

Novel Face Recognition Framework for Plastic Surgery and Unconstrained Facial Datasets



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Abstract: Since from the last decade, the importance of efficient and robust face recognition becomes interesting research problem due to its growing demand in user authentication process across different applications. Several face recognition method designed by considering the challenges of constrained and unconstrained face acquisition. The performance of face recognition systems becomes worst while working with unconstrained and plastic surgery datasets. The unconstrained dataset may contain the significant variations in illumination, expressions, and face image quality. This paper proposed the novel face recognition framework which is built on top of hybrid face descriptor and hybrid features extraction technique. The purpose of hybrid face descriptor is to achieve the bridge the gap between spatial information and histogram representations to address the challenges of unconstrained face conditions efficiently. The hybrid features extraction includes the histogram features (single and multi-level) and invariant features. Since the moment invariant features become effective shape descriptor to address the challenges of unconstrained face images, we proposed 11 different invariant moments from the hybrid face descriptor. To normalize and reduce the features, we applied lightweight features selection technique. The experimental result shows that proposed face recognition framework improves the overall accuracy different datasets.

Index Terms: Face recognition, face descriptor, dual cross pattern, moment invariant features, histogram features, features selection, classification

I. INTRODUCTION

In brilliant universal figuring condition, computers are connecting with us progressively like people. They can perceive our faces, voices and even our looks, however under controlled conditions in the at this time technology. To accomplish these, there is a solid requirement for easy to use systems that can verify our benefits and ensure our security without losing our character. At present, one needs a PIN (personal identification number) to get money from an ATM, a secret key for a computer, twelve others to get to the internet, etc. Since such systems are helpless against imitation, burglary, and slips by in clients' recollections;

biometric distinguishing proof systems, which use pattern acknowledgment techniques to recognize individuals by their physiological attributes, are drawing in significant intrigue [1]. Pattern recognition is a basic characteristic of all living organisms. The process of recognition may vary from creature to creature. Using the perception ability, humans are able to effortlessly and instantaneously recognize objects among thousands of that stored in their memory. The object inspected by the recognition process is also called pattern which is a description of the object that is required to be recognized [2]. In this paper we focus on robust human face recognition in which the face images are digitized in 2D spatial pattern form and under the different illuminations, shapes, expressions, variations.

Different types of face recognition systems designed and evaluated in literature. The graph-based methods [2]-[6] are the best example of such methods in which different facial components used to design and process the face representations. The neighbourhood global chart strategy [2]-[4] is moreover the vast system which depends on Delaunay diagrams and Voronoi decoration to isolate nearby highlights and build a layout for confronting acknowledgment. Such highlights are joined with neighbourhood diagram, and afterward, technique builds the worldwide chart by inter relating all the nearby charts to speak to the face topology. The facial highlights facilitate altogether utilized for the outward appearance acknowledgment. Be that as it may, the issues with geometric element based procedures is that they mostly require dependable and exact face following and highlight recognition which is exceptionally difficult to accomplish under the uncontrolled and extensive variety of fluctuating conditions. The appearance-based methods [7], [8] are based on the design of image filters either the complete face or particular face area to appearance variations in face images. The full face based image filters used to build the holistic features and the specific face area based image filters used to build local highlights. The appearance-based method's execution is satisfactory and acceptable under the controlled environment, however, the same methods performing poor under environmental variations [9].

In literature we studied different types of face descriptors under the different categories such as Local Binary Pattern (LBP) [10], Gabor wavelet [11], Learning based face descriptor LE [12], Local Quantized Patterns (LQP) [13], and Discriminant Face Descriptor (DFD) [14] etc. However such face descriptors failed to address the challenges related to the unconstrained face recognition environment.

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The local directional number (LDN) [15] pattern, Multi-directional-Multi-Level Dual Cross Pattern (MDML-DCPs) [16] etc. are recently introduced techniques based on supervised or unsupervised classification algorithms to optimize the face recognition performance under the unconstrained environment such as pose, expressions, and illumination variations. However low-quality face images, plastic surgery, face occlusions etc. are still research problems for robust face recognition systems. There are certain pitfalls needs to consider for face recognition methods regardless of the effective use of existing face picture descriptors such as (1) in design of previous face descriptors, the texture features of face images mostly overlooked, (2) scalability in sampling size and feature vector size is another point to consider as the larger the size better the results, (3) recent methods are having good performance but processing time is more, (4) the histogram features not enough to address the face descriptors variations. To alleviate such problems, this paper presents hybrid face descriptor along with hybrid features extraction overcomes the robust face recognition under different conditions as it preserves all the unique properties. The hybrid face descriptor designed on top of recent face descriptors such as LDN and MDML-DCPs to connect the semantic hole between the face picture histogram description and spatial information in robust way. Therefore, the hybrid face descriptor not only preserves the histogram representations, but also spatial information generated for face image. The face code generated by hybrid face descriptor is further utilized for the computation of hybrid features extraction consist of histogram and moment invariant features. Different levels of histogram features extracted. As the name indicates, the moment invariants extract the invariants of several transformations from the input face image to address the challenges related to the plastic surgery and unconstrained facial images. On the other side, the geometric features mainly encode the shapes and locations of various face components, and then fused into face feature vector to represent the face in unique way which assists to improve the accuracy for unconstrained and plastic facial datasets. The generated features contains irrelevant features and may leads to incorrect recognition, we additionally proposed correlation weight method (CWM) based on the mathematical terms to select the most unique and relevant features for the classification process. The classification and recognition is performed by using the feed forward neural network (FFNN). In section II, we present the brief review of various face recognition methods. In area III, the design of proposed methodology presented. In area IV, the simulation results are introduced. In area V, end and future work discussed.

II. RELATED WORK

There number of conventional methods introduced for the face recognition, this section presents the brief review of recent face recognition techniques related to proposed approach. First the work reported recently on face recognition is reviewed and then use of moment invariants in different image processing applications reviewed.

A. Face recognition methods

The DCP based method to address the problems in

unconstrained face acknowledgment with varieties in light, posture, and appearance proposed in [16]. They proposed the “Multi-Directional Multi-Level Dual-Cross Patterns” (MDML-DCPs) to quotation the face features. The component vectors produced by MDML-DCPs are very large sized, therefore to effectively perform recognition, the Probabilistic LDA (PLDA) method is combined with PCA.

The recent component extraction strategy named as Local Patterns of Gradients (LPOG) for efficient face recognition proposed in [17]. The LPOG exploited the block-wised elliptical local binary patterns (BELBP), a refined variant of ELBP, and local phase quantization (LPQ) administrators straightforwardly on inclination pictures for catching nearby surface patterns to develop a component vector of a face picture. The novel faces recognition method designed using the LPOG that exploits whitened principal component analysis (WPCA) for dimension reduction.

The compact binary face descriptor (CBFD) highlight the learning method for face portrayal and acknowledgment was introduced in [18]. Initially from the input face image the pixel difference vectors (PDVs) in nearby fixes separated by computing the distinction between every pixel and its neighboring pixels. At that point highlight mapping to extend these pixel contrast vectors into low-dimensional paired vectors in an unsupervised way. In [19], authors exploited the local order constrained IGOs (image gradient orientations) to produce robust highlights for the face recognition. In [20], authors proposed the minimum error entropy-based atomic representation (MEEAR) method for face recognition. The strategy depends on least mistake entropy rule, which isn't reliant on the error conveyance and appeared to be progressively robust to clamour. The face recognition technique that deals with three environment problems such as illumination variations, partial occlusions, and limited training data proposed in [21]. In [22], the multi-assignment Convolutional Neural Network (CNN) for standing up to affirmation where identity course of action is the central errand and Pose, Illumination, and Expression (PIE) estimations are the side endeavours. Second, they developed a dynamic-weighting plan to permit the setback loads to each side task, which takes care of the critical issue of adjusting between various errands in MTL. Third, they proposed a stance facilitated multi-task CNN by social affair unmistakable positions to learn act specific character features, at the same time finished all positions in a joint framework. This technique looks complex for the face recognition. In [23] authors addressed the limitation of uncontrolled face images recognition. They inspired by the success of linear discriminate analysis (LDA) and proposed superposed linear representation classifier (SLRC) to cast the acknowledgment issue by speaking to the test picture in term of a superposition of the class Centroid and the common intra-class contrasts. Notwithstanding its effortlessness and estimate, the new SLRC to a great extent improves the speculation capacity of collective portrayal and contends well with increasingly refined lexicon learning techniques. Practically this method outperformed the state of art recognition methods for uncontrolled datasets.



B. Moment Invariant based methods

In [24], recent approach designed for efficient object recognition using the moment invariant features. They elaborated the appropriate moment invariant features selection technique. In [25], the first technique recently introduced for face recognition using the different moment invariant features. The method was investigated on Infrared face images. They discussed the challenges of face recognition under the illumination, noise and variability in facial expressions.

In [26], the iris recognition system designed using the Hu moments. The Hu moment invariants introduced to extract the 7 invariant features from each sub regions of iris image. They use Hu moment to improve the accuracy.

In [27], authors proposed that blurred image recognition could be achieved with a high degree of accuracy using Legendre moment functions. Legendre moments were deployed in combination with the Point Spread Function of the image.

The proposed face recognition framework is different from above work as the key contributions are:

- Face normalization algorithm using the fusion of different filtering techniques to address the challenges of unconstrained face image conditions.
- Propose robust hybrid face descriptor technique to overcome any issues between the histogram portrayal and spatial information.
- Novel hybrid features extraction technique proposed based on histogram and moment invariant features.
- Features selection and reduction technique CWM proposed to optimize the recognition accuracy.

The performance evaluations of proposed framework presented using the different types of facial datasets.

III. PROPOSED SYSTEM

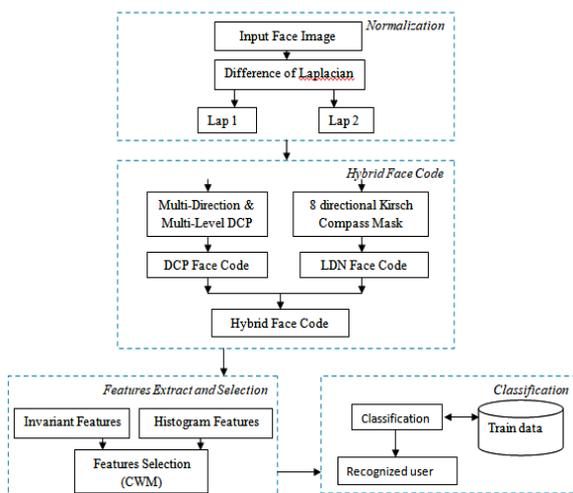


Fig.1. Proposed framework for face recognition

The input face image is normalized using the difference of laplacian (DoL) method as observed in figure 1. The hybrid face descriptor based the multi-level and multi-directional DCP and LDN techniques applied on normalized face image. The outcomes of both approaches are further fused to form the hybrid face code. In features extraction and selection block, first histogram and invariant features extracted and then CWM method applied to normalize and select the

unique features for the classification purpose. At long last, the acknowledgment is achieved by utilizing FFNN classifier. We discussed the each block of proposed framework in below subsection.

3.1. Face Image Normalization: The first derivative of Laplacian operator (FDL) used in this phase. The FDL is converting the input face image into multi-directional filtered images those are effective against the different illumination, pose and expressions. The FDL filter of orientation is represented as:

$$FDL(\theta) = \alpha L / \alpha d = d \cdot \Delta L \quad \dots (1)$$

Where, d is $(\cos \theta$ and $\sin \theta)$ nothing but vector representing the direction of filtering and L is nothing but $t(1+x)^n = 1 + \frac{nx}{1!} + \frac{n(n-1)x^2}{2!} + \dots$ the 2D Laplacian filters which is represented as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad \dots (2)$$

The process of face image normalization described in algorithm 1.

Algorithm 1: Pre-Processing

Inputs:

- T (Test face image)
- $a1$ (smaller laplacian of DoL)
- $a2$ (larger laplacian of DoL)
- γ (parameter for Gamma Correction)

Output

NT (normalized test face image)

1. Perform gamma correction
2. **IF** ($\gamma > 0$)
3. $t1 = T \cdot \gamma$
4. **ELSE**
5. $t1 = T$
6. **END IF**
7. Perform DoL filtering
8. $P1 = L \cdot a1$
9. $P2 = L \cdot a2$
10. $t2 = \text{filter}(P1, t1) - \text{filter}(P2, t1)$
11. Contrast Equalization
12. $t3 = \text{Equ}(t2)$
13. 4. Normalization
14. $t4 = \text{norm}(t3)$
15. **Return** ($NT == t4$)

3.2. Hybrid Face Descriptor: The hybrid face descriptor proposed to address the challenges related to unconstrained face environment effectively by extracting and merging the two different face codes using DCP and LDN in this paper. The novelty is that both codes are extracted in multi-directional way so that all the essential and sufficient spatial and histogram information extracted. The hybrid face descriptor generation works in below steps:

A. DCP Code: In this phase, the extraction such as holistic features extraction and component level feature extraction performed to generate the multi-level and multi-direction DCP face code.

The holistic and component level highlights are extricated from the pre-handled face picture utilizing the two transformations such as similarity and affine transformations. The purpose of using both features to address the variations in illuminations, pose and image resolutions problems. The holistic features are responsible for extracting the features related to facial contour and face components. The component features responsible for extracting the complete face component. The holistic features are addressing the variations in facial components appearance whereas component features are not depending on such variations. After extraction of both level features, it generates the two DCP's encoded maps for input pre-processed image [16]. The encoded map is not further used directly for the histogram features extraction; rather it will be treated as the face code of proposed DCP approach in this paper.

B. LDN Code: To address the variations in expressions and pose, the LDN approach introduced in this paper. This technique preserves the better edge features of input face image which can help for the cases of occlusions as well as plastic surgery as well. Thus, to optimize the face recognition performance under unconstrained environment, we propose to use LDN code. Figure 2 is showing face code generation framework for input face image using the different face descriptors in comparison with LDN code. Figure 2(a) is showing the original image with its edge reaction picture delivered by convolving the first face picture and Kirsch compass veils together with their reaction esteems. Figure 2(b) shows the face code generation process using the 8 directional compass masks, and finally figures 2(c)-(d) shows the face code generated according to the different methods. The LDN is delivers the better representation of edge responses compared to others. Algorithm 2 represents the steps of LDN code computation.

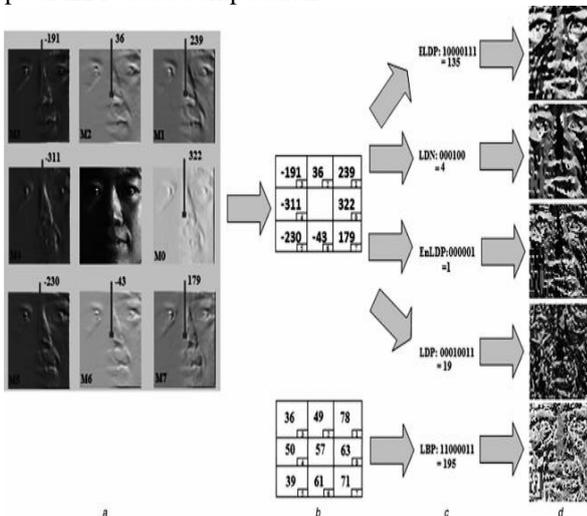


Fig. 2: LDN code generation process

Algorithm 2: Face Descriptor using LDN
Inputs:
NT (normalized face image)
Output
L (LDN code)

1. Define 8-directional matrices
2. Compute edge response images using 8-directional matrices.
3. Convolving image with Kirsch compass masks $M_i; i = 0, 1, \dots, 7$, where M_i is the i^{th} Kirsch compass mask.
4. Start Generating LDN code
5. For each pixel at location (x, y) in NT (e.g. $NT(x,y)$)
6. Assign an 6-bit binary code by
if $(x,y) > 0$,
 $Bi = 11$
else
 $Bi = 0$
end
7. Convert the binary code to decimal value
8. Assign decimal value to position $L(x, y)$.
9. End for
10. Return L

C. Fusion: After generation of DCP and LDN based face codes, we opted to perform the fusion of both face codes in order to generate the hybrid code. The hybrid code further used for the features extractions. The best part of using both DCP and LDN is that both are computationally efficient, therefore this helps to maintain the minimum computation efforts while face recognition.

3.3 Features Extraction and Selection

In this paper we extracted two various kinds of highlights, for example, histogram-based highlights and minute invariant highlights to deliver hybrid features vector.

A. Histogram Features:

To get the in-depth features we used single level histogram and multi-level histogram techniques. It is composed of two histograms such as Single Level Histogram (SLH) and Multi-Level Histogram (MLH). The SLH extracts the information from the hybrid face code such as spots, edges, corners and texture features. For MLH, we divide the input face code into different non-overlapping blocks and for each block we estimate the histogram features. The extracted SLH and MLH features are fused of very large dimension.

B. Moment Invariant Features:

Due to the effectiveness of moment invariant features for face recognition systems under the unconstrained environment, we propose the 11 moment invariant features extracted from the hybrid face descriptor to address the challenges related to unconstrained face recognition conditions. If the image can have nonzero values only in the finite part of xy -plane, then moments exist. Geometric moment of order $(p+q)$ for a two dimensional discrete function is computed using eq. (3),

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^p y^q f(x, y) \quad (3)$$

Where $f(x, y)$ is the image function and M, N are image dimensions. Geometric moments of low orders have an intuitive meaning – m_{00} is a “mass” of the image, m_{10}/m_{00} and m_{01}/m_{00} characterize the focal point of gravity or centroid of the picture.

Second-request minutes m_{20} and m_{02} depict the "dissemination of mass" of the picture as for the arrange tomahawks. The portrayal of the picture by methods for geometric minutes is finished in the accompanying sense. For any picture function, geometric snapshots of all requests do exist and are limited. Invariance to interpretation can be accomplished essentially by apparently moving the object to such an extent that its centroid harmonizes with the source of the arrange framework or, the other way around, by moving the polynomial premise into the object centroid. On account of geometric minutes, we have focal geometric minutes:

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})^q (y - \bar{y})^q f(x, y) \quad (4)$$

where $f(x, y)$ is the image function and M, N are image dimensions, and $\bar{x}=m_{10}/m_{00}, \bar{y}=m_{01}/m_{00}$ are the coordinates of the object centroid. The feature vector FR consisting of 11 different moments where three of them are geometric moments and the rest are eight central geometric moments, given by the following:

$$FR=[m_{00},m_{10},m_{01},\mu_{11},\mu_{12},\mu_{21},\mu_{22},\mu_{30},\mu_{03},\mu_{40},\mu_{04}] \quad (5)$$

Where

$$m_{00} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \quad (6)$$

$$m_{10} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x f(x, y) \quad (7)$$

$$m_{01} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} y f(x, y) \quad (8)$$

$$\mu_{11} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})(y - \bar{y}) f(x, y) \quad (9)$$

$$\mu_{12} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})(y - \bar{y})^2 f(x, y) \quad (10)$$

$$\mu_{21} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})^2 (y - \bar{y}) f(x, y) \quad (11)$$

$$\mu_{22} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})^2 (y - \bar{y})^2 f(x, y) \quad (12)$$

$$\mu_{30} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})^3 f(x, y) \quad (13)$$

$$\mu_{03} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (y - \bar{y})^3 f(x, y) \quad (14)$$

$$\mu_{40} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})^4 f(x, y) \quad (15)$$

$$\mu_{04} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (y - \bar{y})^4 f(x, y) \quad (16)$$

The features of histogram and moment invariant combined to form the large size features vector. Algorithm 3 demonstrates the process of features extraction from the hybrid face descriptor code (H).

<p>Algorithm 3: Hybrid Features Extraction</p> <p>Inputs: H: Hybrid face descriptor</p> <p>Output SF: Selected feature vector</p>
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1. $F1$: extract single level histogram features from H
2. $F2$: extract multi-level histogram features from H
3. $F3$: extract moment invariant features from H
4. F : $\{F1, F2, F3\}$
5. SF : Features selection and Reduction on F using Algorithm 4
6. Return SF

C. Features Normalization and Selection: The large number of features may take longer time for the prediction and having the possibility of irrelevant features as well. The presence of irrelevant features leads to inaccurate face recognition. Hence it is important to select the core features for face recognition. The aim of highlight determination is to decrease the measure of highlights by evacuating the unessential features and normalize them to improve the recognition accuracy and minimize the computation efforts while classification. There are number of feature selection methods available, however the accurate features selection is yet the research challenge. The novel correlation weight method (CWM) proposed based on the terminologies of mathematics and data mining. The CWM method based features normalization and correlation weight computation steps. The normalization step is used to bring all the features values in specific range so that features selection becomes simple task. After the normalization we performed computation of correlation weight among patterns and data. Algorithm 4 shows the CWM working

<p>Algorithm 4: Feature Normalization and Selection</p> <p>Input HF: Histogram features ε: minimum difference threshold value Φ: maximum variance threshold value $q=0$: to ignore the unrelated texture features</p> <p>Output SF: Selected features</p> <ol style="list-style-type: none"> 1. Features normalization using Gaussian method 2. $[m, n] = \text{size}(HF)$ 3. For $i = 1: m$ 4. For $j = 1: n$ 5. If $(HF(i) - HF(j)) > \varepsilon$ && $\text{var}(HF(i)) \leq \Phi$ 6. Cor $(i) = HF(i)$ 7. End if 8. End for 9. End for 10. Compute the weigh for each correlated histogram feature 11. For each correlated feature Cor (i) 12. $SL(i) = 10 * \text{Cor}(i) + q$ 13. End for 14. Return $SL(i)$

Here, the value of q determines the features selection. When $q = 1$, then retain all features, otherwise ignore that features.

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Finally, after the features selection, FFNN classifier applied for the recognition of input test face user.

IV. SIMULATION RESULTS AND DISCUSSION

The experimental evaluation of proposed face recognition model is done using MATLAB image and signal processing toolbox on dual-core Intel processor and 4 GB RAM. The evaluation studies are conducted on four public face datasets such as LFW, CK, CAS, and plastic surgery face dataset. Three performance metrics based on which the performance evaluation is done such as Accuracy, Sensitivity, and Specificity for face acknowledgment. The proposed method of face acknowledgment execution is thought about against two state-of-art techniques such as LDN [15], MDML-DCP-PLDA (MDP) [16], MDML-DCP-FFNN (MDF), H-DCP (hybrid DCP using the DoL for face normalization and PFFNN), Hybrid Model (proposed model which is based on using hybrid face descriptor with CWM and without invariant features) and Hybrid + Normalization (the proposed face recognition using hybrid face descriptor and hybrid features extraction technique with CWM). In short, H-DCP, Hybrid Model and Hybrid + Normalization are the three variants of proposed face recognition system of this paper. The difference between MDP and MDF is the use of classifier only in MDP its PLDA and in MDF its basic FFNN.

4.1 Datasets

LFW: It stands for Labelled Faces in the Wild. This dataset is prepared to study the unconstrained face recognition problem mainly. There are total 13,000 face images collected from the Internet for total 1680 subjects [28].

CK: It stands for Cohn-Kanade which is facial expression database. This dataset is widely used in automatic facial image analysis and expression detections. There are two main versions of CK. In this study we evaluated version I. The version I contains total 486 face images for total 97 subjects with different pose and variations. Therefore it is independent environmental based dataset [29].

CAS: It is CAS-PEAL face dataset. This is another challenging unconstrained face dataset. This dataset was built through the sponsorship of National Hi-Tech program as well as VISION by the group of face recognition. At present, this dataset is composed of total 99594 face images for 595 males and 445 females with varying Pose, Expression, Accessory and Lighting (PEAL) conditions [30].

Plastic Surgery Face dataset: It is the plastic surgery face database that contains 1800 images of 900 subjects for each subject, one pre-surgery and one post-surgery image is provided. This database contains various plastic surgery procedures such as Blepharoplasty (eyelid surgery), Rhinoplasty (nose surgery), Dermabrasion, Brow lift (forehead surgery), Otoplasty (ear surgery), others (Mentoplasty, Malar augmentation, Craniofacial, Lip Craniofacial, Fat injection), Rhytidectomy (face lift) and Skin resurfacing (skin peeling) [32].

4.2 Performance Evaluation

Figures 3, 4 and 5 are showing the comparative graphs for three performance metrics accuracy, sensitivity and specificity for MDP, MDF, H-DCP [31] and proposed

method concerning three research datasets LFW, CAS, CK, and plastic surgery face datasets. The dataset like LFW and CAS having serious real time illumination variations included in between angular rotations from (-60, -45) to (60, 45) with (0,0) as straight face in degrees. The CK dataset is having the facial darkness. While working with neural networks, the general practice is to partition the dataset into three subsets. The preparation set is the main subset utilized for figuring the inclination and refreshing the network loads and predispositions. The second subset is the approval set, and the third subset is the test set to register the accuracy underlying methods. In our work, we divide complete data into training, validation and testing subsets randomly. We used standard divide ratio for each subset such as training (70%), testing (15 %), and validate (15 %). By considering these ratios the all methods with all datasets are evaluated.

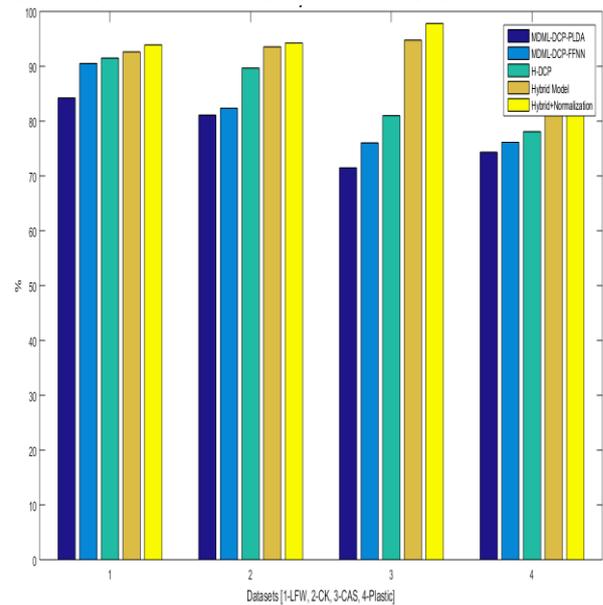


Fig.3. Accuracy Performance Evaluation

Figure 3-5 demonstrate that variants of proposed model such as H-DCP, Hybrid Model, and Hybrid + Normalization shows the significant performance improvement as compared both state-of-art face recognition methods reported in [16]. The performance of H-DCP is lower compared to the one where the hybrid face descriptor and CWM [32] used as the hybrid face descriptor able to suppress the challenges of unconstrained face recognition conditions effectively as well as the CWM helps to normalize and select the unique features for recognition purpose. Similarly, the proposed model Hybrid + Normalization claims the impact of using the moment invariant features over the accuracy, sensitivity, and specificity performances using different datasets. The use of moment invariant features helps to build the effective shape descriptor of face image and generates the more consistent and unique features for each face image.

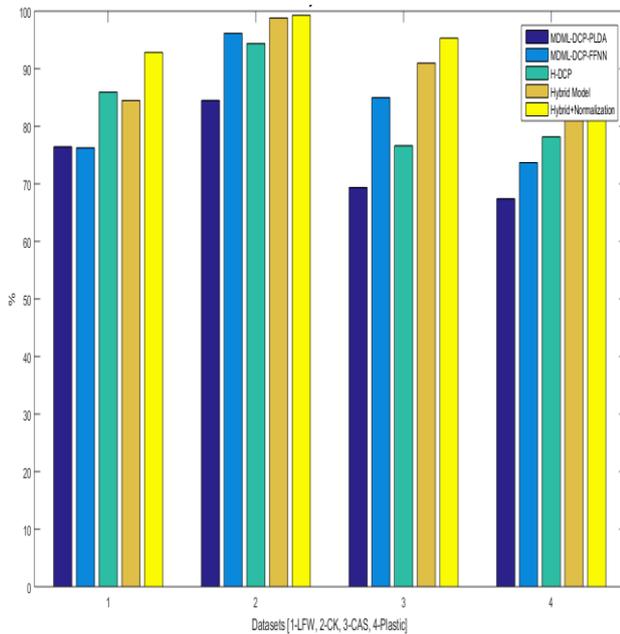


Fig.4. Sensitivity Performance Evaluation

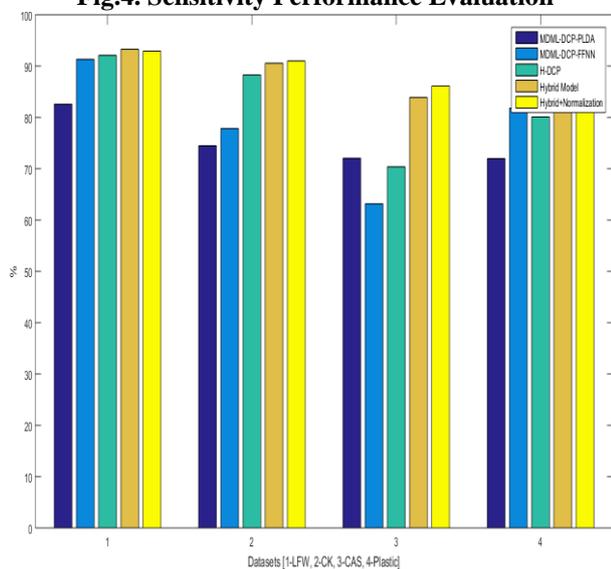


Fig.5. Specificity Performance Evaluation

As the proposed face recognition technique are robust to serious illumination variations and pose variations, the face recognition performance is improved with all underlying datasets including the plastic surgery as well. The variations in illumination and pose are effectively addressed by proposed methodology of face representation. The dataset LFW is having more accuracy than other two datasets due to the better quality face images as compared to the CK and CAS images balanced resolution. Lower the image quality, lower the face recognition performance. The variations in illumination and pose are less as compared to both CK and CAS datasets. The proposed hybrid face descriptor with feature selection method exposed the details texture features of input face regardless of facial illumination conditions and variations when contrasted with the condition of-workmanship descriptors, accordingly improves the acknowledgment results. Similarly the sensitivity and specificity results show the improvement for proposed method.

4.3 Comparison with Similar Methods

This section presents the comparative study of recognition accuracy and computation efforts with previous face

descriptors and recognition methods using different datasets.

Table I: Accuracy Evaluation of LFW Dataset

Face Descriptors	Accuracy (%)
LBP	72.43
LTP	72.65
DCP-P [16]	84.23
DCP-F	90.52
LDN [15]	83.45
Proposed model without Moment Invariant Features	92.64
Proposed model	93.91

The face descriptors such as LBP and LTP are very poor accuracy performance which is further improved by DCP-P and LDN, and then we suppressed it by DCP-F. For the same dataset proposed methods showing 92.64 % (hybrid face descriptor) and 93.91 (hybrid face descriptor + hybrid features) accuracy (Table 1). Similarly, table 2 and 3 are showing the performances of recognition accuracy for datasets CK and CAS. For CAS we consider entire PEAL probe sets rather than individual sets. CAS is most uncontrolled face dataset as it contains a large number of face images with different illuminations, pose, variations, and hence its recognition performance is very poor as compared other two datasets, therefore the performance of accuracy is very poor for state-of-art methods. However the proposed approach shows the significant improvement in accuracy for CAS also. Same results obtained using the plastic surgery dataset as well (showing in table 4). Overall the proposed idea of generating the hybrid face descriptor using LDN and DCP techniques and Hybrid features extraction (Histogram + Moment invariant) with CWM as features normalization and selection algorithm delivers the best recognition results for all the datasets.

Table II: Accuracy Evaluation of CK Dataset

Face Descriptors	Accuracy (%)
LBP	68.34
LTP	70.12
DCP-P	81.11
DCP-F	82.36
Proposed model without Moment Invariant Features	93.56
Proposed Model	94.24

Table III: Accuracy Evaluation of CAS Dataset

Face Descriptors	Accuracy (%)
LBP	63.42
LTP	64.99
DCP-P	71.48
DCP-F	73.70
Proposed model without Moment Invariant Features	94.76
Proposed Method	97.79

Table IV: Accuracy Evaluation of Plastic Surgery Dataset

Face Descriptors	Accuracy (%)
LBP	61.23
LTP	60.35
DCP-P	69.34
DCP-F	71.23
Proposed model without Moment Invariant Features	94.67
Proposed Method	95.94

Along with the recognition accuracy, the face recognition model should be efficient in terms of computation efforts as well. The table V demonstrate the average recognition time performance of all the methods. As observed in table, due to formation of hybrid face descriptor and hybrid features vector, the proposed models takes more computational efforts compared to state-of-art methods DCP-F, and DCP-P. However, the accuracy of such methods is not acceptable by considering their performances for all the datasets. Yet the computation time of proposed models not much higher and acceptable with significant improvement in recognition accuracy. Using any parallel computation techniques in future it can be reduced.

Table V: Average recognition time on Plastic Surgery Dataset

Face Descriptors	Recognition Time (Seconds)
LBP	3.76
LTP	3.64
DCP-P	3.25
DCP-F	3.41
Proposed model without Moment Invariant Features	3.52
Proposed Method	3.61

V. CONCLUSION AND FUTURE WORK

For face recognition systems, the uncontrolled environment includes the variations in expression, pose, illumination conditions, low-resolution images, occlusions, and plastic surgery are challenging problems to address. The robust face recognition is mainly based on designing of face descriptor and features extraction technique. From previous studies, it is noted that single face descriptor does not address all the challenges of unconstrained face recognition environment. To address the face variations, we initially used the difference of Laplacian (DoL) in face image normalization. The hybrid face descriptor using the DCP and LDN approaches proposed to generate the hybrid face code. Then, introduced the hybrid features extraction technique in which the histogram and moment invariant features extracted from the hybrid face code to build the unique features vector. In features extraction, the SLH, MLH, and moment invariant features extracted and fused to form big dimensional features set for the input face image. To improve the recognition speed and accuracy, we further introduced the CWM algorithm which selects the most relevant features and reduce the irrelevant features. The simulation results show the significant performance improvement as compared to

state-of-art methods. To lessen the acknowledgment time we recommend executing the proposed models using the parallel computing frameworks in future work.

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