicated core databases that have been thoroughly evaluated. The proposed descriptor (OD-LBP) has a beneficial effect on all five databases, outperforming the following ten descriptors: LBP, CS-LBP, MB-LBP, OC-LBP, MBP, HOG, ELBP, and OS-LTP. WCLBP and RLBP were found in most of the subgroups [15]. Differences between facial recognition in the suburbs and in the city (in French) LBP is a relatively new local variation of LBP (NCDB-LBP). A four-tag function has been proposed in NCDB-LBP for extracting the most significant features from a three-pixel window. Two first-order derivatives are generated for each neighborhood site: one between the adjacent neighborhood and the current neighborhood, and one between the pixel center and the current neighborhood. The proposed function is expanded to two first-order derivatives to provide four addressable windows (produced by each live site). After that, eight quadrants are put in a 1 x 8 pixel window, resulting in four separate binary patterns. In both anticlockwise (ac) and counterclockwise (c) directions, the descriptors NCDB-LBPac and NCDB-LBPc are utilized to enforce this principle. For each pixel position, four AC-direction converted images and four c-direction transformed images are generated after the binary patterns are encoded. Both vector pictures are divided into three subregions for histogram extraction. Full NCDB-LBPac and NCDB-LBP trait sizes are displayed in histograms organized by pertinent subregions. PCA and FLDA are used to reduce job size. Finally, SVM and NN are used to classify the data. To test the proposed FR solution, the datasets ORL, GT, JAFFE, Yale, YB, and EYB were supplied [16]. A new masked face recognition strategy has been proposed, combining a block-based strategy with a ground-breaking attention block (CBAM). The Al Ain region's CBAM system has been approved and is being explored for optimal transplantation for each condition. Unmasked faces for masked face recognition training and masked faces for unmasked face recognition training have both been considered unusual deployment conditions. The SMFD, CISIA-Web, AR, and Extend Yela B datasets suggest that the proposed approach will greatly increase the performance of masked face recognition when compared to current approaches. [17].

3. Background theory

3.1 Local binary pattern (LBP)

LBP is a simple texture operator that adds a threshold to each pixel's neighbourhood and treats the result as a binary integer to mark picture pixels [18]. This texture operator was created in 1994 and has shown to be an effective texture classification tool since then. The LBP can be paired with the descriptor of directed gradients histograms to improve identification accuracy, and this combination (LBPH) can represent facial images in a simple data vector. It can also be used to distinguish between fruits [18,19].
LBP is calculated by comparing a pixel from the input face's image to its neighbours:

$$LBP_{N,R} = \sum_{n=0}^{n-1} s(x_n - x_c)2^n,$$

$$s(x) = \{1, \quad x \geq 0 \; 0, \quad x < 0\}$$

Where xc is the central pixel value, xn represents the quarter value, R the quarter radius and N the entire quarter value. The values from neighbours do not present in the grids which be estimated by interpolation. Let I*J be the picture size. As a histogram is compiled to show the image texture after each pixel LBP code is computed [18]:

$$H(m) = \sum_{i=1}^{I} \sum_{j=1}^{J} f\left(LBP_{N,R}(i,j), m\right), k\epsilon[0, m],$$

$$f(x, y) = \{1, x = y \; 0, otherwise$$

Where m is the value for maximum LBP code.
The LPB trigger has been updated to account for varying neighbour sizes. In general, the operator refers to the physical size P of pixels uniformly distributed over the radius R. For example, operator 8 utilizes only 8 neighbours, whereas 16.2 employs 16 neighbours at radius 2. Figure 5 depicts various representations of (P, R) values [20], while Figure 1 depicts an example of the LBP.

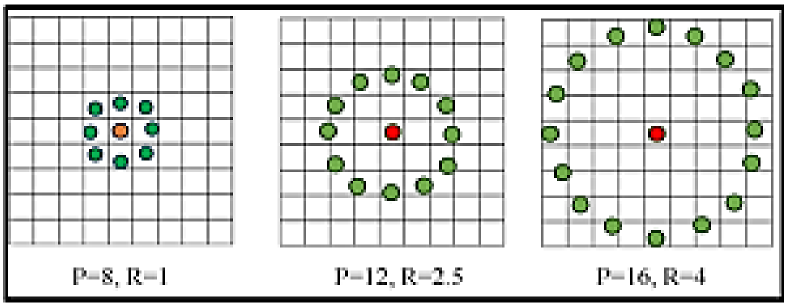


Figure 1. Example of the LBP process

3.2 Support vector machine (SVM)

SVM stands for supervised machine learning and is used to solve problems such as regression and classification. In the solving of classification problems, this approach is frequently utilized. Each data unit is plotted as a point in N-dimensional space (where N denotes the number of features), with each component value as a distinct coordinate value. After that, the grouping is completed by agreeing on the super-level that best distinguishes two classes as sown in figure 2.

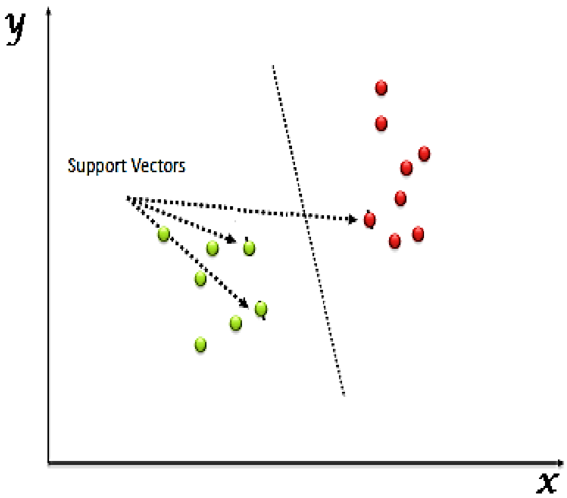


Figure 2. Accustomed to the process of separating two classes with a hyper-plane

Support vectors are nothing more than the coordinates of a single note. The optimal border between two classes (super level/line) is the SVM. to choose the appropriate hyper level (scenario 1); there are three ultra-levels: A, B, and C. To classify stars and circles, the correct ultra-level must first be identified. After that, a hyper-plane that appropriately separates the two classes must be selected. So, in the first scenario, the “B” hyper-plane is the excellent choice to perform this task. This Scenario is explained in Figure (3).

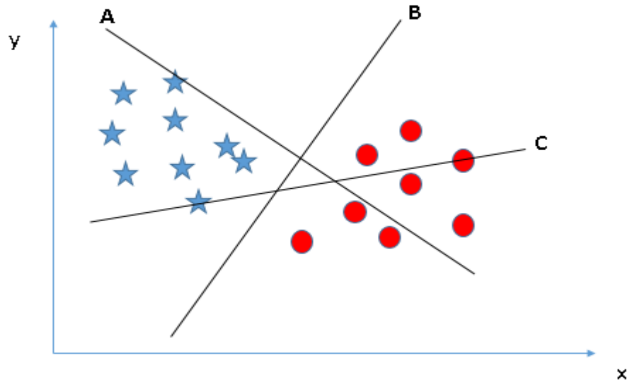


Figure 3. The first scenario

For identifying the proper hyper-plane (The second Scenario); Here, there are three hyper-planes A, B, and C and all these hyper-planes are separating the two classes better. This Scenario is shown in Figure 4.

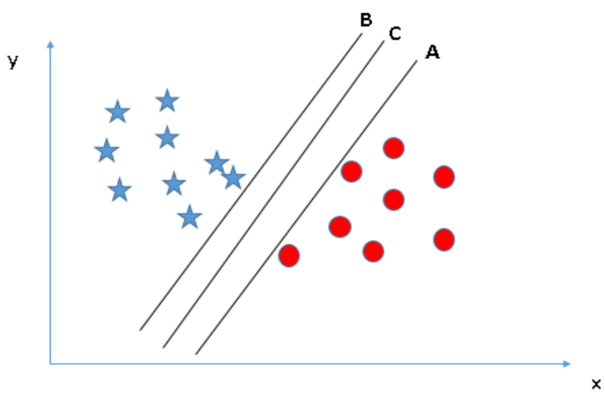


Figure 4. The second scenario

Optimize the distances between the closest data point (of either class) or the hyper-plane to discover the optimal hyper-plane, which is called Margin as shown in figure 5.

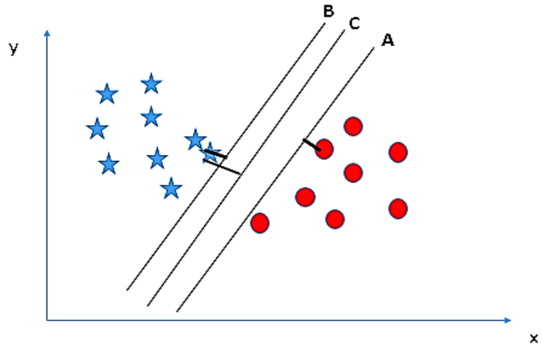


Figure 5. The distances between nearest data point (margin)

As shown in the above figure, the margin to the "C" hyper-plane is high comparing with A and B. Therefore, "C" is the proper hyper-plane. The cause behind choosing the hyper-plane of higher-margin is the robustness since the hyper-plane of low-margin may give a possibility to miss-classification. For identifying the proper hyper-plane (The third scenario), maybe we will decide to select the "B" hyper-plane since it has a higher margin. While SVM selects a hyper-plane that classifying the classes accurately before maximizing distances. So, "A" is the proper hyper-plane that classified all correctly. This scenario is shown in Figure 6.

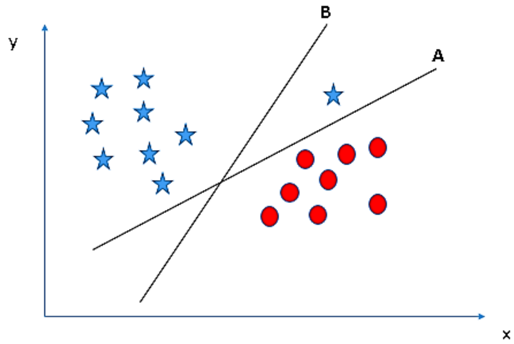


Figure 6. The Third Scenario

For identifying the proper hyper-plane (The fourth scenario); Here, it is difficult to separate the two classes using a straight plan, since one of the stars is lying in the circles' region as an outlier. This Scenario is shown in Figure 7.

Figure 7. The Fourth Scenario

The SVM therefore contains a characteristic to ignore the outliers and locate the highest margin hyperplanes (seen in figure 8). SVM is therefore stable against the outskirts.

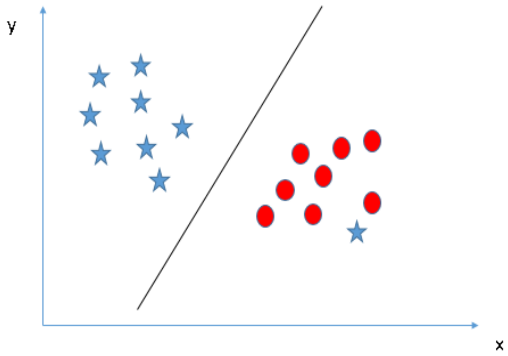


Figure 8. The robustness of SVM to outliers

It is very difficult to place a "linear" hyperplane between the two classes to determine the right hyperplanes for splitting the two classes as shown in figure 9.

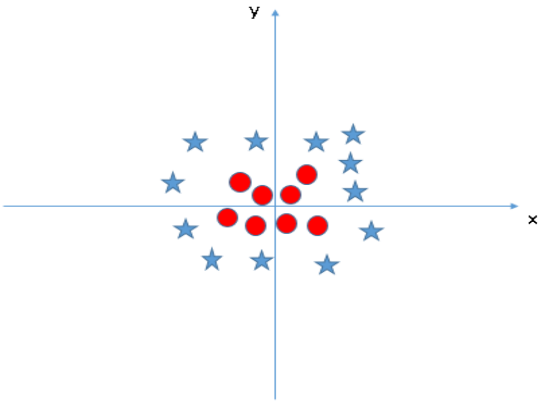


Figure 9. The fifth scenario

SVM is capable of solving this issue by providing an extra feature. Here, the new feature "z=x^2+y^2" can be added. After that, the points of data on the x and z axes are plotted, as shown in figure (10). Where the z values should all be positive because they are the squared sum of the x- and y-axes, and the circles appear close to the x- and y-axes, resulting in a small value of z, and the stars appear distant from the origin, resulting in a high value of z.

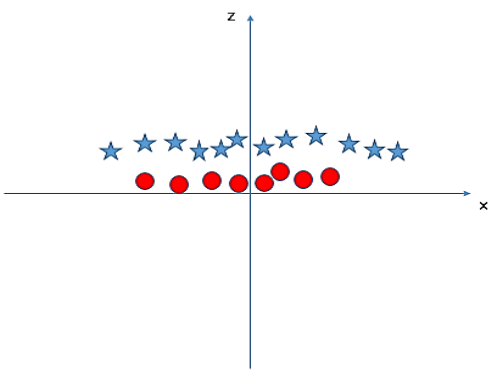


Figure 10. The data points on x and z axes

It is very easy for the SVM to provide a linear hyper-plane between these two groups by inserting additional functions using a kernel trick tool. Kernels are features that transform the non-separable problem to a separable problem. The non-linear separation problem benefits greatly from these functions. Kernels operates to achieve such highly complex data transformations and, according to the specified outputs or the labels, to determine the data separation mechanism. The hyper-plane shown in Figure (11) appears like a circle in the original entry space.

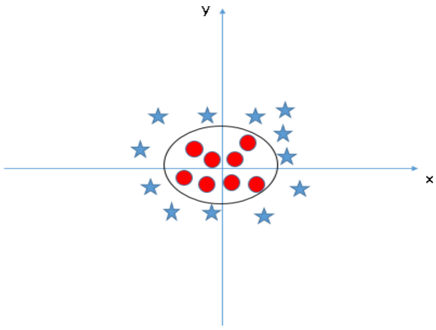


Figure 12. The hyper-plane in original input space

4. Proposed method

The proposed method consists of three stages: the first stage is image acquisition (face classification data set) and image pre-processing; the second stage is facial features extraction, selection of the most appropriate features, and classification to determine the correct face category; and the third stage is facial features extraction, selection of the most appropriate features, and classification to determine the correct face category. Face recognition, as well as the correct identification of SVM, is largely dependent on the careful selection of characteristics. This SVM is used as a classifier for the differentiation of the brain shown in Figure 13.

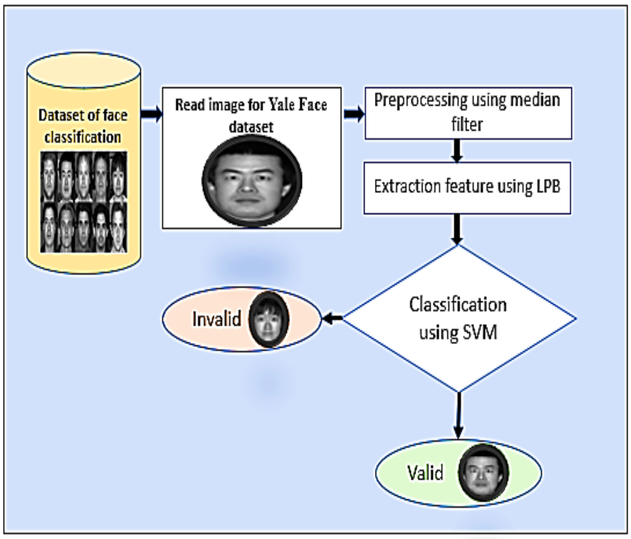


Figure 13. The proposed method of face recognition

4.1 Dataset

Two datasets of face are used in this work where 70% of the images were trained and 30% were tested.

A. Yale Face database (6.4MB) Includes 165 GIF images of 15 people. Each subject has eleven images: central light with glasses, glad, light left, glassless, natural light, light right, miserable, asleep, astonishing, and winking; the following are images for each subject. This dataset is available free of charge and can be downloaded through the following link

B. (http://vision.ucsd.edu/datasets/yale_face_dataset_original/yalefaces.zip) As shown in figure 14.

Figure 14. sample of Yale Face database

C. The Extended Yale Face Database B : This dataset includes 16128 images of 28 people, with 9 positions and 64 conditions of lighting. This database has the same data format as Yale Face Database B. This dataset is available free of charge and can be downloaded through the following link (http://vision.ucsd.edu/~iskwak/ExtYaleDatabase/ExtYaleB.html) as shown in figure 15.

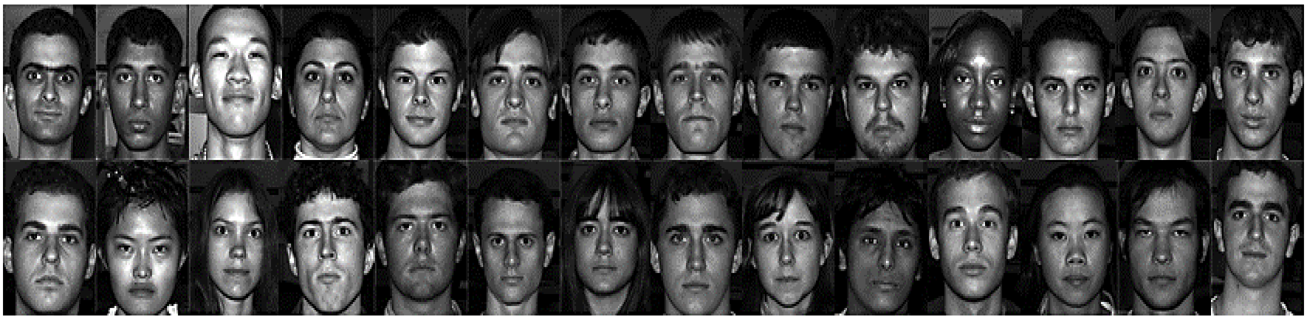


Figure 15. sample of Yale Face database

B. Preprocessing using Median Filter

Since images are often taken in conditions that are unacceptable in terms of light and noise, the proposed pre-processing technique uses the median filter to display image information well. Since the image can contain noisy pixels, the median filter is applied. After applying the median filter, the resulting picture became smooth. The median filter used in this study has a size of 3 x 3 and is used to obtain the best result in the proposed method.

C. Feature Extraction using Local Binary Pattern

The image of the face is divided into several regions. A 3 * 3 mask is added to each area of the face image, calculating the binary patterns of each divided field. To generate facial descriptors, these binary patterns are serialized. Face Descriptor, also known as facial image texture features, is a facial feature. Gray face images are the most common aim for this process. The following measures demonstrate this:

Step1: Dividing the image into cells is a good idea.
Step2: Each pixel in a cell is compared to its neighbors.
Step3: Follow the pixels around a circle, writing "0" where the center pixel's value is greater than its neighbor's value. If this is not the case, write "1" as in eq (2).
This results in a binary number (which is usually switched to decimal for betterment).
Step4 Calculate the histogram of the frequency of each "number" occurring in each cell. A 256-dimension feature vector can be observed in this histogram.
Step5: Normalize the histogram if desired.
Step6: All the cells' histograms should be concatenated (normalized).

D. Classification using SVM

In this section, we discuss three kinds of classifiers used to do machine learning. To test the face image, the facial features required to train the SVM are extracted and validated. Here, the first step is to distinguish the states of the fact that he has, whether he is happy or sad, and so on. To prevent the loss of any facial distinction. Labels were identified from two categories: one to indicate the natural state and two to the state in which a person is an opposite of what they appear after calculating the accuracy of each feature of that sign. The algorithm explains steps for an SVM classifier. and as follows:-

Step1: N=Find Number of Record (Normalized Feature)
Step2: Train of dataset=0.7*N
Step3: Tests=0.3*N
Step4: For i=1 to Tests
Step5: Sv=select feature of facial image (1 to N)
Step6: Trst (i)= (Normalized [s] feature)
Step7: Classifaction= classlable(s)
Step8: Next

Step9: For i=1 to Test
Step10: Tsst(i)= Normalized (st)
Step11: Clts= classlabel(st)
Step12: For i=1 to ts
Step13: Accuracy= (sum(ts))/ts

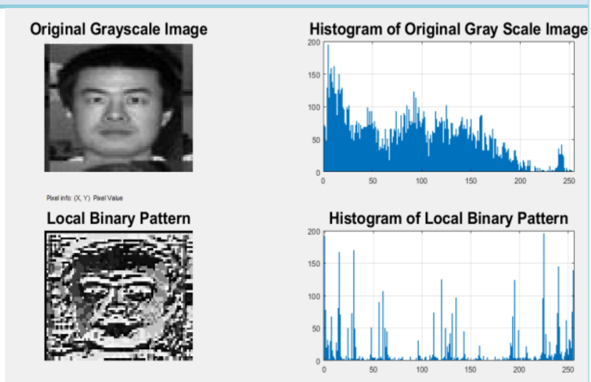
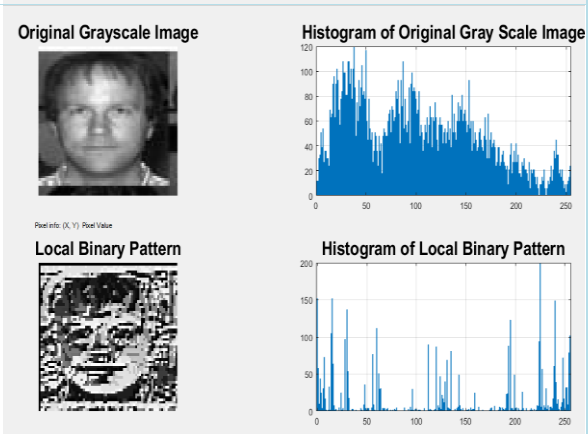
5. Experiment result

The performance of LBP on two datasets, the Yale Face database, and the enlarged Yale Face database B, was compared in this study. Figures 14 and 15 illustrate some samples from the Yale Face database dataset and Yale Face database samples, which comprise a variety of face expressions. The feature vector for the full window is explained in fig. 16. on the figure 17 compares the validation performance or accuracy level of the Yale Face database with the Yale Face expanded database B to different thresholds. As demonstrated in Eqs. (3), (4), and (5), three significant performance score metrics are used: false positive rate (FAR), false rejection rate (FRR), and accuracy score (ACC) (5).

$$FAR = \frac{NO.of\,accepted\ imposter}{Total\,NO.of\ imposter\ assessed} * 100\% \qquad (3)$$

$$FRR = \frac{NO.of\,Rejection\ genuine}{Total\,NO.of\ genuine\ assessed} * 100\% \qquad (4)$$

$$ACC = \left(1 - \frac{FAR+FRR}{2}\right) * 100 \qquad (5)$$

No.	Feature Vector For The Entire Window
1.	
2.	

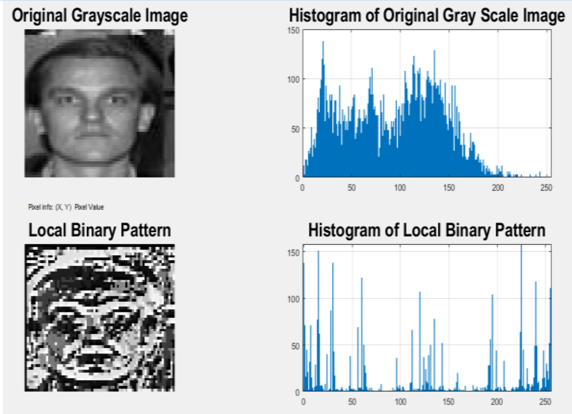
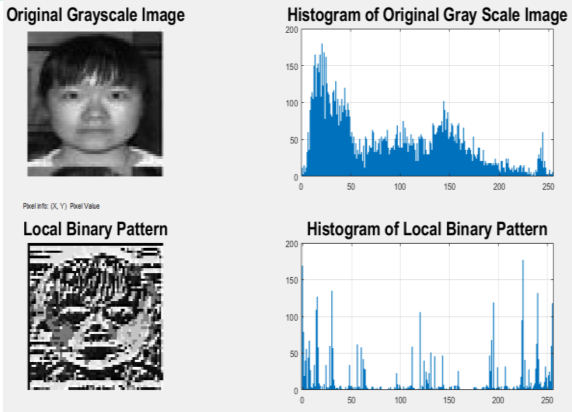
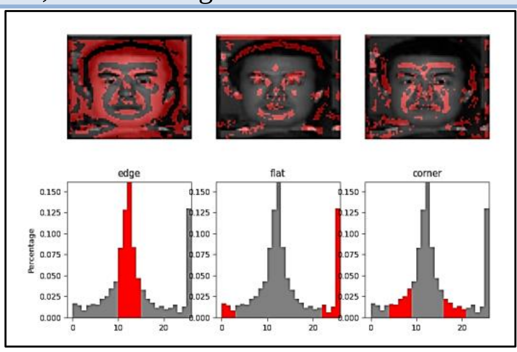
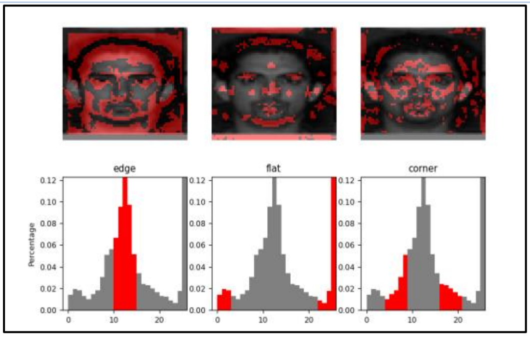
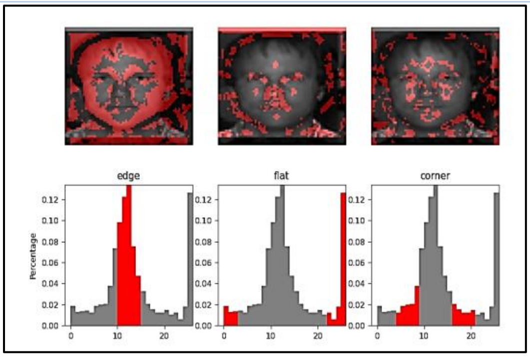
3.	
4.	

Figure 16. the entire window for feature vector

no.of sample	verification performance or accuracy rate versus different threshold values for yale face database and the extended yale face database b datasets respectively based on flat, corner of edge.
1.	
2.	

3.



4.

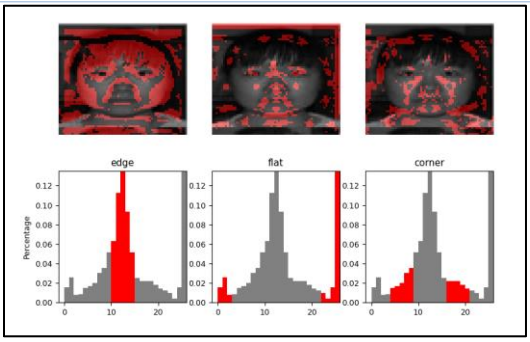


Figure 17. Verification performance or accuracy rate versus different threshold values for yale face database and the extended yale face database b datasets respectively based on flat, corner of edge

6. Conclusion

In the realm of face recognition, the most complicated feature extraction has occurred in the last several decades. To create a face identification system using the LBP Texture Features technique, the Yale Face Database, and the Yale Face Extended Database B. On both datasets, the approach was tested using one of the Vector Machine support methods, with a 70% training phase and 30% test period. The false acceptance rate (FAR), false rejection rate (FRR), and accuracy rate were used to evaluate each facial recognition device's performance. During the preparation and testing period, the movies saved in it proved to be quite dependable, with the system's accuracy reaching 98 percent. The findings showed that the suggested approach is the most efficient for face recognition.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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References

[1] D. S. Trigueros, L. Meng, and M. Hartnett, “Face Recognition: From Traditional to Deep Learning Methods,” 2018.

[2] S. Humne and P. Sorte, “A Review on Face Recognition using Local Binary Pattern Algorithm,” Int. Res. J. Eng. Technol., vol. 5, no. 6, pp. 1031–1034, 2018.

[3] A. Rahim, N. Hossain, T. Wahid, and S. Azam, “Face Recognition using Local Binary Patterns (LBP),” Glob. J. Comput. Sience Technol. Graph. Vis., vol. 13, no. 4, pp. 469–481, 2013.

[4] Kaur P, Krishan K, Sharma SK, Kanchan T. Facial-recognition algorithms: A literature review. Medicine, Science and the Law. 2020;60(2):131–139. doi:10.1177/0025802419893168.

[5] Hassaballah M, Aly S. Face recognition: challenges, achievements and future directions. IET Computer Vision. 2015;9(4):614–626. doi:10.1049/ietcvi.2014.0084.

[6] Zhao W, Chellappa R, Phillips PJ, Rosenfeld A. Face Recognition: A Literature Survey. ACM Computing Surveys. 2003;35:399–458.

[7] Lal M, Kumar K, Hussain R, Maitlo A. Hidayatullah Shaikh. Study of Face Recognition Techniques: A Survey. [8] International Journal of Advanced Computer Science and Applications. 2018;9(6):42–49.

[9] Malhotra H. Di, S. Caifeng, M. Ardabilian, W. Yunhong, and C. Liming, "Local Binary Patterns and Its Application to Facial Image Analysis: A Survey," Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, vol. 41, pp. 765781, 2011.

[10] C. Shan, S. Gong, and P. W. McOwan, “Facial expression recognition based on Local Binary Patterns: A comprehensive study,” Image Vis. Comput., vol. 27, no. 6, pp. 803–816, 2009.

[11] Nishatbanu Nayakwadi and Mohammed Jameel Hashmi “Face Recognition System Using Local Ternary Pattern and Signed Number Multiplication”. International Journal of Engineering Science Invention ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726 www.ijesi.org Volume 5 Issue 1 January 2016 || PP.44-50

[13] Varma, Satishkumar, Megha Shinde, and Satishkumar S. Chavan. "Analysis of PCA and LDA Features for Facial Expression Recognition Using SVM and HMM Classifiers." Techno-Societal 2018. Springer, Cham, 2020. 109-119.

[14] Karanwal, Shekhar, and Manoj Diwakar. "Neighborhood and center difference-based-LBP for face recognition." Pattern Analysis and Applications (2021): 1-21.

[15] Karanwal, Shekhar, and Manoj Diwakar. "OD-LBP: Orthogonal difference-local binary pattern for Face Recognition." Digital Signal Processing 110 (2021): 102948.

[16] K. Meena and N.Malarvizhi “An Efficient Human Identification through MultiModal Biometric System”, Biological and Applied Sciences,vol 59,ISS 5,2016.

[17] Li, Yande, et al. "Cropping and attention based approach for masked face recognition." Applied Intelligence (2021): 1-14.

[18] Ahonen T, Hadid A, Pietikainen M. Face Description with Local Binary Patterns: Application to Face Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2006;28(12):2037–2041. doi:10.1109/tpami.2006.244..

[19] C. Shan, S. Gong, and P. W. McOwan, “Facial expression recognition based on Local Binary Patterns: A comprehensive study,” Image Vis. Comput., vol. 27, no. 6, pp. 803–816, 2009.

[20] Chen, Luefeng, et al. "Multi-support Vector Machine Based Dempster-Shafer Theory for Gesture Intention Understanding." Emotion Recognition and Understanding for Emotional Human-Robot Interaction Systems. Springer, Cham, 2021. 115-131.