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Hybrid Feature Approach of Face Recognition based on Pixel Binary Segmentation

Pattarakamon Rangsee, Raja K B, Venugopal K R

***Abstract**: The pose, illumination, and expression variations are challenging tasks in Facial Recognition (FR) and are a popular research area nowadays. We introduce novel nibbles of pixel technique and hybrid features from nibbles in this paper. The color images are converted into grayscale and then converts decimal values from each pixel into eight-bit binary values. The novel concepts of segmenting eight-bit binary into two groups of four-bit binary as Leftmost Nibble (LN) and Rightmost Nibble (RN) is presented. The nibble concept increases the computational speed and decreases the complexity of the system in the case of a real-time system as the 256 shades of grayscale images are decreased to 16 shades for LN and 16 shades for RN i.e., totally only 32 shades instead of 256 shades. The LN and RN binary is converted back to decimal values. The LL subband which is obtained from the applied Discrete Wavelet Transform (DWT) technique on the LN matrix is considered as the most important information while the Histogram of Oriented Gradients (HOG) is applied on the RN matrix to detect the edge information. The linear convolution of DWT and HOG results in the final hybrid features. In the matching part, the Euclidean Distance (ED) matching and the Artificial Neural Network (ANN) are selected to classify the features and calculate the proposed algorithm's performance parameters. The experimentation is implemented on six standard face databases, which demonstrates an outstanding performance by getting higher accuracy with less computation time compared with the existing techniques.*

***Keywords**: Biometric, Face Recognition, Discrete Wavelet Transform, Histogram of Oriented Gradients, Nibble.*

I. INTRODUCTION

The biometric system has a lot of potential applications in the day-to-day lifestyle of individuals. Biometrics are generally classified as physiological and behavioral biometrics. The characteristics of physiological biometrics are almost continuous for a period, such as a face, iris, fingerprint, palm print, etc. The behavioral biometrics show a discrepancy with an environment and mood of a person; hence it is variable with time such as signature, gait, voice, etc. Facial recognition is a current developing task for biometric security applications for differences in facial expressions, brightness, and posture. The main advantage of face recognition is that the images can be captured with help of cameras at a distance and also without any cooperation from human beings.

The feature extraction and classifications are the important stages in FR systems. The feature extraction techniques are broadly classified into three groups viz., spatial, frequency, and hybrid domain techniques. In the spatial field, the features are extracted unswervingly from the original pixel values.

The techniques such as Local Binary Pattern [1], Local Ternary Pattern [2], HOG [3], etc., are a few examples of the spatial domain. The pixel values of face images are converted into new coefficient values using frequency domain techniques such as Fast Fourier Transform (FFT) [4], Discrete Cosine Transform (DCT) [5], DWT [6], etc. In hybrid domain techniques, both spatial and frequency domain methods are joined together to achieve better performance of the FR system.

The extracted features of the database and test templets are compared to assess the performance of the FR system using matching distance and classifiers. The distance formulae are ED, Mahalanobis, city block, Chebyshev, hamming, etc. The classifiers are Support Vector Machine (SVM), Decision Trees, ANN, etc.

In this paper, the novel nibble pixel technique with hybrid feature domain-based face recognition is proposed. The novel concept of nibbles of the pixel is introduced to decrease the computational time and complexity of the real-time system with an increase in recognition rate. The face images pixel values are converted from decimal values to eight-bit binary values and divided into LN and RN.

The LN and RN binary are transformed back to decimal values vary between 0 to 240 and 0 to 15 respectively. The DWT and HOG are applied on LN and RN respectively to obtain the initial feature sets. The linear convolution is applied on both initial and generated features sets. The ED and ANN matching techniques are used to calculate the performance parameters.

II. LITERATURE SURVEY

In this section, the literature survey on the feature extraction techniques in both spatial and frequency domains is described. Additionally, the classification techniques are also presented.

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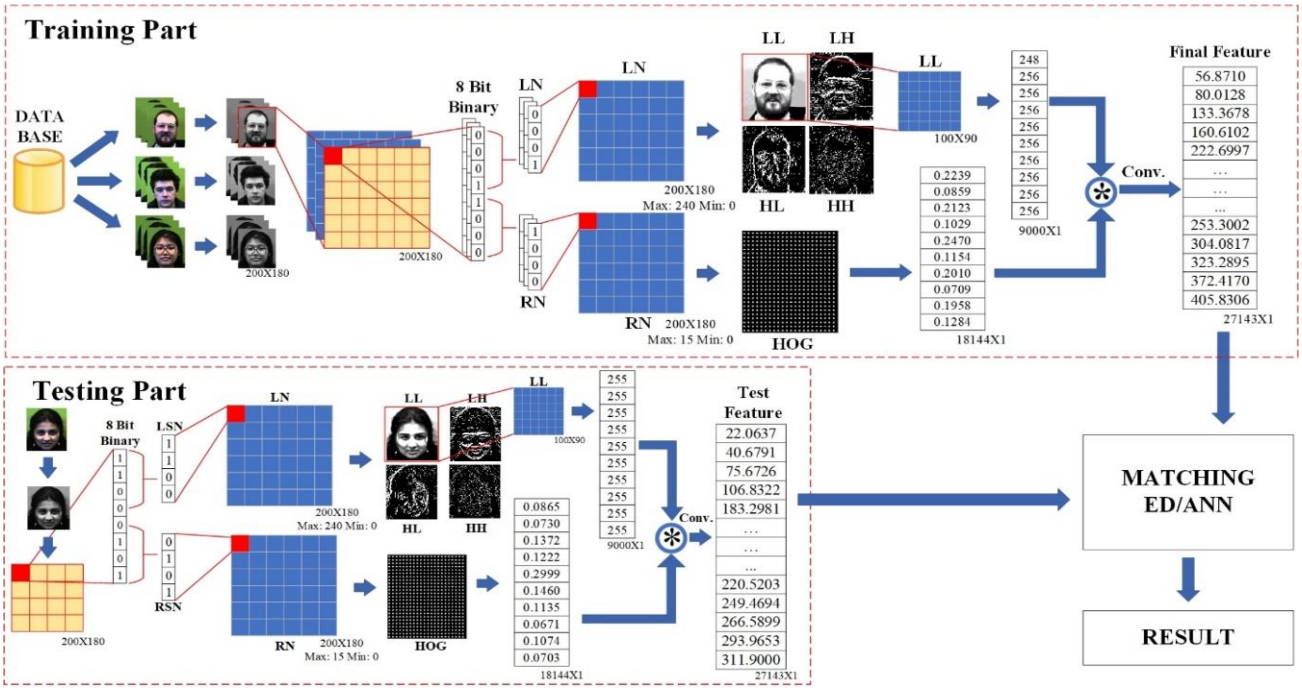

Fig. 1. Block Diagram of the Proposed Model for FR

Sumathi and Christopher Derairaj [7] proposed the occlusion, pose and illumination variations face recognition. The Principal Component Analysis and DWT are applied to extract the features and SVM is used for classification. Rifha Ilyas Bendjillali et al., [8] proposed facial expression and emotion recognition. The method applied the Viola-Jones as face detection, Contrast Limited Adaptive Histogram Equalization to adjust the histogram, and obtained the extracted features using DWT.

The classification stage is applied Convolution Neural Network as the classifier. Taif Alobaidi and Wasfy B. Mikhael [9] proposed a face recognition system that is based on fused feature extraction domains. The DWT is applied on face images to obtain initial features and also applied Discrete Cosine Transform to obtain the final features. The ED matching technique is used to calculate the minimum matching distance between the training matrix and the testing image. Monisha et al., [10] proposed facial identification based on 2D-DWT feature extraction along with Qualified Significant Wavelet Tree to get the correct yield while compressing the face images. The Convolution Neural Network (CNN) is used for classification. Thamizharasi Ayyavoo and Jayasudha John Suseela [11] proposed the face recognition system using DWT to enhance contrast limited and adaptive histogram equalization to adjust the histogram of the face image.

Hafiz Ahamed et al., [12] proposed real-time face recognition with an illumination and intensity variation system. The face images were captured by webcam. The HOG is applied on each face image to capture edge and corner information to obtain the final features. The CNN is used as a classifier. Wipawee Srisawasd and Sartra Wongthanavasu [13] proposed a face recognition system in an unconstrained environment. In the pre-processing stage, histogram equalization is applied to face images to solve the illumination variation problem and used active appearance model to cope with the non-frontal face images to solve the pose variation problem. In the feature extraction stage, the HOG is selected to extract the final feature, and SVM is used as the classifier in the classification stage. R. Angeline et al., [14] proposed the human face recognition in video with illumination and pose variation system. The HOG is utilized as a feature descriptor to detect the face image and extract the features.

The CNN classifier is implemented as the classification to measure the performance parameters of the proposed system. Mostafa A Ahmed et al., [15] proposed multi-biometrics on the face and digital signature recognition systems. The HOG is applied to the multi-biometrics information and adjusted some parameters such as weights of HOG features to obtain the HOG final feature.

In the matching part, Manhattan distance, ED, Angle-based distance, and modified Manhattan distance are used to calculate the accuracy of the proposed algorithm. Thanh Tan Nquyen Thi and Khanh Nquyen Trong [16] proposed the real-time face recognition system which was captures face images from a camera or webcam. The HOG is applied to the face images detected from video frames. The final HOG features from the feature extraction stage are trained using a linear SVM classifier as a classification.

III. PROPOSED METHOD

In this section, the proposed approach includes pre-processing, bit endianness, feature extraction, and classification. The block diagram of the proposed approach of face recognition is shown in Fig. 1.

A. Face databases

The performance of the proposed method is evaluated on the six popular face databases viz., ORL, YALE, JAFFE, EYB, Face94Es, and FERET.

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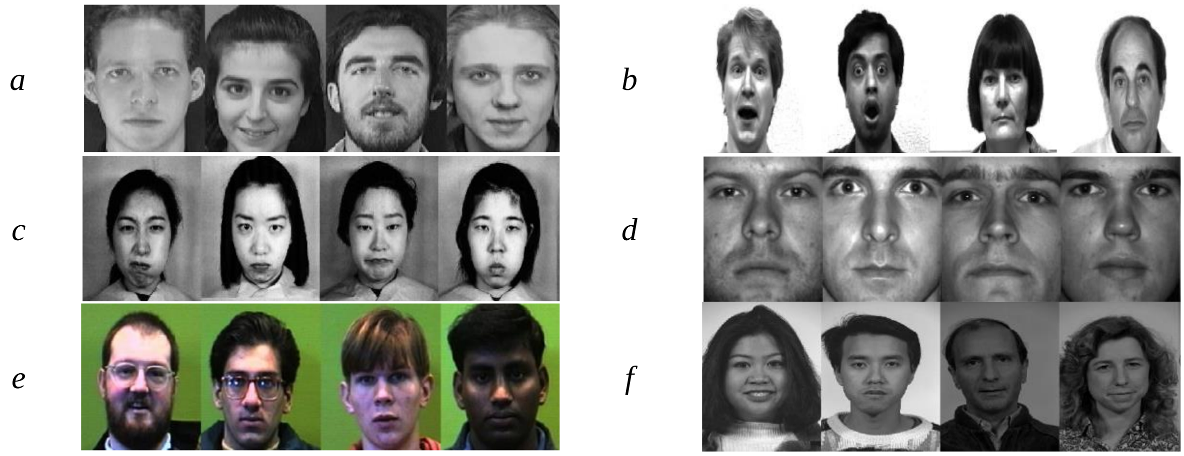

Fig. 2. Sample Face Images of Six Standard Face Database
(a) ORL, (b) YALE, (c) JAFFE, (d) EYB, (e) Face94Es and (f) FERET

1) ORL database [17]: The database consists of 400 pictures for 40 individuals. The images are diverse in pose and expressions as shown in Fig. 2(a).
2) YALE database [18]: The database consists of 165 pictures for 15 individuals. The images are diverse in illumination and expressions as shown in Fig. 2(b).
3) JAFFE database [19]: The database consists of 213 pictures for 10 individuals. The images are diverse only in expressions such as neutral, fear, shock, happiness, unhappiness, anger, and disgust as shown in Fig. 2(c).
4) EYB database [20]: The database consists of 1984 pictures for 31 individuals. The images are mainly diverse in illumination as shown in Fig. 2(d).
5) Face94Es database [21]: The database consists of 3040 pictures for 152 individuals. The images are diverse only in expression as shown in Fig. 2(e).
6) FERET database [22]: The database consists of 14126 pictures for 1199 individuals. This work uses the face images from the FERET dataset total of 5247 images that were captured for 477 individuals. The images are diverse in pose, angle, and expression as shown in Fig. 2(f).

B. Pre-Processing

The RGB images of face databases are changed to the grayscale image which has pixel values between 0 to 255 and the histogram equalization is applied on the EYB database to alter the brightness.

C. Bit Endianness

The pixel values which are in decimals are converted into binary values of eight bits then it is segmented into (Least Significant Bit) LSB and (Most Significant Bit) MSB with 4 bits each. The 4-bit LSB is considered as RN and another 4-bit MSB is considered as LN. The bit endianness is demonstrated in Fig. 3 and an algorithm is given in Algorithm 1. The 3X3 pixel values are considered from an image to show the binary equivalent and its LN and RN's with corresponding decimal values are as shown in Fig. 3(a). It is observed that the equivalent decimal values of 4-bit RN are varied between 0 and 15 as given in (1). The equivalent decimals obtained for 4-bit RN are not significant when weigh up to the original decimal values while the equivalent decimal values of 4-bit LN are varied between 0 and 240 as given in (2) and these values are significant compared to the original decimal values.

$$RN\ Decimal = \sum_{n=1}^{4} x(n) \times \left(2^{n-1}\right) \qquad (1)$$

where x(n) is Binary values from rightmost
n is the Bit position

$$LN\ Decimal = \sum_{n=1}^{4} x(n) \times \left(16 \times 2^{n-1}\right) \qquad (2)$$

where x(n) = Binary values from leftmost

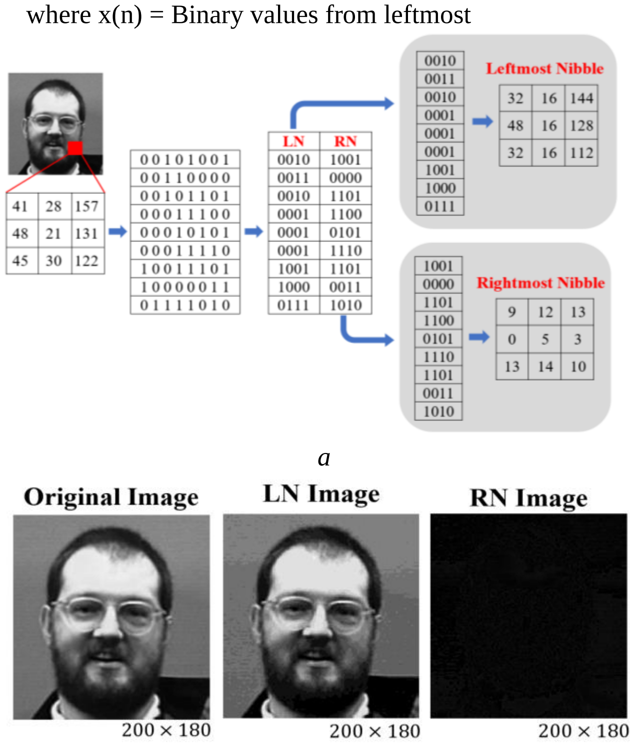

Fig. 3.Bit Endianness Demonstration
(a) Example of Bit Endianness and (b) Bit Endianness in Terms of Images

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The original image and the corresponding LN and RN images constructed by LN and RN decimal values are shown in Fig. 3(b). It is observed that the constructed LN images are almost the same as the original image, whereas the image constructed by RN has insignificant information and can't be compared with the original image. The advantages of bit endianness are as follows

(i) Eight-bit length pixel values are converted into four bits RN and LN separately.

(ii) The 256 grey shades of eight-bit length pixels are converted into 16 grey shades for RN and 16 grey shards for LN i.e., 32 grey shades for each pixel are generated instead of 256 shades.

(iii) The number of shades is reduced from 256 to 32, which reduces the complexity of architecture in a real-time system and also reduces computation time.

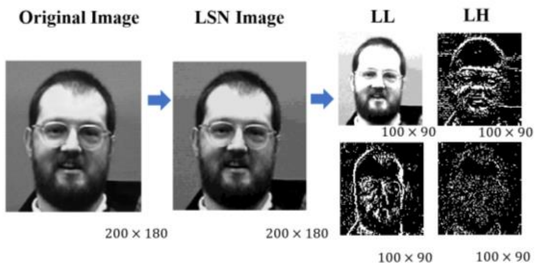
Algorithm 1: Bit Endianness Algorithm
Input: Grayscale face image
Output: LN and RN matrices
Step 1 (Initialization):
-Convert decimal pixel values into binary 8 bits
Step 2 (Bit Endianness):
-Separate the nibble group of 4 bits into LN and RN
-Convert 4 bits RN into decimal values using Eq. 1.
-Convert 4 bits LN into decimal values using Eq. 2.
Step 3 (Output):
Output the RN matrix which is the values between 0 to 15 and the LN matrix which is the values between 0 to 240 and the corresponding image is the same as the original image.

D. Feature Extraction

The final feature vectors are obtained by convolution of DWT and HOG initial features.

1) Discrete Wavelet Transforms (DWT) [23]

It is a popular wavelet-based transform where the wavelets are sampled and capable of capturing information in both frequency and spatial domain. The DWT decomposes the signal into sub-bands with the combinations of wavelets and scaling filters. The 2D-DWT is applied on the rows of original pixel values of the face images by using Low Pass Filter (LPF) and High Pass Filter (HPF) simultaneously. The signals are sampled by a factor of 2 and similarly, the process is performed on columns of the image. At all levels, 4 sub-bands are available and named LL, LH, HL, and HH. The 2D-DWT is applied to obtained LN matrix to divide into 4 sub-bands as shown in Fig. 4. The LL sub-band image is similar to the original LN image and it contains substantial information as shown in Fig. 4(a) and the corresponding LL matrix are shown in Fig. 4(b). The remaining LH, HL, and HH sub-bands consist of irrelevant information. The LL subband coefficients are considered to be significant compared to the other three sub-bands. Therefore, only the LL sub-band is used as an initial feature set by removing the other three sub-bands. This results in only 1/4th coefficients of DWT which helps to speed up the computational time by compression.



a

$$\begin{bmatrix} 248 & 240 & 255 & & 255 & 255 & 255 \\ 255 & 255 & 232 & \cdots & 255 & 255 & 255 \\ 255 & 255 & 240 & & 255 & 255 & 255 \\ & \vdots & & \ddots & & \vdots & \\ 192 & 192 & 192 & & 144 & 176 & 136 \\ 192 & 192 & 192 & \cdots & 104 & 152 & 160 \\ 192 & 192 & 192 & & 88 & 104 & 160 \end{bmatrix}_{100 \times 90}$$

b

Fig. 4.DWT Decomposition of LN image
(a) 2D-DWT on LN image, (b) LL Sub-Band Matrix

2) Histogram of Oriented Gradients (HOG) [24]

It is used for object detection in image processing by calculating and counting the direction of the histogram of gradients in local regions of the image. In the proposed approach, the magnitude and directions of the gradients are considered as features where vital information is available. The HOG is applied on RN to extract the features, the vertical and horizontal kernel filters are used to filter the vertical and horizontal gradients as shown in Fig. 5. The obtained horizontal and vertical gradients are used to find the histogram of gradients.

$$Horizontal\ Kernal\ Filter = \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline \end{array}$$

$$Vertical\ Kernal\ Filter = \begin{array}{|c|} \hline -1 \\ \hline 0 \\ \hline 1 \\ \hline \end{array}$$

Fig. 5.Kernel filters for horizontal and vertical gradients

The gradients of each pixel value containing magnitude and direction are computed using (3) and (4).

$$Magnitude = \sqrt{g_H^2 + g_V^2} \qquad (3)$$

$$Direction(angle) = \tan^{-1}\left(\frac{g_V}{g_H}\right) \qquad (4)$$

where g_H is horizontal gradient and g_V is vertical gradient. The RN matrix is divided into many blocks depending on the size of the matrix, 1 block has 4 cells and each cell has 8X8 pixel size, so 1 block contains 256 pixels.

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In each cell, the histogram of gradients is obtained from the distribution of magnitude values from (3) based on bin selection of direction from (4) into 9 bins of a histogram. The 9 bins histogram of the gradient has an angle between 0 to 180 degrees with unsigned gradients methods, so the range of 1 bin is 20 degrees. The illustration for bins selection of histogram in each cell is shown in Fig. 6.

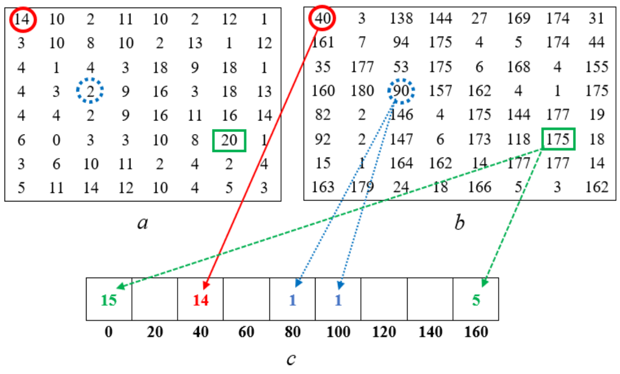

Fig. 6.The Illustration for Bins Selection of Histogram in Each cell (a) Magnitudes, (b) Direction, (c) 9 Bins Histogram of Gradients

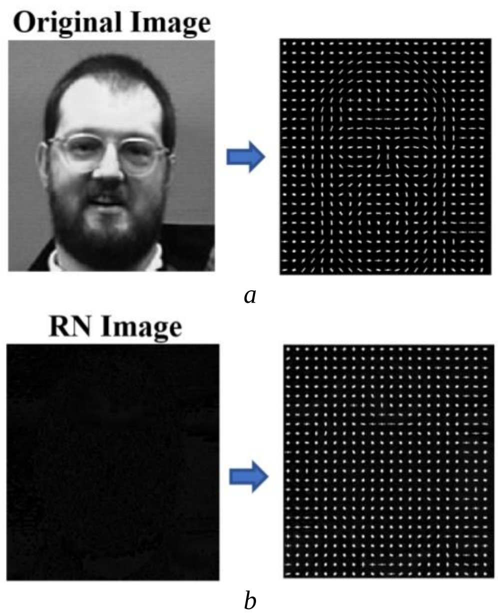

Fig. 7.Visualization of HOG

(a) HOG Visualization of the Original Image and (b) HOG Visualization of Rn Image

The magnitudes, directions, and 9 bins histogram of gradients of 8X8 cell size of RN matrix are shown in Fig. 6. Based on the directions of HOG, the magnitudes are allocated to bins.

The 9 bins histogram of gradients is shown in Fig. 6(c) having 9 slots with each slot of 20 degrees. The RN matrix is divided into several 8X8 cells, then HOG is applied to each cell to get 9 HOG coefficients.

The magnitude 14 from Fig. 6(a) corresponding to a direction of 40 degrees from Fig. 6(b) is transferred to the 3rd bin of Fig. 6(c). The magnitude 2 corresponding to a direction of 90 degrees is transferred to bins of 80 degrees and 100 degrees equally as 90 degrees' bin is not available. Similarly, magnitude 20 corresponding to a direction of 175 degrees is transferred to 160 degrees and 0 degrees with a ratio of 1/4 and 3/4 of magnitude i.e., the magnitude 5 to 160 degrees and 15 to 0 degrees. In 1 block contains 4 adjacent cells and 1 cell contains 9 HOG coefficients, so 1 block obtained 9X4 = 36 HOG coefficients. The final feature of the RN matrix achieved is 24X21, overlapped blocks by considering the only half overlap of each block. Therefore, the number of final features is 24X21X36 = 18144.

The visualization of HOG of original face image and RN images is presented in Fig. 7. The pattern of the original face image is observed in the HOG visualization in Fig. 7(a). The RN image contains only 4 LSB of the original 8-bit binary which does not contain any major information. The HOG conception of the RN image has a random pattern with minor information as shown in Fig. 7(b).

3) Merging of initial features using linear convolution [25]

The final feature is obtained by merging the DWT and HOG feature sets using linear convolution from (5) to develop final operational features for FR. The DWT feature vector of size 9000X1 is converted from the feature matrix of size 100X90 and the HOG feature vector is of size 18144.

$$C(n) = D(n) * H(n) = \sum_{k=0}^{27142} D(k)\, H(n-k) \tag{5}$$

$$Length_k = L_{DWT} + L_{HOG} - 1 \tag{6}$$

where $D(n)$ is DWT feature vector, n = 0 to 8999

$H(n)$ is HOG feature vector, n = 0 to 18143

The number of DWT features is 9000 and the number of HOG features is 18143, hence the total number of final features is equal to 27143 from (6). The final features algorithm is given in Algorithm 2.

E. Classification

The final stage of FR is the classification stage. Two popular methods of classification are used to categorize face images of the proposed algorithms are distance matching and machine learning classifier.

1) Matching based on ED

The distance measure is the most basic and popular technique used to classify in FR system. The distance matching can classify by finding the distance between the matrices of database images and test images. The minimum distance obtained represents the similarity of the test face image to that of database images using (7).

$$ED(x, y) = \sqrt{\sum_{i=1}^{j} \left(x_i - y_i\right)^2} \tag{7}$$

Where ED(x,y) is the distance between database images x and test images y. The xi and yi are the ith coordinate of x and y. The minimum distance represents similar face images, then the face recognition is successful.

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Algorithm 2: Algorithm of Hybrid Features
Input: LN and RN matrices
Output: Hybrid final features
Step 1 (DWT):
- Applied 2D-DWT to LN matrix
- Selected the LL sub-band coefficients as features
- Convert LL sub-band 2D-Matrix to the Column Vector
Step 2 (HOG):
- Divide RN matrix into 8X8 pixels for each cell
- Compute the horizontal and vertical gradients using kernel filters
- Calculate the magnitude and direction of each pixel in the cell
- Compute the 9 bins histogram of gradient bins of each cell
- The 4 neighboring cells are clustered into 1 block
- Consider 50% overlap of each block
- Concatenate the histogram for the entire image to Column Vector
Step 3 (Convolution):
Fuse the DWT feature vector with the HOG feature vector using the linear convolution technique to obtain a hybrid final feature

2) Matching based on ANN

It is a presentation of artificial intelligence that study and evolve by capability without being unambiguously encoded. ANNs can perform both pattern recognition and machine learning. It consists of three layers viz., input, hidden, and output layers. Input layers accept the final features from trained images and feed them to the network. Then the hidden layer calculates the movement of every hidden data and the actions of the input data and the weights influence the input and the hidden parts. The output layers produce output units which be influenced by the activities of the hidden data and the weights among the hidden and output layers. The total outputs are equivalent to the total number of classes. The test feature set is compared to the trained feature set to expect precise recognition accuracy by using the confusion matrix.

IV. EXPERIMENTS AND RESULTS

The definitions of performance parameters and evaluation of the proposed method are tested using 6 standard face databases related to ED and ANN are explained.

A. Definitions of Performance Parameters for ED Matching

There are four parameters used in ED Matching to test and analyze the performance of the proposed approach are as follows

1) False Acceptance Rate (FAR)

It is the ratio of number of Persons Outside Database (POD) falsely accepted as Persons Inside Database (PID) to the total number of POD as given in (8) The values of FAR are zero for lower threshold values. The values of FAR reach 100% for higher values of threshold. The values of FAR must be zero for ideal performance and low for better performance of an algorithm.

$$FAR = \frac{\text{No. of false acceptance from POD}}{\text{Total No. of POD}} \tag{8}$$

2) False Rejection Rate (FRR)

It is the ratio of the number of PID falsely rejected as POD to the total number of PID as given in (9). The values of FRR are maximum at lower threshold values and FRR decreases with an increase in threshold values. The value of FRR must be zero or lower for better performance of an algorithm.

$$FRR = \frac{\text{No. of PID rejected as outside}}{\text{Total No. of PID}} \tag{9}$$

3) Equal Error Rate (EER)

It is the value where both FAR is equated to FRR. The values of FAR and FRR are equal at the optimum threshold value.

4) Total Success Rate (TSR)

It is the ratio of the total number of PID are correctly matched to the total number of PID. It has two parameters as Optimum Total Success Rate (OTSR) and Maximum Total Success Rate (MTSR). OTSR is the TSR at optimum threshold corresponding to EER and MTSR is the maximum TSR value. The TSR can be computed using (10).

$$TSR = \frac{\text{No. of persons correctly matched in PID}}{\text{Total No. of PID}} \tag{10}$$

B. Definitions of Performance Constraints for ANN Classifier

The effective proposed approach is computed by using the confusion matrix as shown in Fig. 8. It is the comparison of the cases between the actual and predicted class which contains 4 terms viz., True Positives (TP), True Negatives (TN), False Positive (FP), and False Negative (FN).

To determine the performance of the proposed method, there are two significant parameters.

1) Classification Accuracy

Precision is the proportion of the complete number of correct predictions as given in (11).

$$\begin{aligned} Overall\ Accuracy &= \frac{TP + TN}{TP + FP + TN + FN} \\ &= \frac{\text{No. of correct match}}{\text{No. of training images}} \end{aligned} \tag{11}$$

Confusion Matrix		Actual (Model)	
		Positive	Negative
Predict	Positive	TP	FP
	Negative	FN	TN

Fig. 8.Confusion Matrix Model

2) Classification Error Rate

The error rate is the proportion of the complete number of incorrect predictions as given in (12).

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$$Error\ Rate = 1 - \text{Overall Accuracy} = \frac{FP + FN}{TP + FP + TN + FN} \quad (12)$$

C. The experimental results of the proposed approach using the ED matching technique

The performance parameters such as percentage EER, OTSR, and MTSR are computed for variations in PID and POD for six face databases based on the ED matching technique.

1) Performance parameters for variations in POD by keeping PID constant

The face databases viz., ORL, YALE, JAFFE, EYB, Face94Es, and FERET are used to test the proposed approach by computing percentage EER, OTSR, and MTSR for different values of POD with constant PID as given in Table 1. It is observed that the variations in POD with constant PID do not affect the performance parameters for ORL, YALE, JAFFE, EYB, and Face94Es, whereas it affects the performance parameters in the case of the FERET face database. The percentage of EER values increases and the percentage of OTSR values decrease for an increase in POD values in the case of the FERET database. The optimum threshold is almost constant and depends on face databases to obtain optimum TSR and EER. The error rate is low and the percentage recognition rate is high in the case of Face94Es face database since the images per person are almost the same and the difference between images of different persons are high. The error rate is high and the recognition rate is low in the case of JAFFE since images of different persons are almost similar.

2) Performance parameters for variations in PID by keeping POD constant

The face databases viz., ORL, YALE, JAFFE, EYB, Face94Es, and FERET are used to test the proposed algorithm by computing percentage EER, OTSR, and MTSR for different values of PID with constant POD as given in Table 2. It is observed that the variations in PID with constant POD affect the performance parameters for every database.

The percentage EER values increases and percentage OTSR values decrease with an increase in PID values in the case of ORL, YALE, EYB, Face94Es, and FERET, whereas the percentage EER values decreases and percentage OTSR values increases with an increase in PID values in the case of JAFFE. The optimum threshold is almost constant and depends on face databases to obtain optimum TSR and EER. The error rate is low and the percentage recognition rate is high in the case of Face94Es face database. The error rate is high and the recognition rate is low for JAFFE.

Table- I: Performance parameters for various face databases keeping PID constant.

DATABASE	PID	POD	TH_{OPT}	EER (%)	OTSR (%)	MTSR (%)
ORL	10	30	0.320	10	90	100
	10	20	0.320	10	90	100
	10	10	0.320	10	90	100
YALE	5	10	0.223	20	80	100
	5	8	0.226	20	80	100
	5	5	0.209	20	80	100
JAFFE	3	7	0.407	33.33	66.67	100
	3	5	0.401	33.33	66.67	100
	3	3	0.400	33.33	66.67	100
EYB	12	19	0.742	8.33	91.67	100
	12	16	0.745	8.33	91.67	100
	12	12	0.790	8.33	91.67	100
FACE94ES	32	120	0.355	1.5	98.5	100
	32	100	0.355	1.5	98.5	100
	32	80	0.355	1.5	98.5	100
FERET	100	100	0.500	8	85	91
	100	200	0.490	9	84	91
	100	300	0.473	13	81.5	91

Table- II: Performance parameters for various face databases keeping POD constant.

DATABASE	PID	POD	TH_{OPT}	EER (%)	OTSR (%)	MTSR (%)
ORL	10	10	0.290	10	90	100
	20	10	0.325	15	85	100
	30	10	0.291	16.67	83.33	100
YALE	5	5	0.250	20	80	100
	8	5	0.259	25	75	100
	10	5	0.245	10	80	90
JAFFE	3	3	0.400	33.33	66.67	100
	5	3	0.346	20.00	80.00	100
	7	3	0.424	14.29	85.71	100
EYB	12	12	0.790	8.33	91.67	100
	16	12	0.755	9.50	90.50	100
	19	12	0.742	10.53	89.47	100
FACE94ES	80	32	0.344	1.25	98.75	100
	100	32	0.318	2.0	98	100
	120	32	0.318	2.5	97.5	100
FERET	100	100	0.500	8	85	91
	200	100	0.480	15	76	87.5
	300	100	0.465	25	65	77.67

D. The experimental outcomes of the proposed model using the ANN matching technique

The performance parameters such as overall accuracy are computed for variations in hidden nodes and the number of training images per person for six face databases based on the ANN matching technique.

1) Performance parameters for variations in hidden nodes by keeping the number of Training Images per person (TIPP) constant

The computed overall accuracy by varying the number of hidden nodes with constant training images using 50% of the total number of images per person for various face databases is given in Table 3. It is observed that the overall accuracy depends on several hidden nodes and also face databases. The overall accuracy is high in the case of the EYB face database and low in the case of the ORL database.

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Table- III: Performance parameters for various face databases keeping number of training images per person constant

Hidden Node	Overall Accuracy (%)					
	ORL	*YALE*	*JAFFE*	*EYB*	*Face94Es*	*FERET*
15	89.00	89.33	98.00	98.99	94.70	83.14
20	90.00	92.67	97.50	98.99	96.15	86.02
22	87.50	95.33	98.00	99.40	97.14	91.51
25	89.25	92.00	97.50	99.04	96.48	92.29
27	85.75	94.00	96.50	99.40	96.45	92.43
30	-	-	-	-	-	93.23
35	-	-	-	-	-	92.47

2) Performance parameters for variations in TIPP by keeping hidden node constant

The computed overall accuracy by varying the number of TIPP with constantly hidden nodes using different face datasets is presented in Table 4. It is perceived that; the overall accuracy is increased with an increase in the number of TIPP. The overall correctness is more for EYB and low in the case of the ORL database.

Table- IV: Performance Parameters of Various Face Databases Keeping Number of TIPP Constant

Database	Hidden Node	Overall Accuracy (%)				
		20% TIPP	*40% TIPP*	*50% TIPP*	*60% TIPP*	*80% TIPP*
ORL	20	62.75	82	90	95	98
YALE	22	83.33	92.67	95.33	96	99.33
JAFFE	22	89.5	97.5	98	99	99.5
EYB	22	90.42	97.68	99.40	99.65	99.85
Face94Es	22	64.41	92.66	99.40	99.65	99.85
FERET	30	66.29	83.61	88.49	92.26	96.74

E. Performance comparison of the proposed approach using ED and ANN Techniques

The computed overall accuracy and computational time using ED and ANN matching techniques for various face databases are tabulated in Table 5. The performance parameters and computational time are computed using a computer with specifications of Inter ® Core ™ i5-8250U CPU@1.6 GHz 1.8 GHz, 16 GB RAM with HDD 1TB. It is seen that; the overall accurateness is high and low computational time in the case of ANN matching compared to the ED matching technique. The computational time depends on face databases and the number of subjects, number of images per subject, and image size.

Table- V: Comparison of ED and ANN Matching Techniques.

Face Database	ED		ANN	
	% Accuracy	*Computational Time (Sec)*	*% Accuracy*	*Computational Time (Sec)*
ORL	80.00	69.612	98.571	15.291
YALE	83.33	152.078	99.167	55.525
JAFFE	87.50	151.780	100	46.872
EYB	92.00	904.493	99.938	222.162
Face94Es	99.23	2655.946	99.692	315.269
FERET	38.00	16017.65	98.590	2830.75

F. Comparison of the proposed approach with the current methods

The comparison between the percentage of recognition accuracy of the proposed algorithm and the traditional algorithms is shown in Table 6. It is observed that the proposed algorithm reaches a higher recognition accuracy than the existing algorithms. To substantiate the increase in the performance level of the proposed method, the following aims have been specified:

1) The LN and RN techniques in this proposed approach are reduced the architectural complexity and increased the computational speed in the real-time application by processing only 32 different gray levels instead of 256 levels from the original 8-bit binary.

2) In the pre-processing stage, the histogram equalization is applied to the EYB face image to avoid the variation of illumination.

3) In the pre-processing stage, the image resizing technique is applied to Face94ES and FERET face images to reduce computational time and complexity.

4) The number of features is reduced to 1/4th of the original image features by selecting only the LL sub-band after applying DWT on the LN matrix.

Table- VI: Comparison of the Proposed Method with Existing Methods Using ANN Technique

Database	Author	Accuracy (%)
ORL	Min and Zhu [26]	88.00
	Omar and Venus [27]	91.10
	Prabhat et al., [28]	93.75
	Zhi Liu et al., [29]	95.00
	Ying Wen [30]	96.54
	Taif and Wasfy [31]	96.87
	Abuzneid and Mahmood [32]	96.90
	Jun Fan et al., [33]	97.10
	Jun Kong et al., [34]	97.50
	Proposed with ANN	***98.00***
YALE	Taif and Wasfy [31]	75.85
	Hamid and Abolhasem [35]	77.47
	Jun Fan et al., [33]	81.22
	Bhumika and Sumita [36]	86.67
	Swarup and Sukadev [37]	92.30
	Omar and Venus [27]	95.70
	Abuzneid and Mahmood [32]	97.00
	Rocky et al., [38]	97.80
	Proposed with ANN	***99.33***
JAFFE	Mamta and Ashok [39]	81.42
	Gopalan et al., [40]	84.00
	Ziyung Han et al., [41]	91.29
	Bayezid Islam et al., [42]	93.51
	Jun Cai et al., [43]	95.24
	Hamid and Abolhasem [35]	95.57
	Yacine Yaddaden et al., [44]	96.19
	Alaa E. [45]	96.33
	Proposed with ANN	***99.50***
EYB	Yuqi and Mingyan [46]	91.60
	Pei-Chun Chang et al., [47]	96.70
	Santosh et al., [48]	96.70

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	Guangyi Chen et al., [49]	97.30
	Swarup et al., [50]	97.64
	Weihong Deng et al., [51]	99.40
	Proposed with ANN	***99.85***
FACES94ES	Annis Fathima et al., [52]	94.02
	Rocky et al., [38]	98.86
	Yukun Ma et al., [53]	99.00
	Salma Mohamed et al., [54]	99.30
	Proposed with ANN	***99.51***
FERET	Taif and Wasfy [31]	64.57
	Zhi Liu et al., [29]	95.00
	Salma Mohamed et al., [54]	95.00
	Rabul and Aditya [55]	96.30
	Proposed with ANN	***96.74***

V. CONCLUSION

The main goal in the real-time FR system is to decrease the complexity and time-consuming process. In this paper, a novel technique of facial recognition based on nibble pixels using hybrid feature extraction is proposed. The performance of the proposed model is tested on 6 popular face databases. The color face images are changed to grayscale images which have 256 different shades from 0 to 255. Each pixel is converted from decimal values to 8-bit binary values then segmented into 4-bit LN and 4-bit RN.

The binary LN transformed back to decimal values from 0 to 240 with only 16 different shades while binary RN converted back to decimal values from 0 to 15 with 16 different shades i.e., totally 32 different shades instead of 256. The DWT and HOG techniques are applied on LN and RN to introduce the initial features respectively. The linear convolution is used to merge the transform domain features and spatial domain features to generate the hybrid final features. In the classification stage, the ED and ANN techniques are used to compare the final features of the train and test section to calculate the performance parameters. It is found that the proposed approach is achieved higher accuracy than the traditional approach. The upcoming work offers to implement on the real-time scheme by consisting of only 4 bits' data to diminish the computational time and complexity.

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