Spatial Domain-based Face Recognition using MSB, and MLTP with ANN Classifier

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Abstract

The human face images are an essential biometric trait in the authentication of individuals as the face images can be taken without the knowledge and physical contact of the person leading to several recent applications. We propose Spatial Domain-based Face Recognition using MSB and MLTP with ANN Classifier in this paper. The benchmarked face datasets are considered for testing the proposed method by converting color images into greyscale images and uniform image sizes. The 8-bit binary of each pixel is segmented into two groups viz., Most Significant Bits (MSB) and Least Significant Bits (LSB). The important information is available only in MSBs than LSBs hence MSBs are considered for feature extraction leading to compression of binary bits. The MSB four bits are converted to decimal values, and Histogram Equalization (HE) is used to enhance the contrast level of images and resize them. The Modified Local Ternary Pattern (MLTP) is applied to an image to extract compelling features. The Artificial Neural Network (ANN) classifies face images to recognize human beings. It is noticed that the proposed method's recognition results are better than the existing techniques.

Keywords: Artificial Neural Network (ANN), Biometrics, Face Recognition, Histogram Equalization, MSB, MLTP.

1. Introduction

Biometrics are the measurements and calculations related to physical human body parts and behavioral characteristics to identify human beings effectively as biometrics are unique to individuals. With the rapidly growing population in the world, traditional methods used for human recognition with Personnel Identification Numbers (PIN), and identification cards are unconfident as impostors may generate PIN, and make identical cards, but reconstructing biometric trait characteristics is extremely problematic. The biometric system works in two basic modes, first, is the verification mode in which the biometric system makes a one-to-one assessment of a taken biometric trait with an explicit pattern saved in a biometric folder in order to verify the claim of an individual. Second is the identification mode, the biometric system makes a one-to-many assessment of a captured biometric trait with a biometric folder in an effort to find the identity of an unidentified individual. The biometric systems are broadly classified into two groups viz., unimodal and multimodal biometric systems. The unimodal biometric systems are simple and operate with a single biometric trait and face various challenges such as lack of secrecy, non-universality of a single biometric sample, spoofing attacks on stored data, etc. Multimodal biometric systems are a little complicated and operate with two or more biometric traits that fuse the information of multiple biometric traits to obtain final effective features. The advantages of multimodal biometric systems are more reliability, and increased security level, if any one of the biometric traits fails to work, then the system still can provide security by employing the other biometric trait. The biometrics are effortlessly combined into virtually all electronic systems for access to evade cybercrime. The few applications of biometric technology are Law implementation and public safety, Military, migration control, resident identification, health care, subsidies, Physical & logical access, and Commercial applications. The limited restrictions of biometrics are (i) The access may be deprived to authorized persons owed to false-negative credentials leads to frustration. (ii) The access may be granted to unauthorized persons due to false-positive credentials leading to serious damage. (iii) The reconstructed false fingerprints may dupe the scheme. (iv) The identity may lead to serious effects if the biometric dataset is hacked.

Contributions: In this paper, spatial domain-based face recognition using MSB and MLTP with an ANN classifier is projected. The 8-binary of every pixel is segmented into two parts MSBs and LSBs, then the HE is used on an image with MSBs only to enhance the contrast level. The features are extracted using MLTP from the contrast-enhanced image. The ANN classifier is working to calculate the performance parameters of the projected face recognition system.

The research paper is planned as follows; sector 2 brings the literature survey on face recognition. The expected method is stated in Sector 3. Sector 4 carries the performance results. In Sector 5, the conclusion and future exertion of the research are specified.

2. Literature Survey

The different face recognition techniques by various researchers are described in this section. Divya Tyagi et al., [1] have proposed an FR scheme built by LTP and Genetic Algorithm (GA) for feature extraction and feature selection, respectively. The features are categorized using SVM. Vasudha and Deepti Kakkar [2] have suggested facial appearance recognition using the Deep Belief Network (DBN). The method uses Local Directional Position Pattern (LDPP) and LTP for feature extraction. Further, General Discriminant Analysis (GFA) and PCA are used to minimize the number of features. The resulting features are trained and classified using DBN. Komal Juneja et al., [3] have proposed Local Tetra Patterns (LTrPs) for texture extraction under different illumination conditions. Gamma correction, contrast equalization, and difference of Gaussian are used for pre-processing. The images are classified using SVM. Khadijs Lekdioui et al., [4] have offered an FR scheme built on facial breakdown and facial landmark detection with seven Regions of Interest (ROI) such as eyebrows, eyes, and between eyebrows using an Intra Face algorithm. Dissimilar local descriptors like LBP, CLBP, LTP, and Dynamic LTP are utilized to get features and are then fed into multiclass SVM for classification. Ejaz Ul Haq et al., [5] have proposed a normalized histogram with LBP and multiclass SVM classifier for classification.

Pattarakamon Rangsee et al., [6] proposed a multi-class Support Vector Machine (SVM) classifier and a modified local ternary pattern (MLTP) FR algorithm An Error-Correcting Output Code (ECOC) multiclass model with a SVM is used to classify the MLTP characteristics of the face images. Six benchmarked face databases are used to test the suggested approach. The experimental results show that when MLTP is combined with SVM, it can obtain greater recognition accuracy than traditional approaches. Sitholimela et al., [7] examined the function of image resolution. The model used two face texture feature-based approaches DLTP and ELTP. This paper presented a thorough examination of investigational outcomes for two LTP and to check the variations in image resolution. The findings show that low and high-resolution versions of similar images do not contain identical information and hence are likely classified differently when compared. Vasudha and D. Kakkar [8] proposed the facial recognition approach, local directional position pattern (LDPP) and local ternary pattern (LTP) were used, both of which have significant advantages over prior techniques such as local binary pattern (LBP) and local directional pattern (LDP). The chosen techniques of LDPP and LTP differ in their algorithms, which only help to extract features from a picture. LDP has been updated to become LDPP. Only the top edge direction was considered in a normal LDP, but the pixel's strong sign was ignored, which might result in the identical code for the opposite kind of edge pixel. LDPP, which is further concatenated with LTP for enhanced feature extraction, overcomes this problem. After the features have been extracted, they are used to train the system.

Kamarajugadda and Movva [9] proposed a face identification using a Feed-Forward Neural Network in order to improve the effectiveness of face recognition systems. Linear Discriminative Analysis (LDA) and Local Tetra Pattern (LTP), which collect both frequency and position information, are used to extract features. In addition, for picture enhancement, feature reduction is conducted using LDA, which allows for better image classification. The classification process is then carried out using the M-FNN approach. It calculates the major component of each class and constructs the classifier based on data projection on the principal components' traversed subspaces. Karanwal [10] suggested Neighborhood Difference LBP (ND-LBP) and Neighborhood Mean LBP (NM-LBP) were proposed as two LBP versions (NM-LBP). In ND-LBP, the comparison is made between neighbor pixels lined up clockwise, whereas, in NM-LBP, the neighbors are compared with their mean. The face descriptor ND-LBP+NM-LBP is constructed by combining the histograms of ND-LBP and NM-LBP. For compression, the PCA idea is used, and for face recognition, the SVMs and NN classifiers are used. Yallamandaiah and Purnachand [11] introduced face recognition using the Histogram of Oriented Gradients (HOG), histogram of LBP, and Convolutional Neural Network (CNN) based face recognition. The extracted features from HOG, histogram of LBP, and deep features from the CNN are linearly concatenated to get the final features, and SVM is used for classification.

Raghavan and Ahmadi [12] introduced face authentication using a local entropy-based adaptive-weight LBP. It is used to create a local histogram for each block, which is then fed into the K-Nearest Neighbor (K-NN) classifier. To offer additional weightage to related parts in the face image, a local entropy concept is employed to apply weights to classifier outputs from distinct sub-blocks. Durmuşoğlu and Kahraman [13] suggested a facial expression recognition system in order to create a stable and dependable system. To build a dependable methodology, the LBP and Local Phase Quantization (LPQ) approaches are applied. The key goal is to figure out which strategy when combined, produces the best results. Alalayah et al., [14] proposed a counteract the Completed Local Binary Count's sensitivity to noise, and a threshold value was added to the Completed Local Ternary Count (CLTC) texture descriptor. Adding the Fast-Local Laplacian filter to the CLTC during the pre-processing phase improves the discriminatory property of the descriptor. Five different face picture datasets are used to test the Fast-Local Laplacian CLTC (FLL-CLTC) texture descriptor for face authentication. In terms of recognition accuracy, the FLL-CLTC surpassed the CLBP and CLTP texture descriptors in experiments.

Song and Ma [15] proposed a non-intrusive face liveliness recognition built on the investigation of texture and color features. It adopted an improved LTP to categorize the nearby pixels. In the face pixel analysis, the endlessness norm of pixel matrices is extra as a new feature. The efficacy of feature selection has been authenticated by three face anti-spoofing databases such as NUAA, CASIA FASD, and Replay-attack. Maheswari et al., [16] presented local directional weighted threshold designs for feature abstraction to identify the facial appearance. Each pixel gradient magnitudes in four directions are calculated, then the gradient image and the original image are multiplied with weights to improve the features of the image. The technique was verified on the CK+ database and achieved well associated with another threshold approaches viz., LBP, LTP, etc. Kamarajugadda and Movva [17] proposed face recognition systems, to improve performance with a Feed-Forward Neural Network (FFNN)-based face identification system was developed. In a hierarchical series of layers, the CNN gives successively larger features. The LDA and LTP, techniques that capture both frequency and position information, are the feature extraction approaches used. For picture improvement, the characteristics are compressed using LDA, which allows for improved image sorting. The Modified-FNN approach is then used to perform the classification method.

Sparsh et al., [18] proposed a face recognition system that uses image improvement methods like bilateral filtering and histogram equalization to improve the excellence of the face image and leverages face identification and extraction from an image-based Single Shot Multibox Detector. The feature extraction method is Principal Component Analysis (PCA), and the classifier is LDA. Yu-Xuan He [19] proposed an image enrichment procedure for the face acknowledgment system. The Harr features are utilized to notice the face, and the eigenface technique is applied to get the characteristic face images. The face authentication system is recognized using image improvement approaches like histogram equalization, Retinex, and Median filtering. Feng and Shao [20] proposed a local-face appearance authentication system using migration learning and the Inception-v3 pre-training model. The image data was subjected to histogram equalization, ROF denoising, affine transformation, image rectification, and image preprocessing. The Inception-v3 model is used to extract characteristics from preprocessed data and then feed the recovered feature info into a novel classifier for classification.

3 Proposed Method

A systematic and technical basis for human recognition required for security in many sectors of our society has generated tremendous interest in biometrics. The proposed human recognition based on face images using MSB, MLTP, and ANN is shown in figure 1 for better recognition.

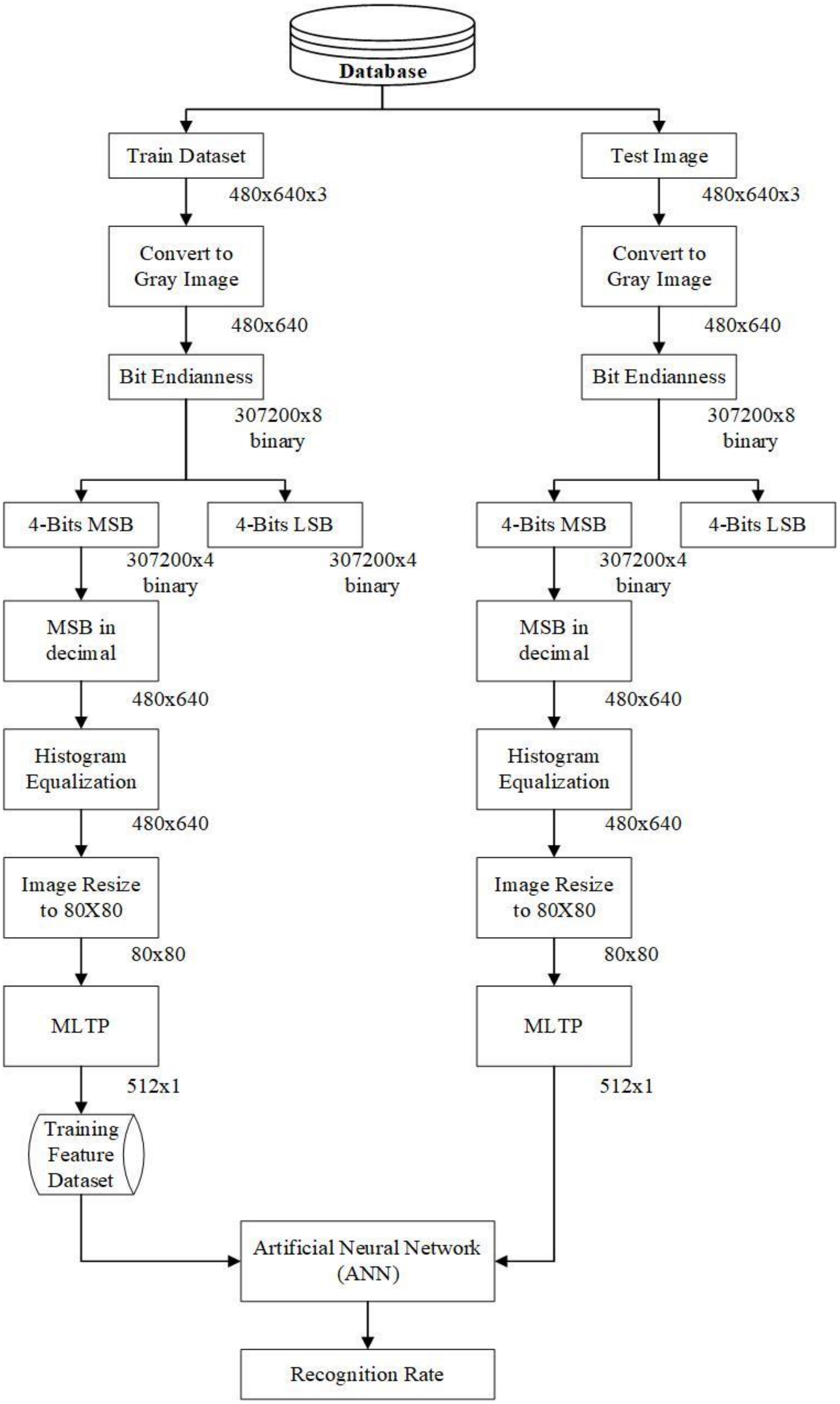


Figure 1. The projected model block diagram

3.1 Face databases

Six standard face datasets viz., ORL, JAFFE, YALE, Indian Females, and Indian Males are used, to validate the reliability and efficiency of the projected research model.

(i) Olivetti Research Laboratory (ORL) face database [21]

The database, which contains 400 photos for forty people and ten photographs per person, is commonly utilized in facial recognition research. Every image size of 112X92 in grayscale format, the face photographs feature a variety of poses and facial emotions. The ORL dataset sample face photos of six people are shown in Figure 2.

Figure 2. Samples of face images from six ORL dataset persons [21]

(ii) The Japanese Female Facial Expressions (JAFFE) [22]

The dataset, which consisted of 213 face images with 256X256 grayscale facial photos taken from ten people, was published in 1998. The collection included photos with facial appearances such as neutral, fear, shock, happiness, dissatisfaction, wrath, and contempt. The sample face photos of six people from the JAFFE dataset are shown in Figure 3.

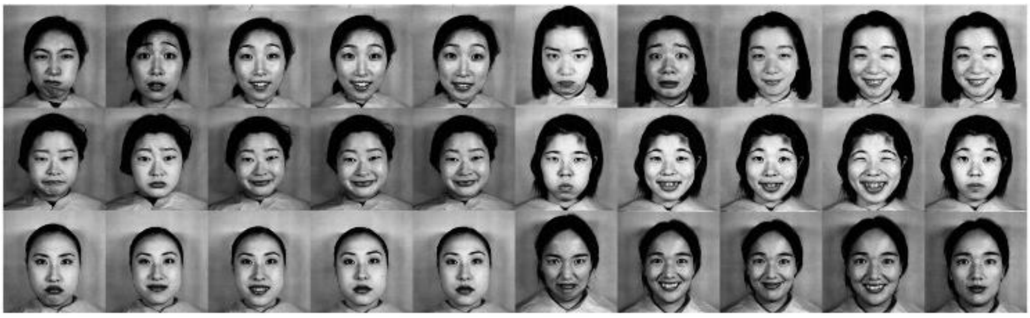


Figure 3. The JAFFE dataset samples of six subjects [22]

(iii)YALE face database [23]

Yale University provided the dataset in 1997, including 165 photos of fifteen people, each with eleven images of facial appearances and illumination. Every face image is 243X320 grayscale pixels in size. The facial image samples of six people from the YALE database are shown in Figure 4.

Figure 4. The YALE Face image dataset Sample of six persons of [23]

(v)The Indian Female Face Database [24]

A total of 242 photos from around 12 different images of each of 20 different people make up the Indian Female face dataset. Every image of a single person has a variety of facial orientations and expressions, including smiles, laughing, sadness, contempt, and neutral. The face image is 480X640 pixels in size. Figure 5 shows four sample face photos from the Indian Female dataset.

Figure 5. The Indian Female Dataset face images of four persons [24]

(vi)The Indian Male Face Database [24]

There are 220 photos in the Indian Male Face collection, with around eleven dissimilar images of 20 dissimilar persons. On the white background, each photograph of a single individual has multiple facial alignments and expressions, similar to the Indian Female face dataset. The face image is 480X640 pixels in size. Figure 6 shows the Indian Male dataset sample face images of four individuals.

Figure 6. The Indian Female Database face images of four persons [24]

3.2 Binary segmentation

The face images of dissimilar face datasets with diverse sizes are transformed into one uniform size of 480x640 and colour face images are converted into greyscale images. Each pixel decimal value is transformed into eight bits binary and is separated into four-bit Least

Significant Bits (LSB) and four-bit Most Significant Bits (MSB). It is realized that the corresponding decimal values of four-bit LSBs fluctuate between 0 and 15 with Equation 1 and are unimportant related to original image decimal values. The decimal corresponding values of four-bit MSB fluctuate between 0 and 240 via Equation 2 and are very important related to original image decimal values.

$$LSB\ Decimal = \sum_{n=1}^{4} x(n) \times (2^{n-1}) \tag{1}$$

where *x(n)* = The LSB binary values from right side

n = Bit positions

$$MSB\ Decimal = \sum_{n=5}^{8} x(n) \times (2^{n-1}) \tag{2}$$

where *x(n)* = The binary MSB values from right side

The demo of decimal changes for the split of LSB and MSB are shown in Figure 7. The MSB 4-bits and the equivalent decimal value is nearly similar as the original 8-bit decimal value with a very trivial change. The eight-bit binary pixel of the original image has 256 intensity levels, that arise to complications and inefficient processes in real-time systems. This drawback is eradicated via only four-bit MSB in the projected method and has only 16 intensity levels in place of 256 intensity levels. The benefit of this method is the necessity of memory is fewer and the computation speed is higher.

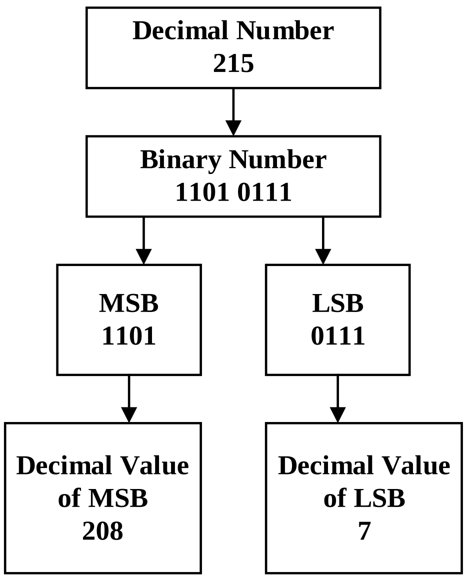


Figure 7. Segmentation

The original colour image is transformed into a greyscale image, and the segmented MSB and LSB images are shown in figure 8. It is noticed that the MSB image is nearly identical to the original image, however, the LSB image is a distorted one that can't be related to the original image.

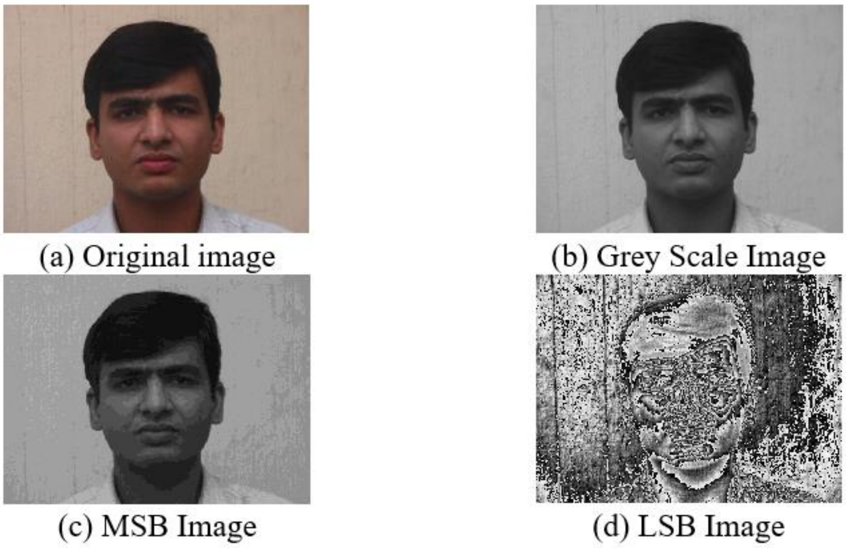


Figure 8. The MSB and LSB Images

The histogram equalization is applied on a 4-bit MSB image to adjust contrast and illumination variations as shown in Figure 9. The HE image is resized to 80x80 pixels.

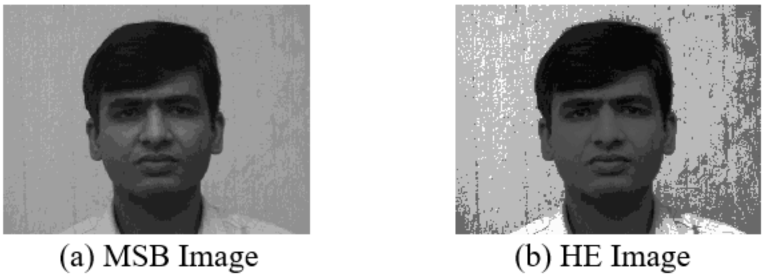


Figure 9. The Histogram Equalization on MSB Images

3.3 Modified Local Ternary Pattern (MLTP) [6]

It is the modified version of LTP, which is applied to an MSB image of size 80x80 to get effective features by setting zero threshold values in LTP. The three shades of binary values are obtained by comparing neighbour pixel intensity values with the center pixel intensity of the 3X3 block as given in Equation 3.

$$b_i(x_c, y_c) = \begin{cases} -1, & P_n < P_c \\ 0, & P_n = P_c \\ 1, & P_n > P_c \end{cases} \tag{3}$$

Where b_i (x_c, y_c) = Binary value of neighbor pixels.
P_n = value of neighbor pixel intensity.
P_c = value of center pixel intensity.

The binary b_i (x_c, y_c) is split into two segments viz., Left Side Pattern (LSP) and Right-Side Pattern (RSP). The negative binary values of the 3X3 matrix are considered positive binary values and positive binary values as zeros in LSP. The negative binary values of the 3X3 matrix are considered as zeros binary values and positive binary values as positive binary values in RSP. The binary values of LSP and RSP are transformed into decimal values and assigned to center pixel of 3X3 using Equation 4.

$$MLTP = \sum_{i=0}^{7} b_i(x_c, y_c)2^i \quad (4)$$

The computation of MLTP on 3X3 matrix is illustrated in Figure 10. The neighboring pixel intensity values are related with the centre pixel intensity value and converted into binary based on Equation3. The LSP is obtained by assigning zeros to 1's and 1's to -1's. The RSP is obtained by assigning zeros to -1's. The LSP and RSP binary values are converted into decimal values.

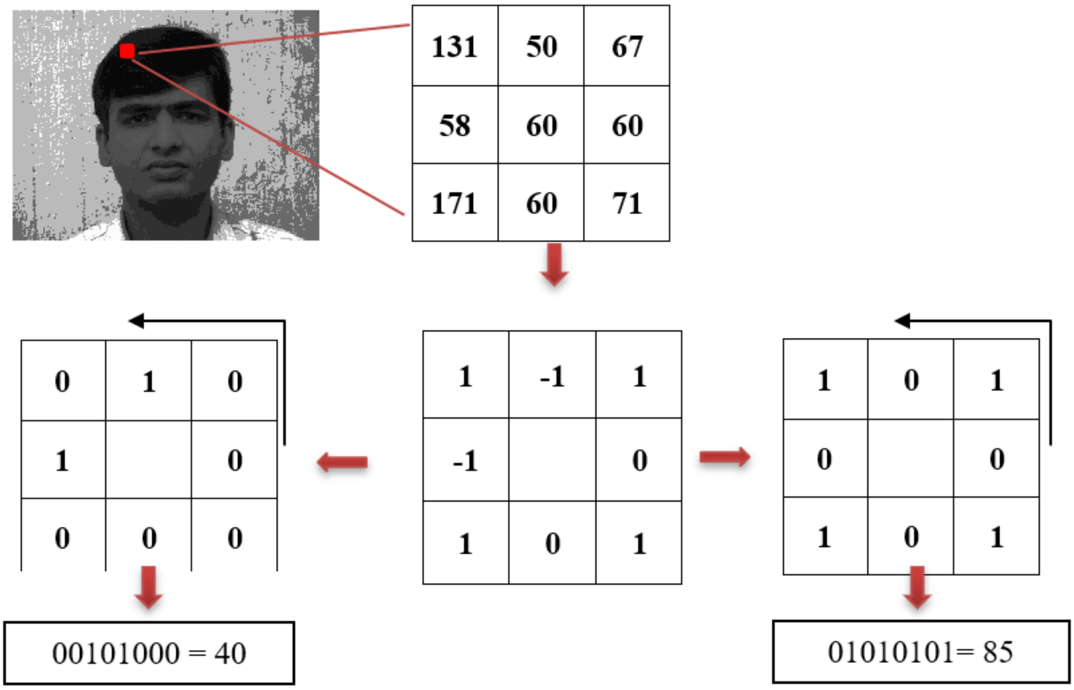
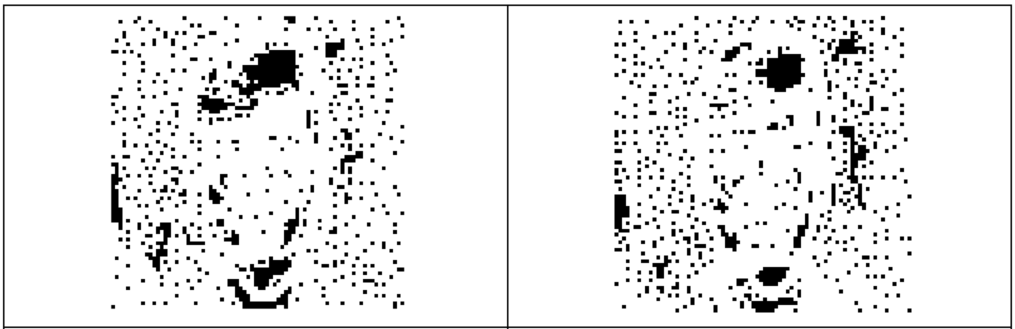


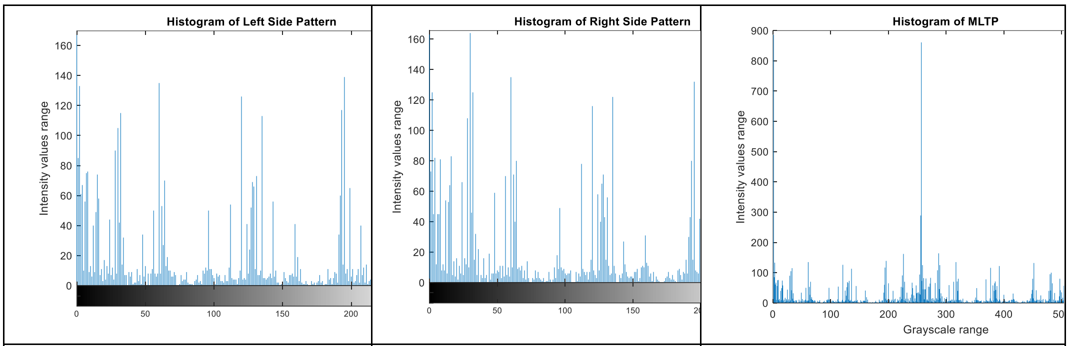
Figure 10. The illustration of MLTP



(a) LSP Image (b) RSP Image

Figure 11. The LSP and RSP image of MLTP

The images of size 80X80 are considered with pixel intensity values matrix and applied MLTP to convert into LSP and RSP as shown in Figure 11. It is noticed that the images are not clear compared to the original image but the coefficient values are effective in identifying human beings efficiently. Then, the histogram is applied to LSP and RSP to obtain histogram coefficients of length 1X256 as shown in Figure 12. The initial feature-length of LSP and RSP before using histograms is 78X78 = 6084. The histograms are applied on LSP and RSP to reduce the number of features of LSP and RSP from 6084 to 256 only. The concluding features are extracted by concatenation of LSP and RSP histogram features as shown in Figure 12c. The length of final features of the proposed method is only 512 coefficients for each face image in place of 6400 pixels, hence the computation time to compare test images with stored database images is less.



(a) Histogram on LSP	(b) Histogram on RSP	(c) Histogram of concatenation

Figure 12. Histograms of MLTP

3.4 ANN Classifier

It uses face photos and computational blocks accomplished by machine learning and pattern recognition to detect people. The input, hidden, and output layers are the three primary layers. The final features from trained images are accepted by the input layer, which feeds them to the network. This layer's number of neurons is equal to the number of final features, which is 512. The activity of each hidden unit is computed by the hidden layer. On one or more hidden layers, the input units' activities weights on the contacts between the input and hidden units. This layer can have as many levels as you want, and as many neurons as you want. This study uses a hidden layer for one hidden layer that combines 1 to 100 neurons to obtain the optimum model for classification performance. The output layer generates output units based on the hidden units' actions as well as the weights among the hidden and output units. The number of neurons in the output layer is equal to the number of classes and corresponds nodes in the output layer, in this case, are 40, 10, 15, 22, and 20, respectively, based on the number of people in the ORL, JAFFE, YALE, Indian Female, and Indian Male face databases.

4 Result Analysis

The proposed method's performance is verified with the help of the Percentage Recognition Rate (PRR) by a varying number of hidden nodes. From the table 1, it is detected that the ORL database obtains the maximum accuracy at 96% at a hidden nodes number equal to 54, the JAFFEE database obtains the highest accuracy at 99% at a hidden nodes number equal to 35 and 86, YALE database obtains the highest accuracy at 96.67% at a hidden nodes number equal to 28, 57 and 68, Indian Female database obtains the highest accuracy at 98.76% at a number of hidden nodes equal to 38 and Indian Male database obtains the highest accuracy at 98.5% at a number of hidden nodes equal to 42, 55 and 67.

Table 1. The PRR variations with the number of hidden nodes

Hidden Nodes	% PRR				
	ORL	JAFEE	YALE	Indian Female	Indian Male
1	7.75	25.50	28.00	18.18	19.00
5	67.50	92.00	91.33	93.80	92.00
10	91.75	97.00	95.33	95.04	73.50
15	93.25	95.50	93.33	94.21	96.00
20	93.00	97.00	96.00	95.45	98.00
25	93.00	96.50	94.00	95.87	95.50
30	93.75	94.00	96.00	93.80	97.00
35	93.25	99.00	92.67	95.04	96.50
40	92.50	98.00	92.67	94.63	95.50
45	95.25	96.00	93.33	94.63	96.00
50	95.75	96.00	96.00	95.04	95.50
55	94.25	93.50	94.00	96.28	98.50
60	94.75	97.50	93.33	97.93	96.50
65	93.25	97.00	92.67	96.69	97.50
70	94.00	97.00	92.67	97.52	97.00
75	93.75	96.00	92.00	95.87	96.50
80	93.75	98.00	96.00	96.28	95.50
85	93.25	96.00	92.67	95.04	96.00
90	92.25	97.50	94.00	96.69	96.00
95	95.50	95.50	94.67	96.69	96.00
100	93.50	98.00	94.00	97.93	95.50

The PRR variations with different hidden nodes numbers for face datasets viz., ORL, JAFFF, YALE, Indian Female and Indian Male are shown in figure 13. It is noticed that the values of PRR are low with a smaller number of hidden nodes. The PRR values increases with increase in initial number of hidden nodes up to 15 and attain maximum PRR values and almost constant up to 100 hidden nodes.

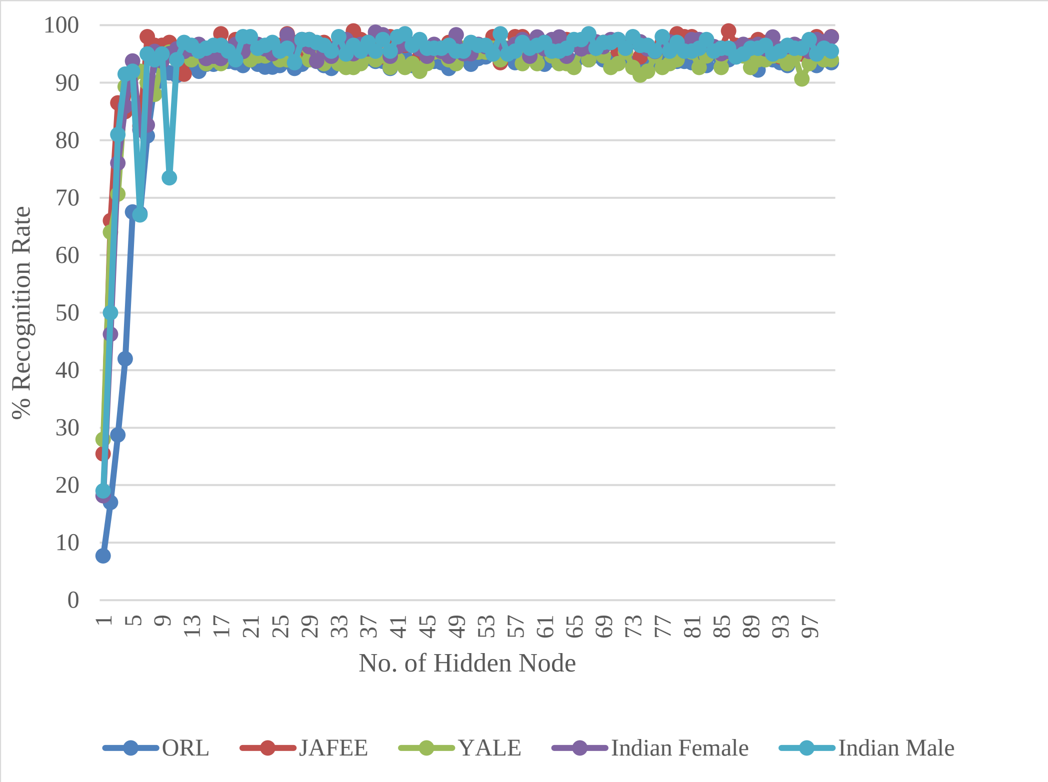


Figure 13. Variations of PRR with number of hidden nodes

The projected technique is related to the current approaches established by El Houssaine Hssayni and Mohamed Ettaouil [25], Hla Myat Maw et. al., [26] for the ORL face database. The JAFFE face dataset is used by Ibnu Utomo Wahyu Mulyono et. al., [27] and Kashif Fareed et. al., [28]. The YALE dataset is used by Ibnu Utomo Wahyu Mulyono et. al., [27] and Mohammed Ahmed Talab et. al., [29]

Table 2. The proposed method compared with existing methods for different face datasets

Databases	Authors	PRR
ORL	El Houssaine Hssayni and Mohamed Ettaouil [25]	81.23
	Hla Myat Maw et. al., [26]	91.6
	Proposed Method	96
JAFFE	Ibnu Utomo Wahyu Mulyono et. al., [27]	90
	Kashif Fareed et. al., [28]	97.99
	Proposed Method	99
YALE	Ibnu Utomo Wahyu Mulyono et. al., [27]	67
	Mohammed Ahmed Talab et. al., [29]	95.30
	Proposed Method	96.67

5. Conclusion

Human recognition is a crucial common faith for the proper functioning of society by identifying fellow humans based on biometrics for decades. In this paper, Spatial Domain-based Face Recognition using MSB and MLTP with ANN Classifier is proposed. The benchmarked face datasets are considered to verify the projected method, and the color images are transformed into greyscale images with uniform image sizes. The pixel binary is segmented into two groups MSB and LSB with 4 bits each. The significant information is available only in MSBs hence, these are considered for further processing leading to a smaller number of binary bits. The MSB four bits are converted to decimal values having only 16 intensity levels, and HE is used to enhancing the contrast level of 4-bit MSB images and resize them. The MLTP is used on an image to extract effective features. The ANN classifier is considered to distinguish individuals. The results of the planned method are improved than the current methods.

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