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Original Article

An Analytical Approach for Reconstruction of Cosmetic Surgery Images using EUCLBP and SIFT

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Abstract *- Plastic surgery is a surgical procedure with outcomes often opposite to facial ageing. Face recognition algorithms find it difficult to anticipate such non-uniform face transformations because any changes brought on by plastic surgery procedures happen quickly. In this paper, the performance of face reconstruction is compared with that of two commonly used feature extractors, Extended Uniform Circular Local Binary Pattern (EUCLBP) and Scale Invariant Feature Transform (SIFT). An open plastic surgery facial dataset of 1800 before and after operation picture samples for 900 human face photographs has been used to test all algorithms. For each human subject, two front-facing image samples with appropriate luminance and neutral motions are gathered; the first is taken before, and the second is obtained after surgery. The proposed method is validated using parameters like accuracy, sensitivity, specificity, F-Score, G-mean and Precision. These results consistently show superior performance and high identification accuracy of 97% in combination with using both feature extractors EUCLBP+SIFT rather than using any one [EUCLBP or SIFT]alone.*

Keywords *- Face Reconstruction, plastic surgery, granular computing, Extended Uniform Circular Local Binary Pattern, Scale Invariant Feature Transform.*

1. Introduction

The face is an important component of the human body because it conveys information such as a person's identity, gender classification, and age estimation [1-3]. Every day, the number of people receiving these plastic operations is growing rapidly. The desire among people to appear young, aided with improved technology with a shorter cure period and lower costs, have all contributed to this transition. Skin texture changes across photos of the same individual (intra-subject) are introduced by cosmetic procedures on the face, making facial identification more difficult than in a typical setting. Plastic surgery is frequently misused, although it is generally performed for cosmetic and treatment objectives like burns and tumours or to correct any flaws. Cosmetic surgery is of distinct types.

Local surgery: It's a type of surgery in which a person has local plastic surgery performed on them to rectify birth abnormalities and anomalies or improve skin texture. This procedure is used to repair the structure of the jaw, teeth, nose, chin, forehead, and eyelids, among other things. Local plastic surgery also aims to enhance the attractiveness of face features by reshaping and restructuring them [3-5].

Global surgery: Rather than improving an individual's appearance, global plastic surgery focuses on recreating features to remedy some functional problems [6]. In this surgery, an individual's appearance, texture, and facial characteristics are altered to depict a normal human face, but they are rarely identical to the original one. Plastic surgery techniques can dramatically modify facial biometric traits, as seen in Figure 1, leading to an automated system misclassifying a person's pre-surgery and post-surgery facial images as two separate subjects. As a result, it's critical to develop a face reconstruction system that can distinguish face photos that have been altered by cosmetic surgery. While developing strong face reconstruction algorithms, the consequence of differences in position, illumination, age, and conceal has been explored [6-10]. Despite its various essential applications in areas such as security access control and identity identification, face recognition has become one of the greatest widely investigated study issues across multiple disciplines.

Fig 1. Demonstrating how cosmetic surgeries significantly change facial biometric characteristics(sample images from the available resource)

1.1. Key Highlights

This paper focuses on comparing various methods for face construction. Following are the objectives:

- Brings a comparison of 2 main feature extractors for the face reconstruction technique.
- The "scale-invariant feature transform (SIFT) and the extended uniform circular local binary pattern (EUCLBP)" are two techniques that are compared.
- The given methods extract critical features from a dataset and determine how much difference occurs at the classifier stage.

1.2. Organization of the paper

Section 1 presents an overview of face reconstruction from surgical images, Section 2 depicts a literature survey, the 3rd Section describes the proposed approach, the 4th Section provides a performance evaluation and its graphical analysis, and Section 5 concludes.

2. Literature Review

Anwarul et al. (2020) [11] provide a detailed assessment of the most important and effective face recognition strategies now in use, their face recognition accuracy and the factors that hinder the study's performance. Singh et al. (2020) [39] highlight how a face recognition algorithm's resilience is tested, which can significantly impact its intended functionality. GANs have been used to discuss many assault types. Moreano et al. (2020) [13] use Matlab 2015a functions to project the face models out of the BU-3DFE database to 3 planes and, after that, consider them as 2D pictures for recognition. The project's primary objective is to create a powerful 3D facial recognition system. Lin et al. (2020) [14] employed the proposed feature extraction technique to transform thermal images into features and then built a face prediction model utilizing deep learning, random forest, also ensemble learning. The proposed feature extraction approach separates the facial image (RGB into 12 and thermal image into 48) blocks and then generates the feature image and this feature matrix. Rathgeb et al. (2020) [41] present the new Hochschule Darmstadt (HAD) plastic surgery database of pre and post-surgical facial pictures. This database complies with the "International Civil Aviation Organization (ICAO)."

Quality standards for electronic travel documents and include facial pictures. This database meets the ICAO quality requirements for electronic travel documentation and includes face photos of the five most often performed facial plastic operations.

3. Proposed Methodology Design

3.1 Pre-processing

Pre-processing, face image granulation, feature extraction, feature selection, feature matching, and classifications represent the four primary processes in the suggested algorithm. Figure 2 shows the proposed methodology. The proposed algorithm's phases are depicted in Figure 3, and the following subsections discuss each step in depth. Utilizing the Cascade object detector, the face pictures are recognized and normalized, and a region of interest has been retrieved. The ROI is made grayscale after being shrunk to 196 x 224 pixels. Later, two-point eye coordinates are used to normalize the pictures geometrically. The final stage in enhancing image contrast is histogram equalization. The final normalized picture produced after detection and pre-processing is shown in Figure 4. [16-18].

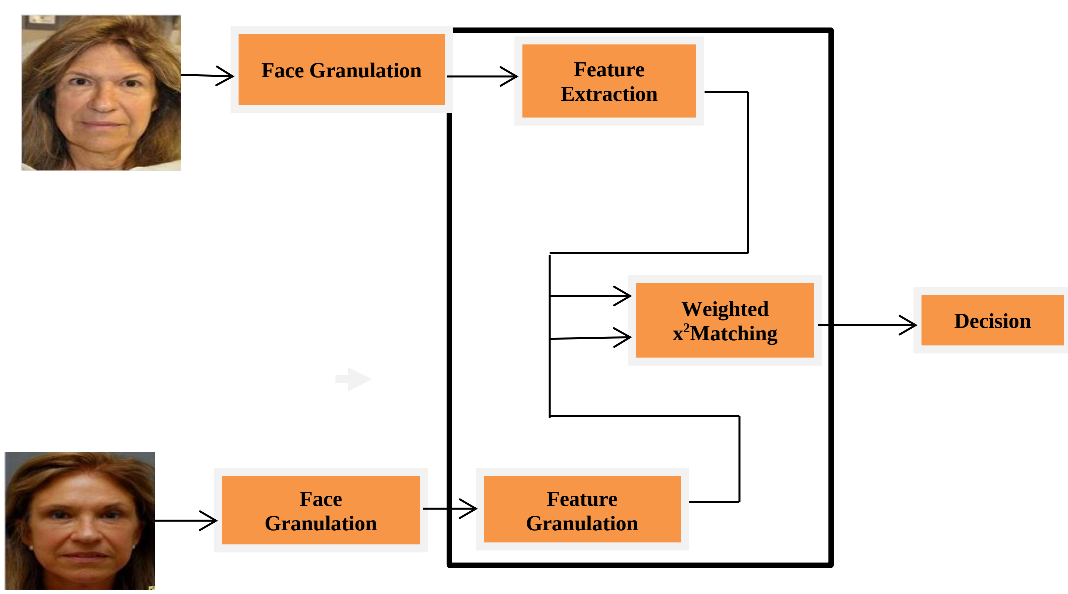


Fig. 2 Proposed methodology diagram

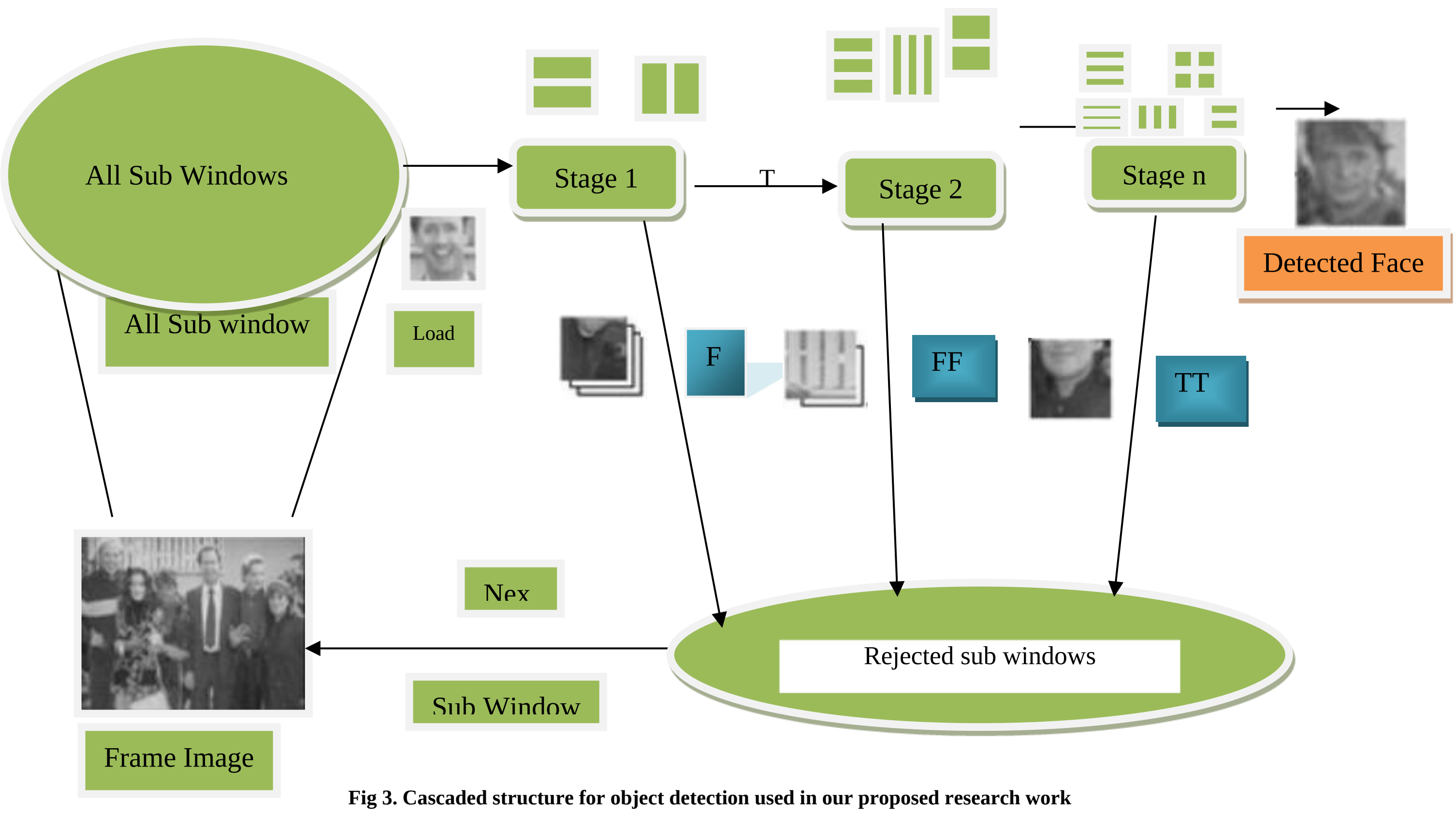


Fig 3. Cascaded structure for object detection used in our proposed research work

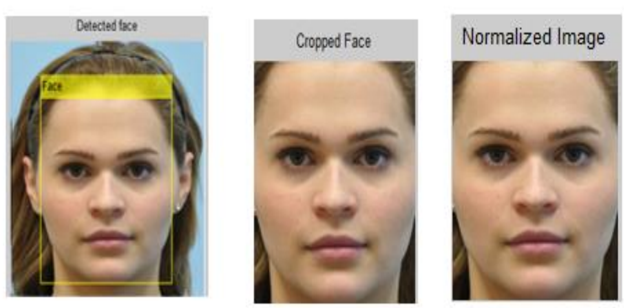


Fig. 4 Normalized output image obtained after pre-processing

3.2. Facial Image Granulation using Laplacian and Gaussian Filter

Non-disjoint facial image characteristics are extracted in the granular technique at distinct levels. Greater versatility in recognizing underlying information like nose, ears, forehead, chin, and cheeks, along with combinations of two or more characteristics, is attained with granulated information. The granulation scheme aids in gaining important insights into the impact of plastic surgery techniques upon various facial features in their surrounding areas. Assume I as the size n×m identified frontal facial image. The image is low pass filtered using the Gaussian Operator. The Laplacian operator generates the bandpass filtered version of the photos. By separating the facial image into separate parts, horizontal and vertical granules are created. Figures 5 and 6 show granules generated using the Gaussian and Laplacian operators from G1 to G6, respectively.

The horizontal granules range from G7 -G15, while the vertical granules range from G16 - G24. It takes a relationship between horizontal and vertical granules to contend with cosmetic surgery-induced changes in the chin, forehead, ears, and cheeks. The second granularity level aids in analyzing various blends of local attributes, which give resilience to concurrent fluctuations among many areas [19-23]. Granules G17 to G40 denote the 3rd level of Granularity from a particular eye coordinate. 16 local areas are derived using a face template with the golden ratio. Figure 7 and 8 depict the horizontal and vertical granulation, and Figure 9 depict the granulation from G25-40 with the golden facial template.

Fig. 5 Granules G1 to G3 using Gaussian Filter for facial image

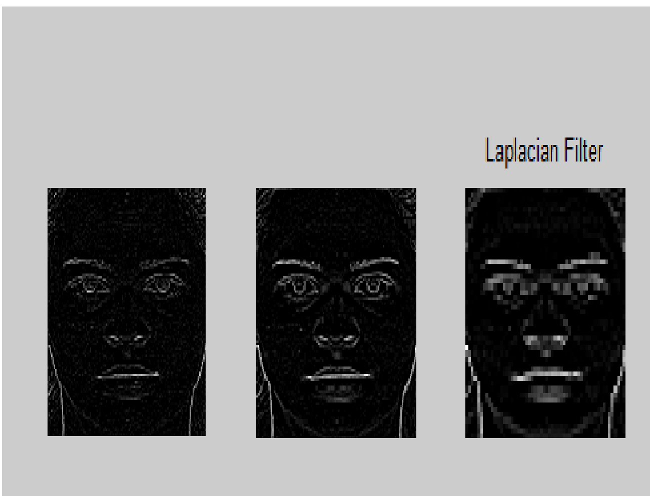


Fig. 6 Granules G4 to G6 using Laplacian Filter for facial image

Fig. 7 Horizontal Granules from G7 to G15 for facial image

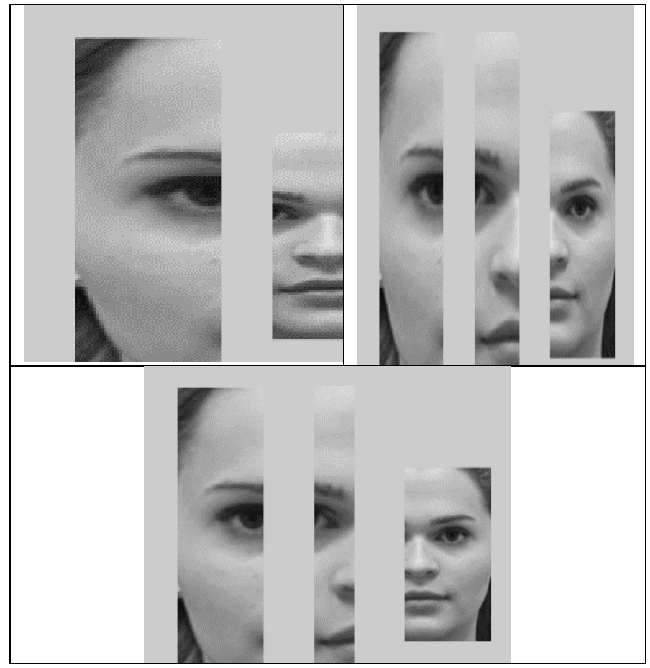


Fig. 8 Vertical Granules from G16 to G24 for facial image

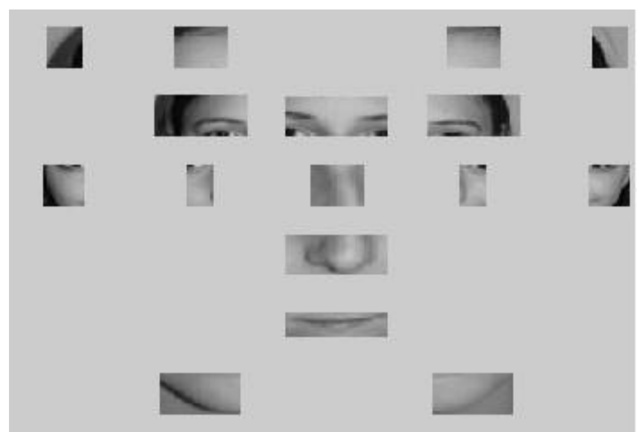


Fig. 9 Granules from G25 to G40 using Golden ratio face template.

3.3. Feature Extraction

It is described as the process of retrieving meaningful data out of a face database. This information should be useful in determining which subjects have a tolerable minimum error rate in the following phases. To extract distinguishing facial features from diverse face granules, two prominent feature extractors are utilized, combined with "Extended Uniform Circular Local Binary Patterns (EUCLBP) and Scale Invariant Feature Transform (SIFT)".Certain granules have fiducial features like eyes, nose, and mouth at the current granularity level. In contrast, others largely comprise skin areas, including the forehead, cheeks, and outer facial region. Because of this, different feature extractors are needed to encode different data from the face granules.[22-26].

3.3.1. Extended Uniform Circular Local Binary Patterns (EUCLBP)

EUCLBP (Extended Uniform Circular Local Binary Pattern) represents an appropriate way to store Gray-level disparities and sign differences between neighbouring pixels. To determine the "EUCLBP", the provided image is initially converted into 32x32 non-overlapping uniform local patches. The "EUCLBP" descriptor for every local patch is constructed using 8 nearby pixels. The descriptors extracted from each local patch are concatenated to create the image signature. It uses the weighted 2 distance to match two EUCLBP descriptors. Various texture analysis applications seek features resilient or invariant to input picture rotations. Comparing uniform patterns to alternative patterns has improved recognition results in several applications. Figure 10 shows an extended LBP operator with a circular neighbourhood

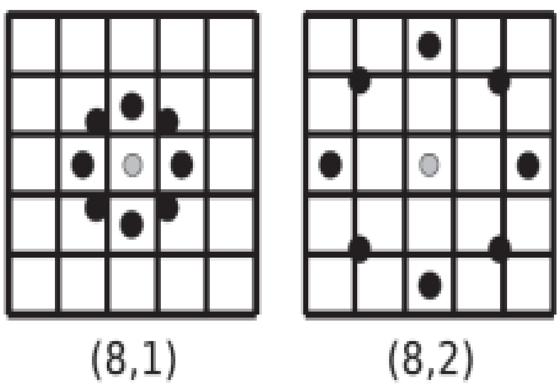


Fig. 10 The extended LBP operator with circular neighbourhood

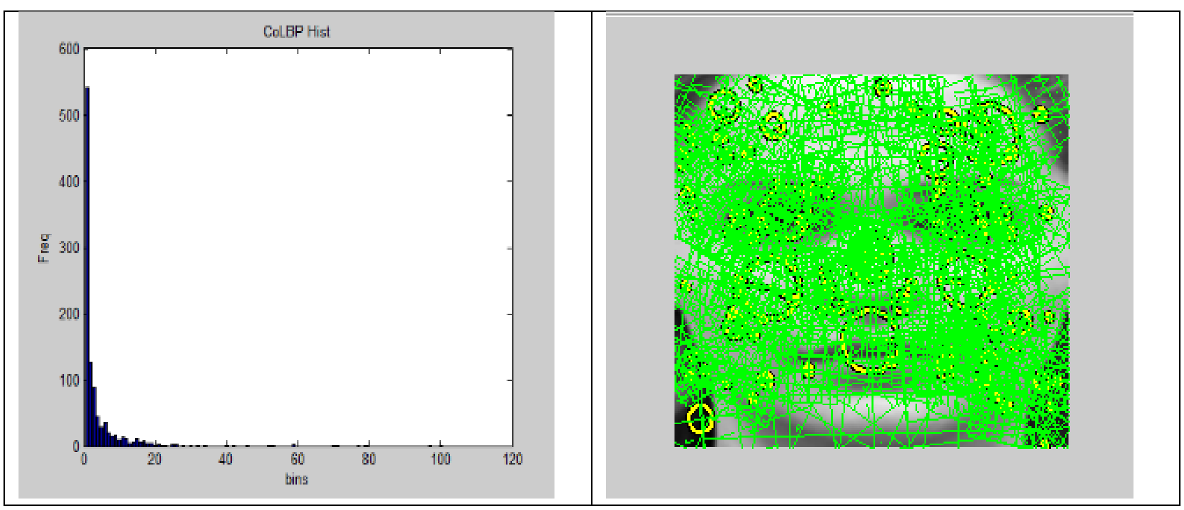
$$\mathrm{X2}(\mathrm{S},\mathrm{M}) = \sum_{r,i} \frac{(S(i)-M(i))^2}{S(i)+M(i)} \qquad (1)$$

$$\mathrm{X2}(\mathrm{p},\mathrm{q}) = \sum \mathrm{i\ j, w\ j}\{(\mathrm{p\ ij} - \mathrm{q\ ij})2/(\mathrm{p\ ij} + \mathrm{q\ ij})\} \qquad (2)$$

The $\chi 2$ is the distance metric for comparing the histograms in eq 1:
where S and M are the histograms for comparison, and i is the i-th bin of the histogram.

3.3.2. Scale Invariant Feature Transform [SIFT]

It's a scale and rotation invariant descriptor that uses the direction, magnitude, and spatial proximity of image gradients to build a compact image representation. SIFT employs a sparse descriptor generated around predetermined interest points. In any case, SIFT can be employed densely, with the descriptor formed around observed interest spots. The SIFT descriptor is calculated densely upon the group of evenly distributed non-overlapping local areas of size 32x32 in this method.



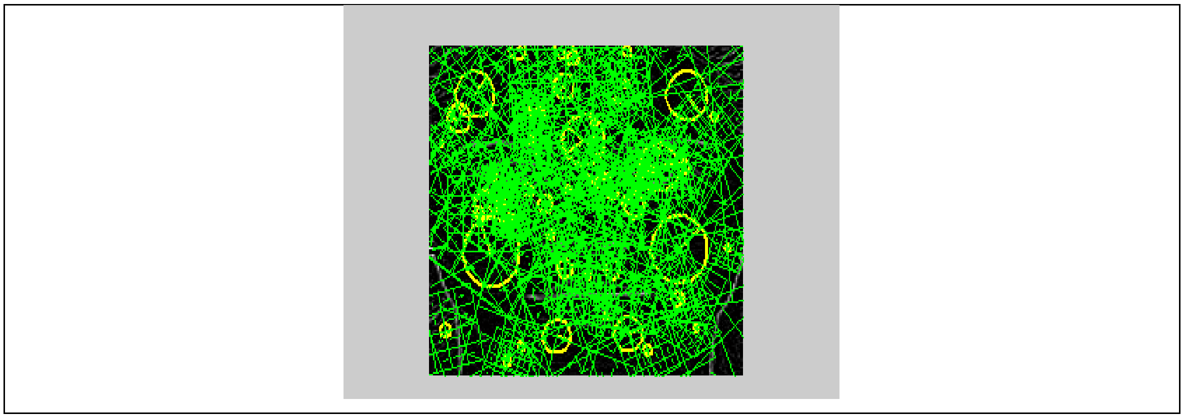


Fig. 11 Feature histogram, EUCLBP and SIFT output

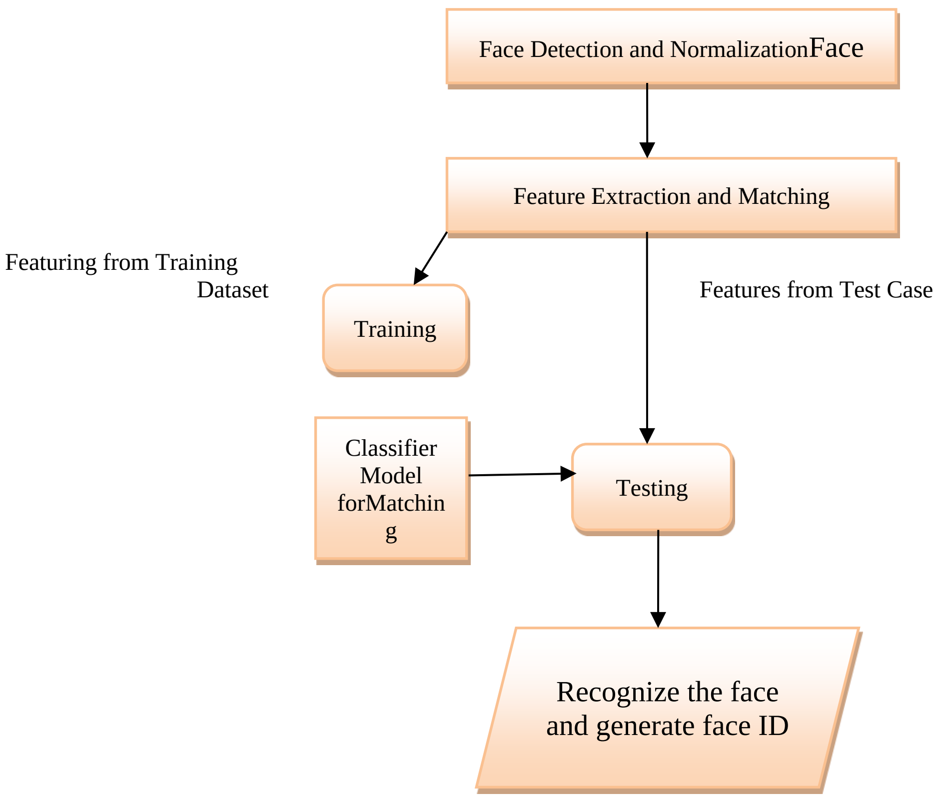
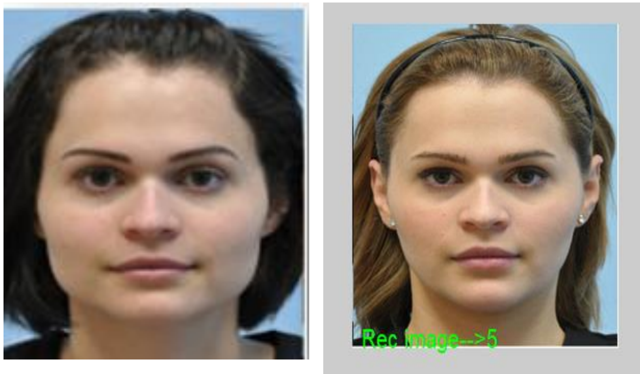


Fig. 12 A basic flowchart for feature extraction and matching of the input facial image.



(a) **(b)**

Fig. 13 (a) gives the input image (b) Feature matching output

Figure 11 shows the feature histogram, EUCLBP and SIFT output. The image signature is constructed by concatenating SIFT descriptors determined at the sampled areas. The weighted χ2 distance, analogous to EUCLBP, is utilized to evaluate two SIFT descriptors [27-29]. These descriptions can then be applied to a training image data set when trying to discover an object in a test image with numerous other objects, these descriptions taken out of a training image data set could be utilized for finding an object (Figure 9).

3.4. Feature Matching

By merely summarizing the processes below [31-35], it is possible to match face images using extracted characteristics mixed with a multi-objective evolutionary learning algorithm for precise face recognition. Figure 12 shows a flowchart for feature extraction and matching the input facial image. Figure 13 depicts the input image and feature-matching output

1) Multiple face granules were retrieved for each image in a data gallery.
2) Using training data, EUCLBP or SIFT features were generated for every face granule.
3) Descriptors taken from the database gallery were compared using the weighted X2 distance measure. If p and q represent the descriptors calculated from face granules, then weighted X2 can be determined in equation 2 using the determined formula:

$$X2(p,q) = \sum i\ j, w\ j\{(p\ ij - q\ ij)2/(p\ ij\ + q\ ij)\} \qquad (2)$$

4) The process is continued for all the database images as well as top matches (Figure 10) are accessed depending on the match scores within the identification mode (1: N).

4. Experimental analysis

This model is implemented over hardware specifications such as Ryzen 5/7 CPU, 1TB HDD and Windows 10 OS and for software specifications like Google Collaboratory, an open-source Google environment for developing frameworks. So the 2 extraction methods are compared individually and also in a combined version. Table 1 shows the overall analysis of EUCLBP. Table 2 depicts the overall analysis of SIFT. Table 3 represents the combined analysis of EUCLBP + SIFT under various measures like accuracy, sensitivity, specificity, recall, precision, F1-score, G_Mean and computation time. From table 1, i.e. using the EUCLBP method, we got an accuracy of 77%, specificity of 76%, and sensitivity of 75%.

By using EUCLBP model as shown in table 1, image 1 will get an accuracy of 0.77,sensitivity of 0.754,specificity of 0.761,precision of 0.172,recall of 0.742,f1 score of 0.291,gmean of 0.811. Image 2 will get an accuracy of 0.776,sensitivity of 0.759,specificity of 0.763,precision of 0.181,recall of 0.736,f1 score of 0.296,gmean of 0.825. Image 3 will get an accuracy of 0.78,sensitivity of 0.798,specificity of 0.812,precision of 0.184,recall of 0.751,f1 score of 0.243,gmean of 0.818. Image 4 will get an accuracy of 0.783,sensitivity of 0.812,specificity of 0.825,precision of 0.188,recall of 0.775,f1 score of 0.252,gmean of 0.865.Image 5 will get an accuracy of 0.789,sensitivity of 0.867,specificity of 0.873,precision of 0.196,recall of 0.821,f1 score of 0.281,gmean of 0.849.

Figure 14 depicts a graphical representation of EUCLBP over various measures. Figure 15 depicts a graphical representation of SIFT under various measures. Figure 16 displays the analysis of the predicted image vs the original image over EUCLBP and SIFT. Figure 17 depicts the overall graphical representation of the combined feature extraction method.

By using SIFT model as shown in table 2 , image 1 will get an accuracy of 0.815,sensitivity of 0.798,specificity of 0.811,precision of 0.198,recall of 0.757,f1 score of 0.329,gmean of 0.897. Image 2 will get an accuracy of 0.821,sensitivity of 0.821,specificity of 0.825,precision of 0.236,recall of 0.862,f1 score of 0.328,gmean of 0.885. Image 3 will get an accuracy of 0.835,sensitivity of 0.863,specificity of 0.853,precision of 0.227,recall of 0.858,f1 score of 0.316,gmean of 0.979. Image 4 will get an accuracy of 0.851,sensitivity of 0.863,specificity of 0.821,precision of 0.258,recall of 0.861,f1 score of 0.355,gmean of 0.930.Image 5 will get an accuracy of 0.865,sensitivity of 0.857,specificity of 0.857,precision of 0.265,recall of 0.875,f1 score of 0.381,gmean of 0.938.

By using SIFT and EUCLBP models together as shown in table 3, image 1 will get an accuracy of 0.91,sensitivity of 0.851,specificity of 0.902,precision of 0.33,recall of 0.911,f1 score of 0.501,gmean of 0.955. Image 2 will get an accuracy of 0.913,sensitivity of 0.892,specificity of 0.901,precision of 0.335,recall of 0.924,f1 score of 0.512,gmean of 0.967. Image 3 will get an accuracy of 0.917,sensitivity of 0.953,specificity of 0.914,precision of 0.338,recall of 0.925,f1 score of 0.514,gmean of 0.978. Image 4 will get an accuracy of 0.92,sensitivity of 0.925,specificity of 0.936,precision of 0.34,recall of 0.943,f1 score of 0.521,gmean of 0.963.Image 5 will get an accuracy of 0.924,sensitivity of 0.954,specificity of 0.931,precision of 0.345,recall of 0.952,f1 score of 0.523,gmean of 0.967.

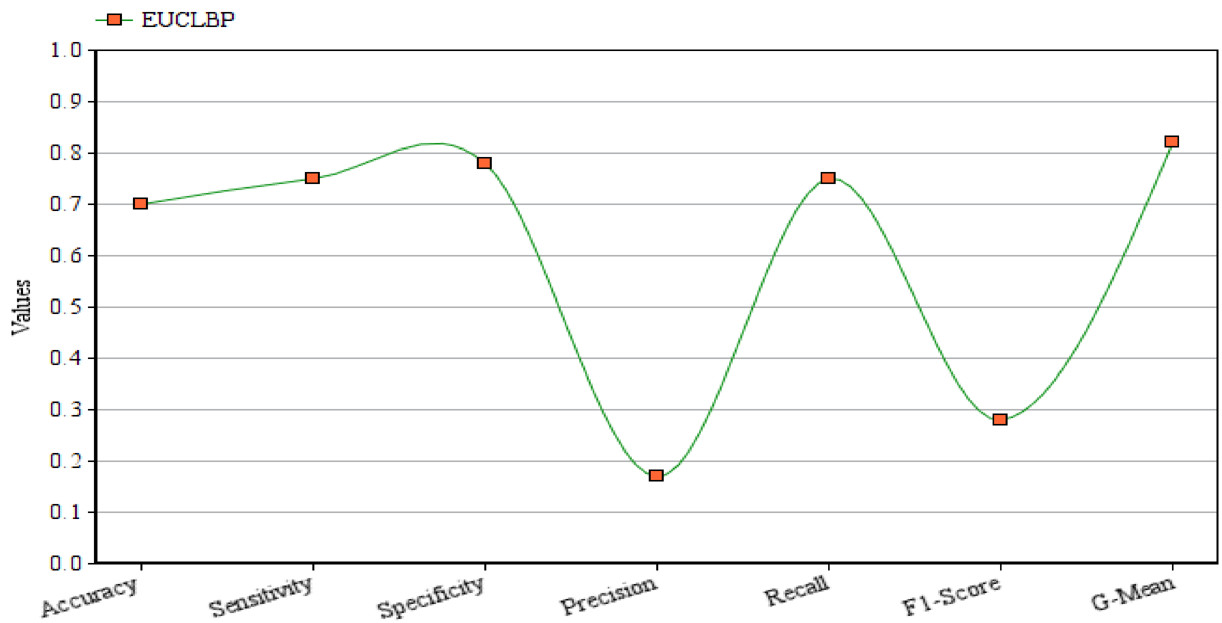


Fig. 14 EUCLBP vs Measures: Overall Analysis

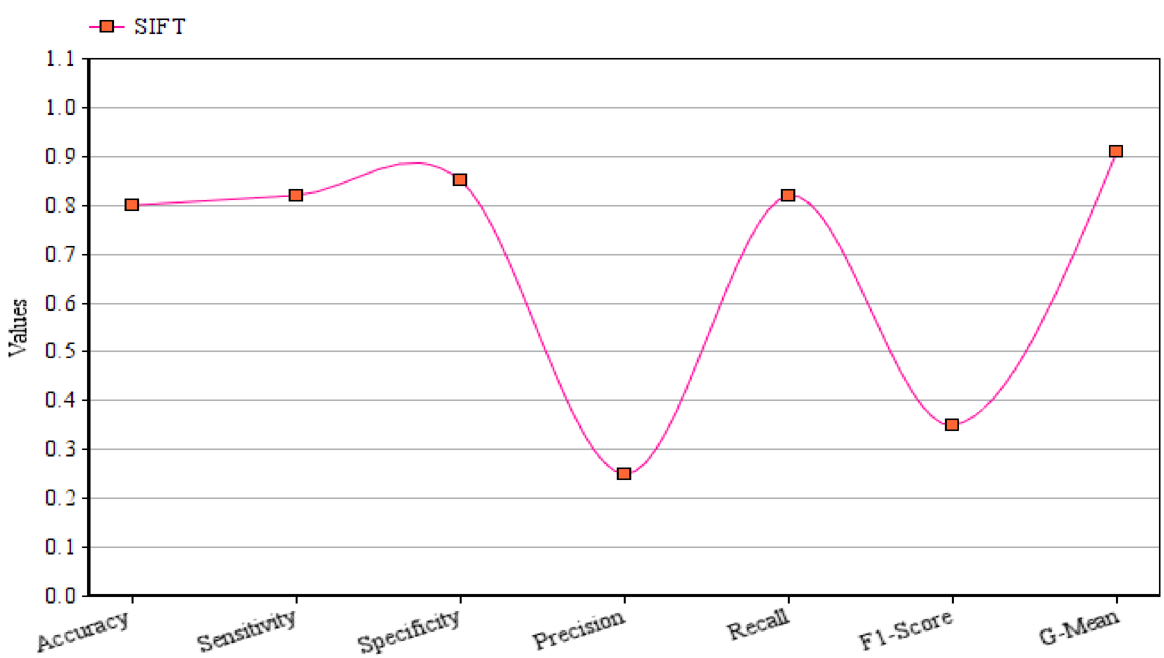


Fig. 15 SIFT vs Measures: Overall Analysis

Table 1. An overall analysis of EUCLBP

Model	Accuracy	Sensitivity	Specificity	Precision	Recall	F1-Score	G-Mean	Images
EUCLBP	0.77	.754	0.761	0.172	.742	0.291	0.811	Image 1
	0.776	.759	0.763	0.181	.736	0.296	0.825	Image 2
	0.78	.798	0.812	0.184	.751	0.243	0.818	Image 3
	0.783	.812	0.825	0.188	.775	0.252	0.865	Image 4
	0.789	.867	0.873	0.196	.821	0.281	0.849	Image 5

Table 2. An overall analysis of SIFT technique

Model	Accuracy	Sensitivity	Specificity	Precision	Recall	F1-Score	G-Mean	Images
SIFT	0.815	0.798	0.811	0.198	0.757	0.329	0.897	Image 1
	0.821	0.821	0.825	0.236	0.862	0.328	0.885	Image 2
	0.835	0.863	0.853	0.227	0.858	0.316	0.979	Image 3
	0.851	0.863	0.821	0.258	0.861	0.355	0.930	Image 4
	0.865	0.857	0.857	0.265	0.875	0.381	0.938	Image 5

Table 3. An Overall Analysis of SIFT+ EUCLBP

Model	Accuracy	Sensitivity	Specificity	Precision	Recall	F1-Score	G-Mean	Images
SIFT + EUCLBP	0.91	0.851	0.902	0.33	0.911	0.501	0.955	Image 1
	0.913	0.892	0.901	0.335	0.924	0.512	0.967	Image 2
	0.917	0.953	0.914	0.338	0.925	0.514	0.978	Image 3
	0.92	0.925	0.936	0.34	0.943	0.521	0.963	Image 4
	0.924	0.954	0.931	0.345	0.952	0.523	0.967	Image 5

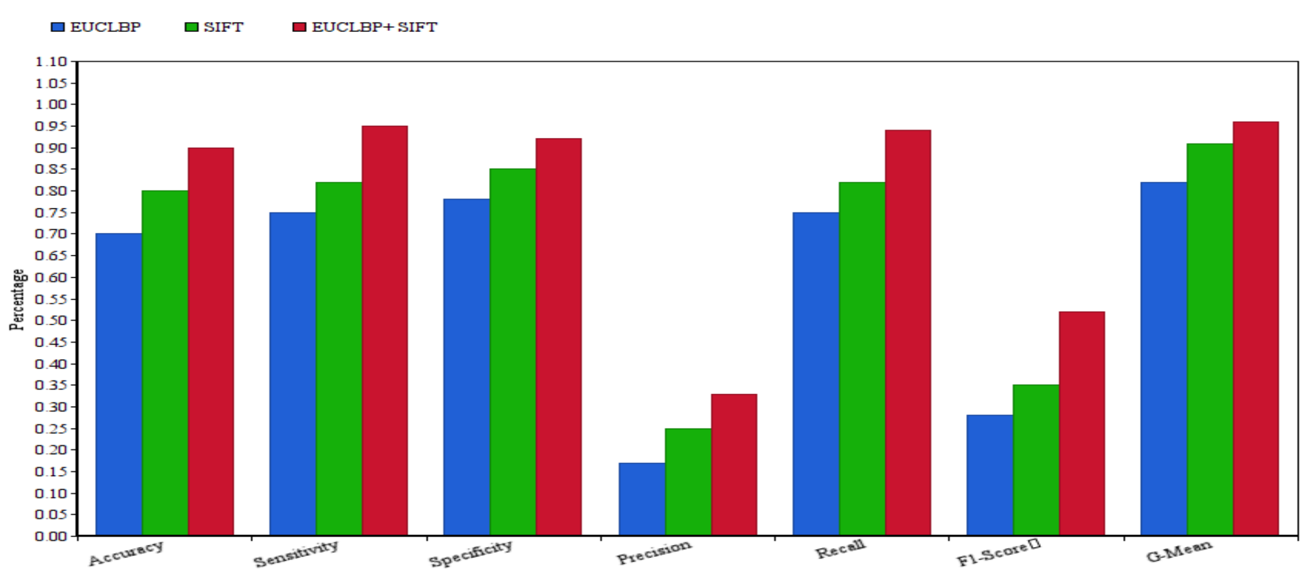


Fig 16. EUCLBP+ SIFT vs Measures

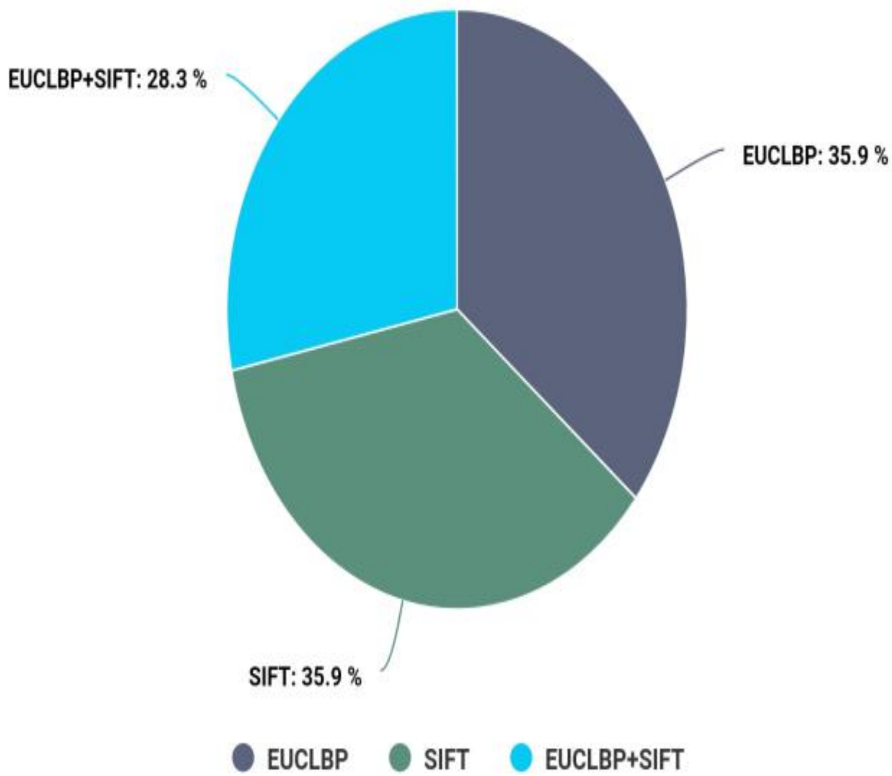


Fig. 17 EUCLBP, SIFT and EUCLBP+SIFT vs Computation time

Various experiments have been carried out to determine the performance of the feature extractors. The EUCLBP and SIFT were contrasted to the genetic algorithm in terms of performance. In the process, we chose the pre-and post-surgery images and converted them to greyscale images. Granularity was divided into three tiers, each of which produces face granules. On the 40 face granules, feature extractors were used. Additionally, we investigated the efficacy of feature selection using the multi-objective evolutionary genetic technique, both on its own and in conjunction with feature extractor results. We can deduce from the following data that the suggested combination of EUCLBP and SIFT outperforms employing either feature extractor independently.

5. Conclusion

Plastic surgery has been used to treat cosmetic and medical issues for a long time. Due to advancements in medicine and cutting-edge techniques, this process can also be used to steal someone else's identity or conceal one's own identity. Plastic surgery has already evolved as the latest face reconstruction covariate. Its appeal has also made it mandatory for face reconstruction algorithms to be resilient in correlating medically modified face images. This proposed method takes advantage of the fact that the human mind recognizes faces by evaluating the association between non-disjoint spatial data obtained at various resolution levels. Alternating among two feature extractors (SIFT and EUCLBP) is facilitated by the evolutionary selection of feature extractors, which aids in encoding discriminatory information for every face granule. This combination of employing Extended Circular Local Binary Pattern and Scale-invariant feature extractors is shown in a precise evaluation of how to use feature extractors. To manage non-linear variations in pre- and post-surgery photos while preserving the maximum level of identification accuracy, transform integrates data from every granule. We intend to upgrade the algorithm in the future to improve the selection technique to obtain more accurate outcomes.

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