International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-10, August 2019

An Integrated Technique for Face Sketch Recognition Using DCNN

Shivaleela. Patil, Shubhangi.DC

Abstract- Face Recognition (FR) is considered as one of the chief use in the investigation of criminals. In the majority of the cases, information about the criminal is not available. In such situations, sketch artist draw the sketch of the guess with the oral explanation provided by the eyewitness. These sketches can then be matched manually against mug shot photos. This process is time-consuming. Hence there require a method that efficiently goes with composite sketches to the gallery of mug shot databases. Thus the proposed system uses a scheme for matching composite sketch and photo images, photo image features are extracted and fused to train the system. Composite Sketch feature is matched with face photo images. Feature extraction (FE) is done using Multi-Scale Local Binary Patterns (MLBP) Tchebichef Moments and Multiscale Circular Weber Local Descriptor (MCWLD), Principal Component Analysis (PCA) is used for fusion of extracted features, DCNN used as a classifier to recognize the face. The experiments are conducted using PRIP-HDC dataset and the proposed system gives good accuracy in face recognition.

Keywords- Composite Sketch, MCWLD, Tchebichef Moments and MLBP and Tchebichef Moments and DCNN Classifier, Knowledge Base (KB)

I.INTRODUCTION

FR has been one of the most attractive and significant research fields in the past two decades. FR is also considered as an important application in catching various types of criminals. If the suspect's facial photograph is on hand, then the criminals are identified easily. But in most of the situations, all these images are not available in a mug shot. In such situations, the suspect sketch is drawn based on the oral illustration provided by the eye witness. As the sketch based on the style of artists, it is not possible for an artist to present a feature of victims perfectly. FR was conducted manually and accuracy depends on the expert level of humans. Normal face recognition and original images differ in shadow, texture, and shape therefore, it is very complicated to match accurately. The handwritten sketch is sent to law enforcement and media outlets. Matching facial composites to mug shot allows faster identification of suspects. Composite sketches are commonly used to recognize the victims, whereas a forensic sketch needs a well-trained artist for drawing and sculpting. As per the survey is given in 80% of law enforcement uses composite sketches. It has become a popular substitute for illegal justice and other agency of law enforcement. A small number of extensively used software kits to produced computerized sketches contains IdentiKit, Mac-a-Mug, and FACES. This software allows synthesizing sketches by selecting a sketch by choosing a set of facial component, examples of eye, hair, eyebrow, mouth, shape, nose, and eyeglass [12].CS created by viewing the mug shot will not be much useful in criminal investigations. Surveillance composites can also be created by viewing the image of the mug-shot these images are of having low quality.

. In our research, we choose hand-drawn composite sketches [22] shaped by forensic artists. Matching these CS to photographs is a not simple task because the sketches are drawn based on the eyewitness report, much law enforcement organization uses facial composite sketches, which permit the user to build Composite Sketches (CS).

The proposed system has presented a CS face reorganization based on photo image. The system is trained using photo images, FE by each facial component and the FE points are fused and trained to the system. The knowledge base is created using the extracted features of each facial component. The CS face is recognized using the features stored in the knowledge base. DCNN used as a classifier

II.LITERATURE SURVEY

Mohammad Reza Faraji et.al [01] has proposed a face recognition system against lighting variations. This system presented a technique related to the logging purpose and fractal analysis to generate an LFD picture which will not be changed due to variation in illumination. The proposed Fractal Analysis component related technique is an extremely successful edge enhancer method to remove and improve facial features such as nose, eyebrows, eyes, and mouth. System extensive experiment depicted that the proposed manner performs the best identification accuracy using when compared to six lately proposed states of art techniques. Xuelong Li et.al [02] has proposed an efficient approach for a sketch photo fusion. Sketch-photo fusion plays a major role in act enforcement and digital entrainment. Only utilizes pixel intensities as a feature in most of the existing techniques face images represented by a number of attributes, this paper presented a novel multiple representations related face sketch-photo synthesis technique which will adaptively combine these multiple representations to represent as a patch of the image.

Shutao Li et.al [03] has proposed a technique for the reorganisation of the face using multi-scale WLD and multi-level data fusion approach. The experimental result shows good accuracy in recognition. This system introduces the WLD, a novel, and efficient local descriptor to illustrate the facial pictures and uses a non-linear quantization approach to improve its discriminative power. Result of the experiment shows the effectiveness of the proposed technique on three standard datasets.

Manuscript published on 30 August 2019.
*****Correspondence Author(s)
Shivaleela. Patil, Department of Computer Science and Engineering Godutai Engineering College for Women, Kalaburgi, India.
Dr. Shubhangi.DC, Department of Computer Science and Engineering VTU Regional Centre, Kalaburgi, India.

Jiwen Lu et.al [04] has proposed a new joint feature learning method to automatically learn feature depicted from raw pixels for face identification. Many existing face identification system used

feature descriptors such as LBP and Gabor features for representing the face. They have proposed an unsupervised feature learning technique to train hierarchical feature representation. Experimental results conducted on five extensively used face dataset and give a good performance.

Yonggang Qi et.al [05] has proposed an automatic sketch creation approach. Substitute for gathering insight from the photograph, forth first time: they have extracted data from a large pool of person sketches. Further, illustrated that by resolving the problem of gestalt confliction of encoding relative data of each rule, more identical to sketches drawn by human were generated. Since they had released a manually labeled sketch data set of 96 object classified and 7680 sketches.

Jin Zhou et.al [06] has presented a technique for generating an automatic pencil sketch drawings from photos. They have also proposed a gradient estimation technique, which could serve the purpose superiorly than the conventional techniques. Experimental results depicted that the proposed techniques can be used for face images as well as another kind of images.

Hu Han et.al [07] has presented a component-based illustration method to detect the resemblance between a CS and a mug shot. Specifically, they have automatically detected facial landmarks in CS and face photos using an active shape model (ASM). Features are then extracted from all facial components using MLBPs and to every component resemblance is determined

Nannan Wang et.al [08] has presented that there are usually two drawbacks for most obtainable heterogeneous image transformation techniques: (1) the nearest neighbor is constant which incurs blur effect (2) some significant details data loses due to an average of overlapping areas. They correspondingly proposed two techniques to overcome or enhance these two defects; SFS and SVR based image improvement.

Nannan Wang et.al [10] has presented an efficient transductive photo sketch synthesis technique. They first build a probabilistic framework to create the sketch-photo. Then provide a different optimization technique to overcome the proposed problems. The tests are done on CUHK face sketch dataset illustrating the performance of this approach by comparing it with representative inductive learning-based face sketch-photo synthesis procedure.

From the above survey, it is concluded that many papers have been published to overcome variation parameters and to increase performs for better recognition rate, but still, the system is lagging to achieve better accuracy in recognition rate. Hence we proposed a system to over the addressed problem and get better accuracy.

The paper organization is as follows: section II explains Literature Survey, section III explains Methodology, section IV explains Experimental Results and section V explains Conclusion.

III.METHODOLOGY

In figure 1 shows the proposed system. It includes two phases of testing and the training Phase. In the training phase, the knowledge base (KB) is created by considering normal image features. Normalization and gamma correction techniques are used to the images to maximize the visual effect of the image. FE algorithms are applied to collect the respective features of each image, FE is trained using DCNN and the KB is created.

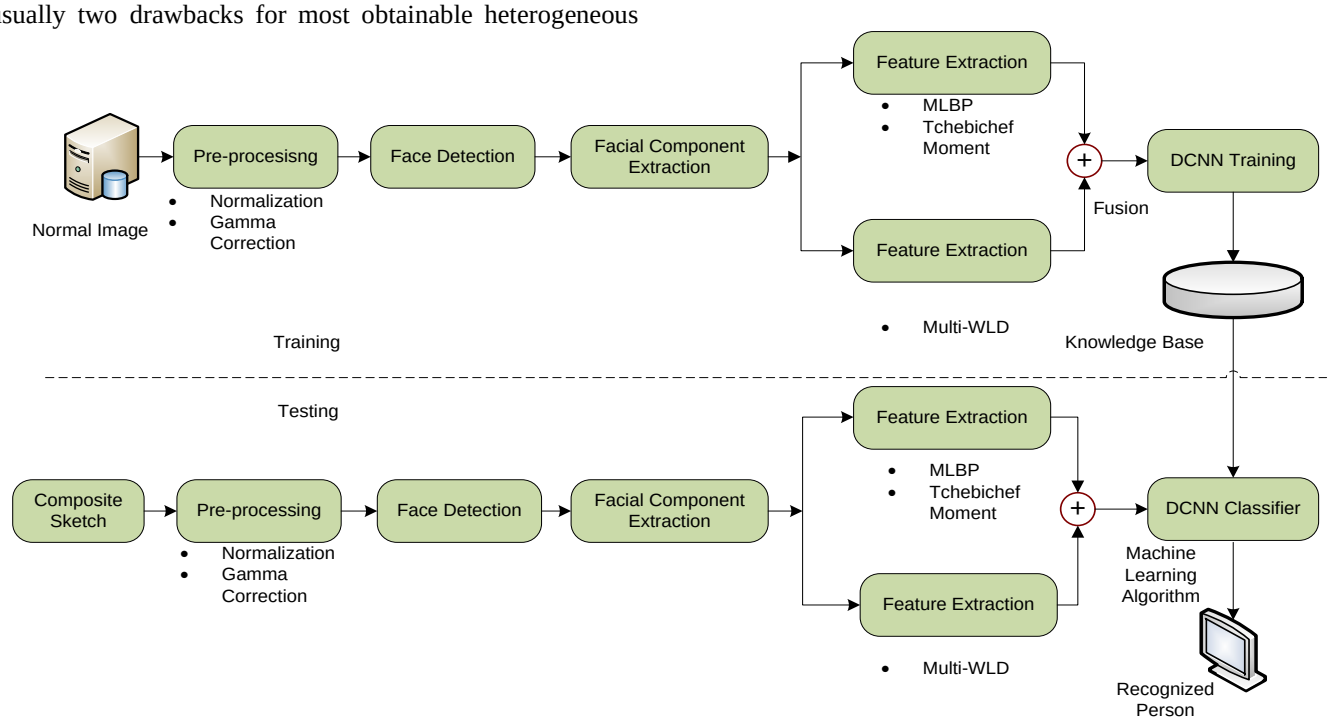


Figure 1: Architecture of a Proposed System

In the testing phase, CS is considered as an input to create a database. The composite images are pre-processed; gamma correction and normalization are the pre-processing applied to the input images. After pre-processing face detection and extracting the facial components of the query image is carried out. MLBP,

Tchebichef moments and Multi-CWLD are the FE algorithms are used to get all the possible features from the facial components of the image. DCNN is used as a classifier.

3.1 Pre-Processing

Pre-processing is the initial step when we are dealing with images, in FR system normalization and gamma correction are the two pre-processing steps carried out. The pre-processing step increases robustness and results of the system by increasing discriminative information contained in the image.

Normalization

Normalization is a technique to make an altar in the pixel value to adjust the dynamic range of gray level of the image.

Gamma correction

Gamma Correction is a nonlinear gray-level transformation that replaces gray-level I with $I\gamma$ (for $\gamma > 0$) or $\log(I)$ (for $\gamma = 0$), where $\gamma \in [0,1]$ is a user-defined factor. It enhances the dynamic range of the image while compressing it.

3.2 Face Detection (FD) and Facial Components Extraction

AdaBoost is an algorithm used to FD in a pre-processed image as shown in figure 2. Typically AdaBoost is an algorithm for constructing a strong classifier as a linear combination of weak classifier$h_t(X)$. The $h_t(X)$ can be thought of as one feature.

(a) Input Image **(b) Face Detection**

Figure 2: Face Detection

An image $(X_1, Y_1), \ldots\ldots, (X_L, Y_L)$, where $y_i \in \{1,0\}$ indicates positive or negative examples $g_j(X_i)$ is the jth Haar-Like features of ith example X_i

- Initialize weights

$$w_{i,j} = \begin{cases} 0.5/m & i \le m \\ 0.5/n & otherwise \end{cases} \quad (1)$$

Where m, n denotes the number of positive or negative examples respectively $L = m + n$.

- For t=1,…., T

Normalize the weights

$$W_{t,i} = W_{i,t} / \sum_{j=1}^{L} W_{t,j} \quad (2)$$

For each feature J, train a weak classifier h_j, and evaluate its error ϵ_j with respect to W_t

$$\epsilon_j = \sum_{i=1}^{L} W_{t,i} |h_j(x_i) - y_i| \quad (3)$$

$$h_j(x) = \begin{cases} 1 & p_j g_j(x) < p_j \theta_j, \\ 0 & otherwise \end{cases} \quad (4)$$

Where $p_j \in \{1, -1\}$ is a parity bit and θ_j is a threshold.

Choose the classifier h_t with the lowest error ϵ_t

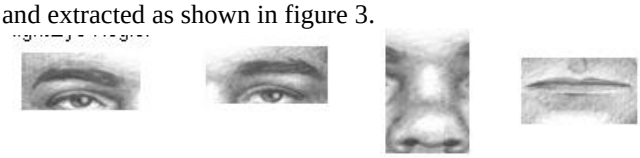
Update the weights $W_{t+1,i} = W_{t,i}\beta_t^{1-ei}$, where $ei = 0$ if the example x_i is classified correctly, $ei = 1$ otherwise and $\beta_t = \epsilon_t / (1 - \epsilon_t)$

- Final classifier

$$H(x) = \left\{ \begin{matrix} 1 \\ 0 \end{matrix} \sum_{t=1}^{T} a_t h_t(x) \ge 0.5 \sum_{t=1}^{T} a_t \right\} \quad (5)$$

Where $\alpha_t = \log\left(\frac{1}{\beta_t}\right)$

Once the FD is done, all facial components are detected and extracted as shown in figure 3.



(a)Left Eye Region (b)Right Eye Region (c)Nose Region (d)Mouth Region

Figure 3: Facial Components Extraction

3.3 Feature Extraction (FE)

FE is done using M-WLD, Chebyshev moment and MLBP method, which effectively enhance the edge using the edge enhancer method to extract facial components. Summarizing local gray level structure is called LBPs. LBP method gives effective result against pose and illumination variation. It considered surrounding pixels, thresholds the surrounding pixels by taking the value of the central pixels. The result is a binary value or decimal value. Then the histogram of each image patch is used as a local descriptor.

LBP is basically described for 3*3 neighbor pixels, which then gives 8-bit integer value. The extension version of LBP is MLBP, which gives more complete image information then LBP. In some cases facial datasets, it needs enhanced facial features classification for good performance. By using MLBP, performance is improved.

3.2.1. FE using MLBP

The pre-processed image is processed with the FE. Facial FE has done using MLBP as shown in figure 4. MLBP is the combination of LBP descriptors with different radii.

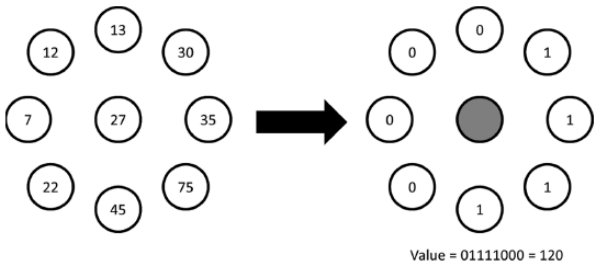


Figure 4: MLBP Working

Facial components extracted are divided into a region of $d * d$ pixels overlapping by m pixels. Within each region, a histogram of LBP is derived from components at each pixel. The LBP value V, calculated at a very pixel is computed using comparisons to P neighboring sample points at a radius of length R.

$$V_{PR} = \sum_{P=0}^{P-1} s(g_p - g_c) 2^p \quad (6)$$

Where g_p symbolize the gray value at each of the P surrounding pixels, g_c stand for the gray value at the center and $s(x) = 1 \text{if } x \geq 0 \text{ and } 0$, otherwise. The selection of parameters is tuned to each component. All facial components use the radii combination $r = 1$ and $r = 3$ and employ uniform binary patterns. Figure 6 shows the flow chart of MLBP.

3.2.2. FE using Tchebichef Moments

The kernel $r_{pq}(x, y)$ denoted as a filter for computation of T_{pq}. The extent of T_{pq} will be better for oscillating images at the comparative rate to r_{pq} (x, y) along with the two directions. It is a facial property for texture examination since the surface contains the spatial reiteration of force designs. Consequently, demonstrates a surface asset can be obtained by estimation of the dependence present apart from everything else size on the request, which is recognized with the recurrence substance of pieces. For this reason, the accompanying component vector M(s) $(s = 1 \ldots 2N - 2)$ is proposed defined as Eq. (7):

$$M(S) = \sum_{p+q=s} |T_{pq}| \quad (7)$$

The component M(s) gives information about the property of texture and can be seen as a face mask. To compute the particular characteristic caught by M(s), the conduct of Tchebichef pieces in both spatial and frequency domains is studied. The total features extracted from each sample is 50.

3.2.3. FE using MCWLD

Each facial components are given to FE, MCWLD is one of the FE technique is used to extract features. MCWLD includes of two main components

1. Differential Excitation (DE)
2. Gradient Orientation (GO)

Algorithm 1: MCWLD

Input: *Facial Components*

Output: *the MCWLD feature vector H.*

Step 1. The 2D histogram $CWLD(\varepsilon\_j, \theta\_t)$ is encoded into 1D histograms. DE, ε are grouped into T orientation sub histograms, $H(t)$, where $t = 0,1,\ldots\ldots,T-1$ corresponds to each dominant orientation.

Step 2. Within each dominant orientation, the range of differential excitation is evenly divided into M intervals and then reorganized into a histogram matrix. Each orientation sub histogram in $H(t)$ is thus divided into segments M, $H_{m,t}$ where $m = 0,1,\ldots\ldots,M-1$ and $M = 6$. For all DE interval l_m, lower bound is computed as $\mu_{m,1} = ({}^{m}/_{M-1}/2)\pi$ and upper bound $\mu_{m,u} = \left[{}^{(m+1)}/_{M-1}/_{2}\right]\pi$ (10)

Each sub histogram $H_{m,t}$ is further composed of S bins and is represented as:

$$H_{m,t} = h_{m,t,s}$$

Where s=0,1,.....,S-1, S=3 and $h_{m,,t,s}$ is represented as

$$\sum_j \sigma(S_j == s), \left(S_j = \left[\frac{\epsilon_j - \mu_{m,l}}{(\mu_{m,n} - \mu_{m,l})/_S} + \frac{1}{2}\right]\right) \quad (11)$$

Here $j = 0,1,\ldots\ldots,N-1$, m is interval to which DE ϵ_j belongs that is $\epsilon_j \in l_m$, t is the index of quantized orientation and $\sigma(.)$ is defined as below

$$\sigma(.) = \begin{cases} 1 & if\ function\ is\ true \\ 0 & otherwise \end{cases} \quad (12)$$

Step 3. Sub histogram segmentation, $H_{m,t}$

Step 4. M sub histograms are concatenated into a single histogram thus representing the final $6 * 8 * 3\ (M * T * S)$ circular WLD histogram. The range of DE is segmented into separate intervals to account for the variations in a given face image and assigning optimal weights to these H_m segments further improve the performance of CLWD descriptor.

End algorithm.

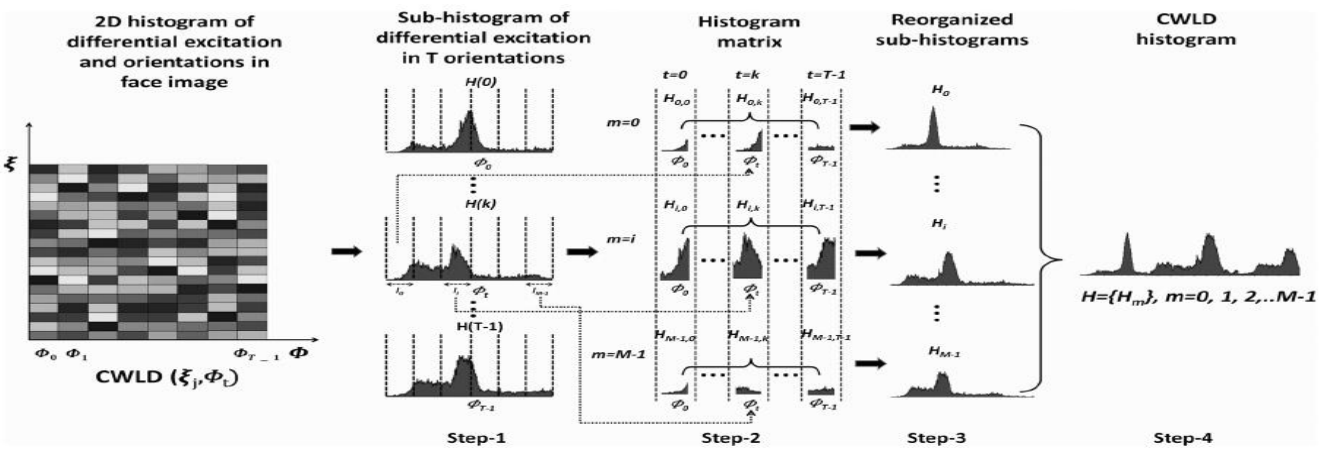


Figure 5: Describes the Steps of MCWLD

All the extracted features are fused using the PCA method. PCA is one of the mathematical procedures used to convert a set of correlated N variables into a set of uncorrelated k variables called principal components. The number of principal components will be less than or equal to a number of original values i.e., $K < N$.

3.4 DCNN Classifier

The number of layer and filters are more DCNN. It increases the performance of the system. Neural networks are used in many numbers of application. Face recognition is one of the application. a significant amount of training data is needed to reduce over-fitting consequence. The trained network enables faster convergence, decrease the probability of finding poor local minima and leverages the regularisation effect that enables better generalization. The work in this paper also benefits from transfer learning by using the original photo images and composite images to fine-tune the that was trained with 30 face images. It was designed for recognition of faces as done in this work, the face photos used for training represent one of the modalities used in the task of face photo composite sketch recognition.

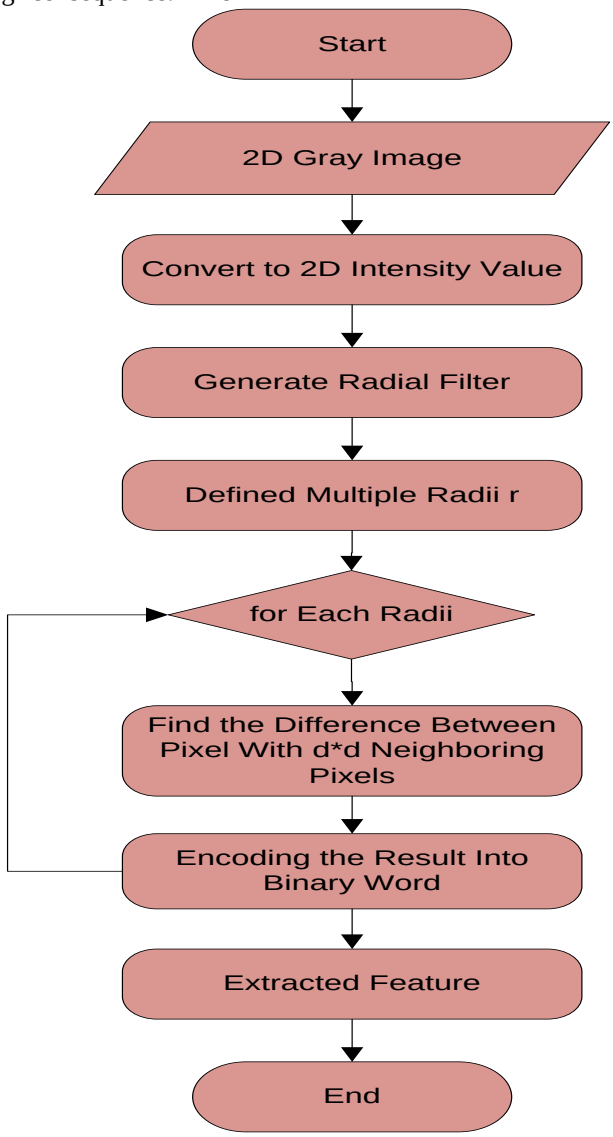


Figure 6: Flow Chart of MLBP

IV.EXPERIMENTAL RESULTS

The system has presented an integrated approach to face recognition using DCNN classifier. It consists of two stages, training and testing phase. In the training phase, normal images are used. These photo images are trained and stored in the knowledge base. In testing phase composite sketch is taken as the input image, which is matching to the photo images by using DCNN classifier. PRIP Composite (PRIP-HDC) database used in the paper contains 47 composites sketch. Out of which 35 samples are taken for training.

Figure 7(a) shows photo images considered to train the system. Figure 7(b) composite sketch taken as a query image from the dataset. Figure 7(c) and (d) shows the face detection and components are detected, from the detected face facial components are extracted as shown in figure 8.

The amount of precision of a quantity is called accuracy which is given by the formula,

$$ACC = \frac{T_P + T_N}{P + N} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (13)$$

Precision is nothing but scientific or mechanical exactness which is given by,

$$PPV = \frac{T_P}{T_P + F_P} \quad (14)$$

Sensitivity, True positive rate and Recall rate is given by,

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN} \quad (15)$$

Sensitivity is a degree of responsiveness or awareness of external or internal changes.

Table 1: Confusion Matrix

N = 35	Predicted No	Predicted Yes	
NO	TN = 4	FP = 1	5
Yes	FN = 0	TP = 30	30
	4	31	

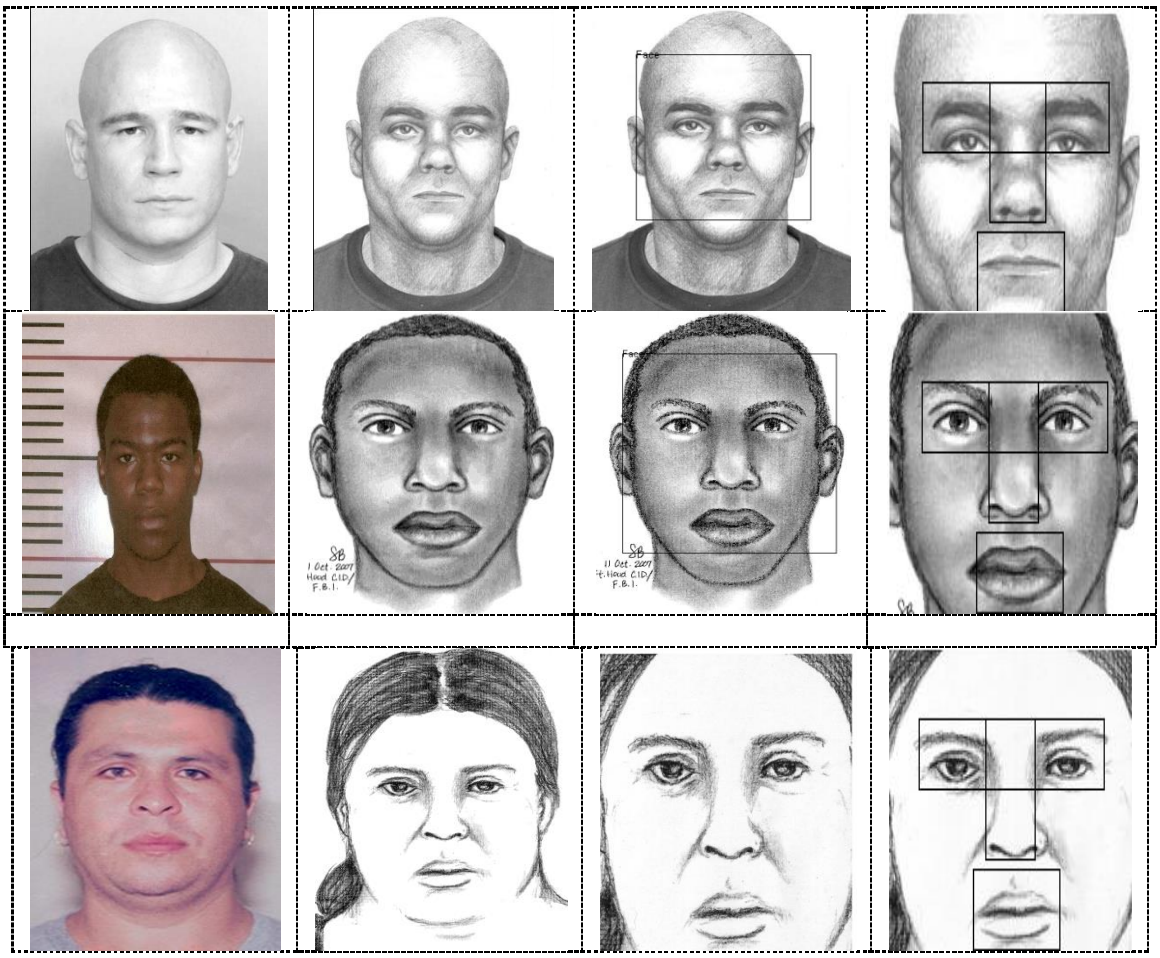
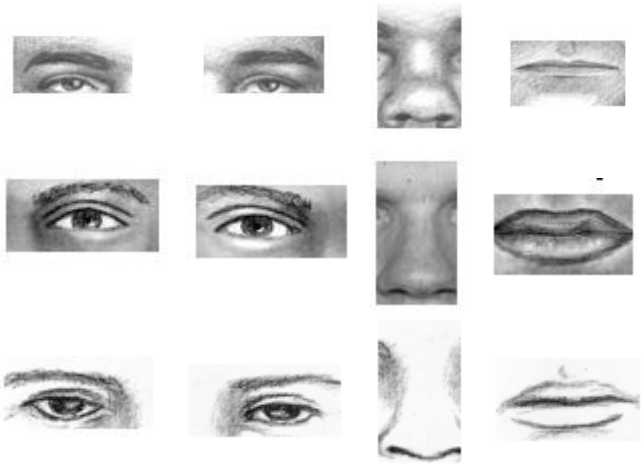


Figure 7: (a) Input photo Image; (b) Composite Sketch (c) Face Detection; (d) Facial Components Detection



Left Eye Region | Right Eye Region | Nose Region | Mouth Region

Figure 8: Facial Components Extraction

Table 2: Accuracy Comparison of Existing and Proposed Model

S.NO	Author Name	Feature Extraction	Classifier	Accuracy
01	Jing Wang et.al [19]	MLBP	ASRC	94.71%
02	Jiwen Lu et.al [03]	MLBP and Gabour feature	SVM	89.4%
03	Amit R. et.al [13]	Gabor feature and geometric feature	Artificial Neural Network	92.7%

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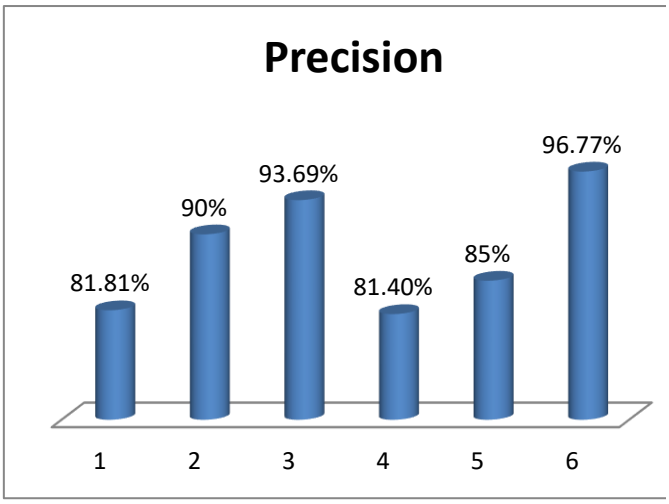
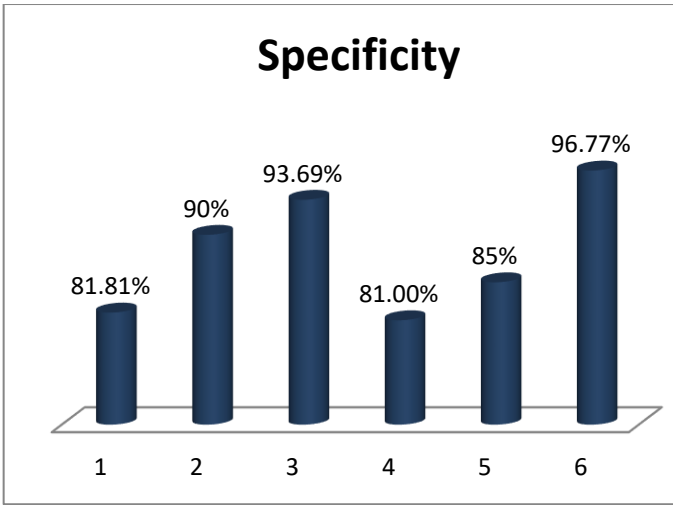
04	Mehal K et.al [07]	LBP	Haar feature	87.0%
05	Amirhosein et.al [14]	Geometric feature	K-Nearest neighbor	91.0%
06	Proposed model	MLBP, Tchebichef, and Multi-Weber local descriptor	DCNN	97%

Table 2 shows the accuracy comparison of the existing and proposed system. Table 3 shows the comparison Table 3 and Figure 9 proposed and existing systems precision, specificity, Recall, and sensitivity, it helps to find the quality, condition, or fact of being exact and accurate.

Table 3: Comparison Table for Proposed and Existing Systems for Precision, Specificity, Recall and Sensitivity

S.NO	Author Name	Methods	Precision	Specificity	Recall	Sensitivity
01	Vinay A et.al [16]	SIFT+ EOH	81.81%	81.81%	89.98%	89.98%
02	Shruthi et.al [18]	Gabor features+PCA	90%	90%	92.2%	92.2%
03	Amit R et.al [14]	Gabor feature and geometric feature+ANN	93.69%	93.69%	95%	95%
04	Mohan M et.al[20]	HOG +SVM	81.4%	81.%	77.8%	77.8%
05	Yuanyan et.al[15]	AROP	85%	85%	91.65%	91.65%
06	Proposed model	MLBP, Tchebichef and Multi-WLD+ DCNN	96.77%	96.77%	100%	100%





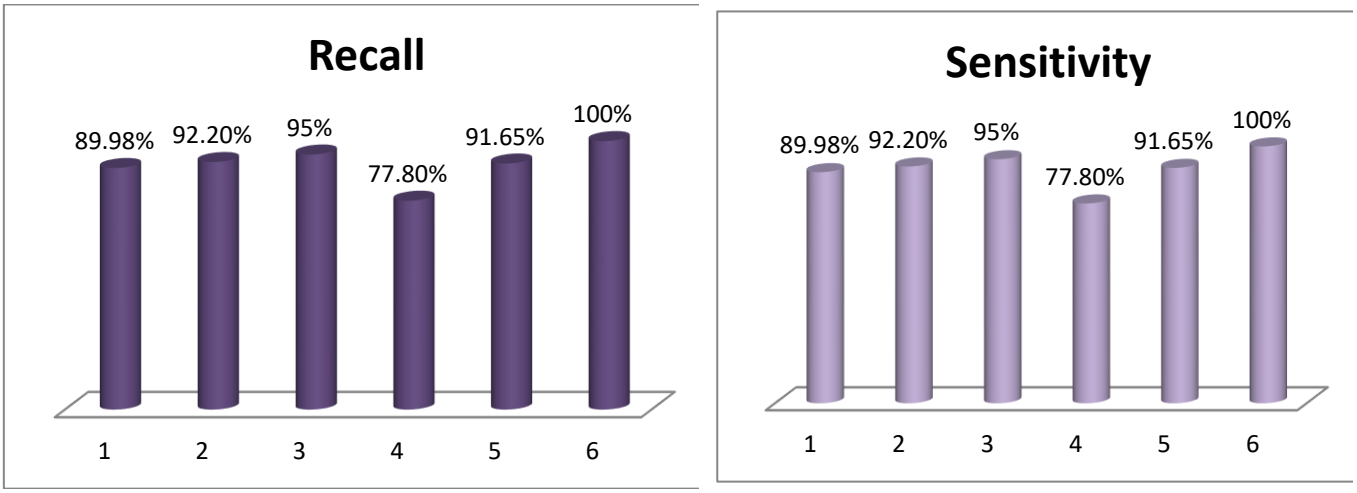


Figure 9: Performance Graph

V.CONCLUSION

This paper proposes an automated system for face identification using texture features extraction approach like MLBP, Tchebichef moment and MCWLD. Our proposed scheme mainly consists of a two-phase called training phase and testing phase, both training and testing include five modules, Pre-processing, Face detection, Facial components extraction, FE and DCNN classifier. The experimental results explained that the proposed method is effective. Experiments are conducted on 35 composite images of PRIP Viewed (PRIP-HDC) database. The model used multiple feature extraction methods to reduce complexities and increase accuracy. In order to increase classification performance, DCNN classifier is used. The proposed algorithm is evaluated on PRIP-HDC dataset resulting inaccuracy of 97%.

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