Multimedia Tools and Applications (2023) 82:34147–34162
https://doi.org/10.1007/s11042-023-15107-4

Deconstructive human face recognition using deep neural network

Ratnesh Kumar Dubey[1] **· Dilip Kumar Choubey**[1]

Received: 17 August 2021 / Revised: 2 February 2023 / Accepted: 12 March 2023 /
Published online: 28 March 2023

Abstract

Confront reproduction or confront optimization as a biometric, encompasses a few points of interest in measurable application. The estimate and structure of confront are inactive of a person for reliable human face image reconstruction, the implementation system requires huge facial image datasets. Further the assessment of the system should be done by employing a testing procedure. This paper deals with the analysis and rectification of human face images for reconstruction and optimization of human face images. The advantage of using input human face image for reconstruction in forensic application and automatic face recognition system is that they are free from wide variety of poses, expression, illumination gestures and face occlusion. The whole research is divided into two phases; in the first phase reconstruction of destructed part of human face image is being done with template matching. Second phase deals with deep neural network applications to match the image carried out in phase one. The proposed algorithm is used to reconstruct the image and at the same time, reconstructed image is used as test image for biometrical face recognition. After reconstruction of image, it is examined with various well-known algorithms (SVMs, LDA, ICA, PCA & DNNs) of face recognition system for the evaluating the performance of speed, memory usage and metrics of accuracy.

Keywords Human face recognition system · Deep neural networks in face recognition · Image matching · Deep neural network · Preprocessing · Segmentation · Feature extraction · Classification.

✉ Ratnesh Kumar Dubey
ratneshdub@gmail.com; ratnesh.cse.2103001@iiitbh.ac.in

✉ Dilip Kumar Choubey
dilipchoubey_1988@yahoo.in; dkchoubey.cse@iiitbh.ac.in

[1] Department of Computer Science & Engineering, Indian Institute of Information Technology Bhagalpur, Bhagalpur, India

1 Introduction

In today's scenario digital image processing is identified as an emerging technology finding its application in many fields. This technology is used in many areas like engineering, computer science, and many other fields. One of the most interesting areas where image processing is used is forensic science. In forensic science and archaeology, the most alluring method in image processing uses facial reconstruction method. The carver who is facial anatomy expert performs facial reconstruction. For detection of gender, age, ancestry of gopher, forensic anthropologists along with the carver analyze skeleton features. For positive recognition of individuals, and to divulge anatomical features including affirmation of wounds like broken nose, teeth and facial asymmetry, the carver uses either the 2D or 3D reconstruction techniques [1, 12, 47, 48].

If the carver employs a 3D technique for recognition, the tissue is placed on the skull at predefined points. This ends in a good reconstruction as the clay when placed seems to be at the maximum possible nearest location to the gopher increasing the probability of gopher identification. Conventional methods of depth measurements based on gender, age and ethnicity were used to determine the points where the markers are placed [19–21, 46]. Fake eyes also play a part in efficient reconstruction. To determine position of eyes, length/width of nose and mouth, various iteratively measurement has been taken into consideration. When the tissue markers are affixed on the skull, the sculptor starts to place clay on the skull. This initiate sculpting and finally a face are formed [22, 23]. When the elementary or primary shape is constructed, the sculptor can work on the skull, the aim being making the skull look alike a gopher. All these steps are facilitated by means of the information provided by the forensic anthropologist, including the lifestyle of gopher and the geographical location where the gopher lived. In addition to this, for better identification of the gopher, the sculptors may add clay or wig representing hair [13, 14, 16, 17].

The properties are not limited to the above-mentioned ones but can be anything such as articles of clothing, glasses or any other aspects that could end up in a good identification. The basics of the 2D reconstruction techniques are similar to 3D techniques involving the placement of tissue markers on the skull at pre-defined depths and particular places by means of dome measurements for finding age, sex and ancestry [15, 18, 24, 25]. As mentioned above, once the skull is in the Frankfort horizontal position, an 1X1 image of the skull is photographed from both the profile view and frontal view.

The artist follows the boundaries or to be specific skull contours and by referring the tissue markers sketches the skull. By means of 3-D reconstruction techniques size and position of mouse, nose and eyes can be found. The type of hair and style is found by estimating sex and ancestry, data given by the forensic anthropologist, from scene evidences or from other methods. Another type of reconstruction technique involves reconstruction of a human face from a decaying body. Here the artist makes use of their knowledge regarding the position of the soft tissue of the skin on the skull and the process of body decomposition. The goal is to obtain an exact imagery of the gopher during the lifetime. The 2D techniques are advantageous over 3D techniques in terms of time even though they both end up in the same results. The rest of the paper is arranged as follows, in Section 2, the literature review is analyzed and the motivation of the research. The proposed Methodology with mathematical formulations is explained in Section 3, Results and Discussion are given in Section 4 and the conclusion and Future work section is presented in Section 5.

2 Literature review

A 3D face can be reconstructed using the anatomical condition of human head. Deep Neural Networks can be used for detecting such kind of models. In this project, a novel method for recovery of face recognition is put forward by the researcher using deep neural networks [26, 27]. Deep learning is a branch of machining learning. It helps in learning hierarchical representations of the given data. Multiple nonlinear processing layers are a major part of it and by stacking them pattern classification is enabled. The major architecture of a DNN involves an input layer followed by a huge number of hidden layers and an output layer. The network is initialized at the beginning by means of unsupervised training. Consequently, they are tuned in a supervised manner. Figure 1 shows the difference between deep learning and regular machine learning [28–30, 32].

Amongst regular machining learning methods and deep learning methods, deep learning methods focus on learning different useful feature representations, the raw material being the available input data. This is done by means of capturing significant statistical irregularities from the input data. Next the representation features can be framed for regression, classification and other information retrieval problems [2, 31, 33–35]. Some of the major advantages of deep learning include human effort in feature learning and independence from prior knowledge.

In the starting module, initially the frontal human-face image has been studied. This is done to extract significant features for forming a corpus termed as human-face model. In the successive phase, a face image under test with every possible orientation's have been captured resulting in the application of high-end computing approach of advanced computing for the successful recognition of the subject's face. In the current research work based on the created data sets, a proper matching-classification- decision process has been performed [10, 36–38]. Keeping this objective, in the present work, a methodology based on deep neural network has been proposed for the reconstruction of destructed human face image for forensic application [39, 41].

Jangir et al., [11], Choubey et al., [3, 9] have used similar data science and machine learning algorithms for the identifications and predictions of medical diabetes.

The idea conceived through the review of many published articles, text and references like comparative analysis of classification methods [7, 32], performance evaluation of classification methods [8, 33], rule-based diagnosis system [6, 31] and classification techniques and diagnosis for diabetes [4, 5, 34, 35] are found to be of great help in accomplishment of the present work.

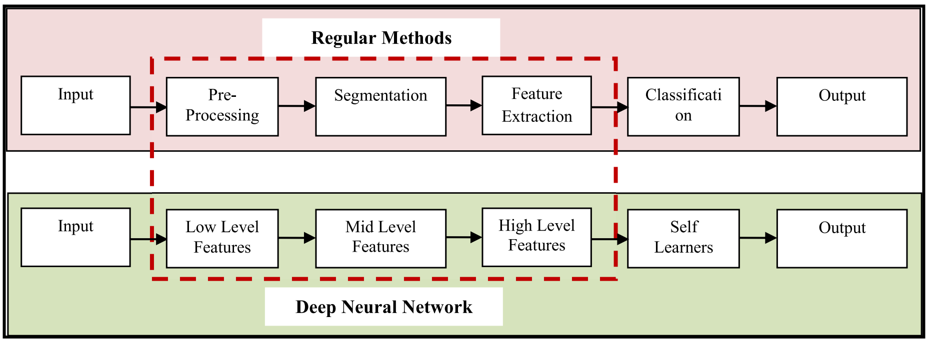

Fig. 1 Comparison between Deep Neural Network and Regular Methods

3 Proposed methodology with mathematical formulations

Generally, two methods namely simple structure analysis and template matching approach are used to compute the estimated outline of the wavelet in noisy environment, and its occurrence time. Figure 2 depicts the architecture of the proposed methodology which is shown below.

In order to compute the wavelet coefficients, present in the noisy images, consider a group of wavelet, $W_i(t)$ belonging to the range $i = 0, 1, \ldots, N - 1$, for an entire structural characteristic possibilities. By considering additive noise, the corrupted image can be expressed as [40, 42, 43],

$$P(m,n) = q(m,n) + \mathrm{G}r(m,n) \tag{1}$$

In which, q(m, n) represents the original image without noise, r(m, n) illustrates the noise present in the image and G is known as signal-to-noise ratio. Windowing of the image is expressed as represented in Eq. (2) when G is set to 1.

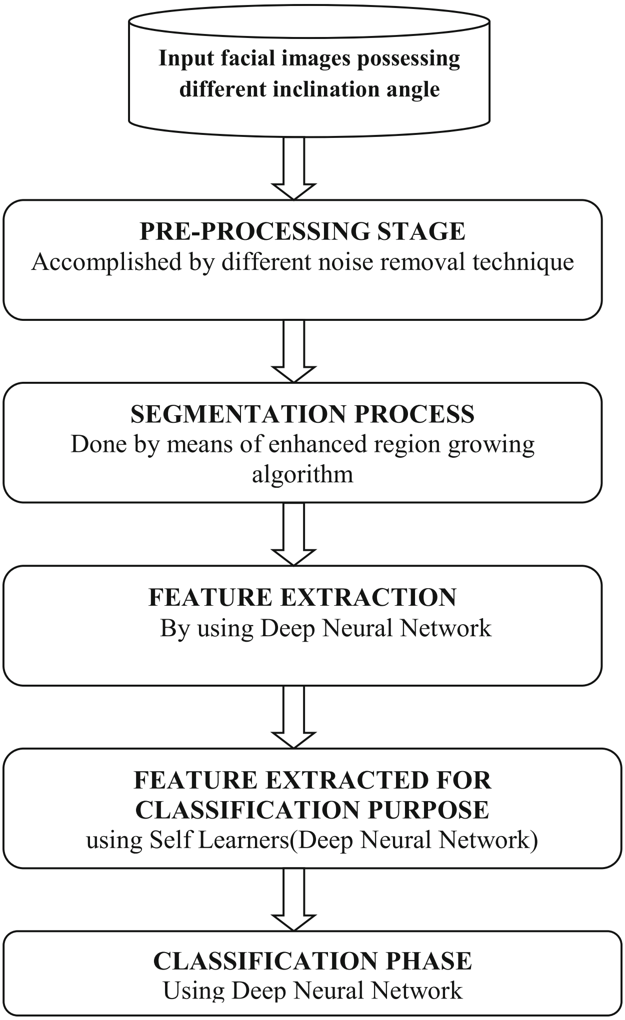

Fig. 2 Architecture of the proposed methodology

$$P_w(m,n) = q_w(m,n) + r_w(m,n) \tag{2}$$

Applying the Fourier transform, we get

$$P_w\left(e^{j\omega 1}, e^{j\omega 2}\right) = Q_w\left(e^{j\omega 1}, e^{j\omega 2}\right) + R_w\left(e^{j\omega 1}, e^{j\omega 2}\right) \tag{3}$$

Where, $\begin{cases} P_w\left(e^{j\omega 1}, e^{j\omega 2}\right) & Fouriertransformofwindowednoisyimages \\ Q_w\left(e^{j\omega 1}, e^{j\omega 2}\right) & Fouriertransformoforiginalimage \\ R_w\left(e^{j\omega 1}, e^{j\omega 2}\right) & Fouriertransformofnoisyimages \end{cases}$

ϕ(t) signifies the fundamental mother wavelet and is illustrated as

$$\varphi(t) = e^{\left(\left(j2\pi ft - t^2/(2)\right)\right)} \tag{4}$$

Applying Continuous Wavelet Transform CWT (a, τ), the above expression is modified as,

$$CWT(a,\tau) = \left(1/\sqrt{a}\right)\int p(t)\phi\{(t-\tau)/a\} \tag{5}$$

Discretization of CWT is performed by applying discrete parameter wavelet transform (DPWT) and the resultant discretized output is presented in Eq. (6).

$$DPWT(m,n) = 2^{-m/2}\sum_k \sum x(k,l)\left(2^{-m}k - n\right) \tag{6}$$

In which

$$\begin{cases} m, nintegers \\ a_0, \tau_0\ samplingintervalforand\tau \\ x(k,l)\ enhancedimages \end{cases}$$

By substituting $a_0 = 2$ and $\tau_0 = 1$, the wavelet coefficient can be calculated for Eq. (6).

Sampling of the enhanced images is done at periodic time interval T to obtain sampled image sequences {q(mT, nT)}, with size X x Y, belonging to ranges m = 0,1, …, X-1 and n = 0,1,…,Y-1 significantly. By applying discrete Fourier transform (DFT) [44, 45], the equation is dictated as below

$$I(u,v) = \sum_{x=0}^{x-1}\sum_{y=0}^{y-1} i(x,y)\exp(-j2\pi(um/x + vn/N) \tag{7}$$

where u = 0,1,…,X-1 and v = 0,1, ……..,Y-1.

The magnitude, phase angle and power spectrum are evaluated by time-domain to frequency-domain transformation. If $R(u,\ v)$and $A(u,\ v)$ signifies the real and imaginary part of $Q(u,\ v)$its magnitude spectrum can be expressed as

$$|I(u,v)| = \left[R^2(u,v) + A^2(u,v)\right]^{1/2} \tag{8}$$

And the phase angle can be defined as

$$\phi(u,v) = \tan^{-1}\left[\frac{A(u,v)}{R(u,v)}\right] \tag{9}$$

The power spectrum with the inclusion of magnitude and phase angle is depicted as

$$P(u,v) = |I(u,v)|^2 = R^2(u,v) + A^2(u,v) \tag{10}$$

The dynamic range seems to be very high as the power spectrum is expressed as the squared value of the magnitude. Hence, logarithmic transformation is applied for normalization purpose and the normalized equation can be defined as

$$|I(u,v)|_{normalize} = \log(1 + |I(u,v)| \tag{11}$$

The expectation value, variance and its auto covariance of the enhanced images are represented as in Eqs. (12), (13) and (14) respectively.

$$E[I(u,v)] = \frac{1}{XY}\sum_{u=0}^{X-1}\sum_{v=0}^{Y-1} I(u,v) \tag{12}$$

$$Var[I(u,v)] = E\left\{\left|I(u,v) - I'(u,v)\right|^2\right\} \tag{13}$$

$$C_{xx}(u,v) = E\left\{\left[I(u,v) - I'(u,v)\right]\left[I(u,v) - I'(u,v)\right]\right\} \tag{14}$$

The power spectral density can be calculated as

$$P_E(f) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} C_{xx}(m,n)W(m,n)\exp(-j2\pi f(m=n)) \tag{15}$$

Where, C_{xx}(m,n) and $W(m, n)$are auto-covariance and Blackman-window function respectively with $'m'$and $'n'$ samples.

By applying discrete cosine transform (DCT), the data can be compressed by the given equation.

$$\mathrm{DCT_c}(\mathrm{u},\mathrm{v}) = \sum_{x=0}^{X-1}\sum_{y=0}^{Y-1} I(x,y)\cos\left(\frac{2\pi T(x+y)}{XY}\right) \tag{16}$$

For the calculation of Eigen-values and respective Eigen-vectors, a pattern vector $\overline{p_n}$is considered that is represented by similar low dimension vector$\overline{q_n}$,which can be expressed in terms of linear transform characteristics.

$$\overline{p_x} = [X]\overline{q_x} \tag{17}$$

Where$[X]$ = $[I(x, y)]$, $form$ = 0 to $X - 1$&n = 0 to $X - 1$,

$\overline{q_x}$ = min([X]), $where\,\overline{q_n}$> 0.

By taking the covariance of Eq. (17), the Eigen-vectors are estimated as shown in Eq. (18),

$$\overline{P} = cov\left(\overline{p_n}\right) \tag{18}$$

$$\overline{p}.X_i = \lambda_i.X_i \tag{19}$$

Where, λ_i denotes the respective Eigen-values.

Although using PCA with covariance finds the components that are useful for representing the data but may not be useful for discriminating the data between classes. Thus, Fisher's Linear Discriminate Analysis (FLDA), has been applied in present work for reducing the feature vector dimensionality from 'x' into A $=Y - 1$ (where Ydenotes the total class involved). Hence the main idea in adopting FLDA is to project the feature vector of 'x' dimension into least dimensional region. These regions are selected in such a manner that the partition among the classes have been at minimal distance from the regression line.

Clustering is an unsupervised method and needs a training set where belong to different classes are known as priori. Image clustering and categorization is a means for description of image features. When no such training set is available one should adopt unsupervised methods such as clustering. Clustering can be used for training as well as classification in an unsupervised manner. In clustering, the basic objectives to partition the feature space data points into several groups that follow a pre-defined set of procedures. Image clustering enables the creation of a user-friendly interface to the database and the implementation of efficient retrieval algorithm. There are two widely used methods namely c-means clustering and k-means clustering. Figure 3 depicts the training stage of the proposed method.

Figure 4 depicts the testing stage of the proposed methodology on complete face. K-means is a simplest clustering approach that adopts square-error criteria algorithm where the total partitions are pre-defined. The implementation process of K-means clustering is simple and the time required for computation is minimal. For predefined number of clusters, the cluster centers are randomly initialized and every data point is allocated to any of the neighboring cluster. But the selection of the predefined cluster affects the output of k-means algorithms. If the selection of initial clusters is unclear, then the algorithm outputs wrong cluster location along with improper clustering. C-means is a clustering technique that allows single pixel of data to present in more than two clusters. A machine learning algorithm called as Support Vector Machine is applied for classifying and characterizing the progressive switching pattern of facial test images taken from the side-view (Figs. 5, 6, 7, 8 and 9). Figure 5 depicts the testing stage of the proposed methodology on Destructive Face.

Various facial image database is collected and the proposed technique is applied for automatic generation of seven numerous facial datasets. Table 1 shows the statistic comparison of each database with various Database Faces given in [14].

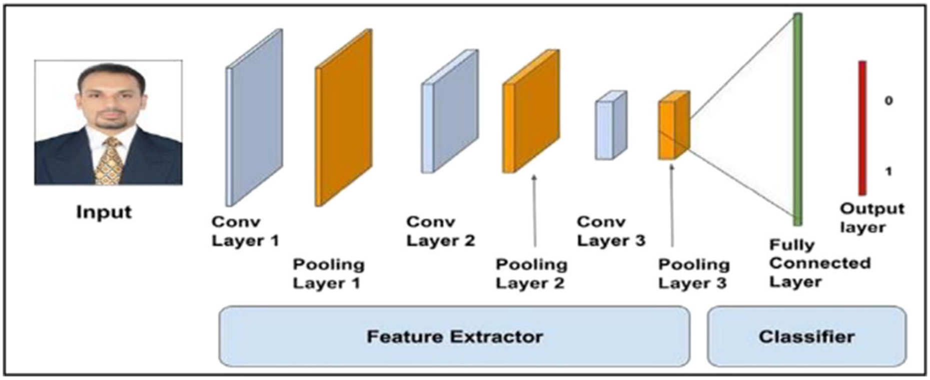

Fig. 3 Training Stage of Proposed Methodology

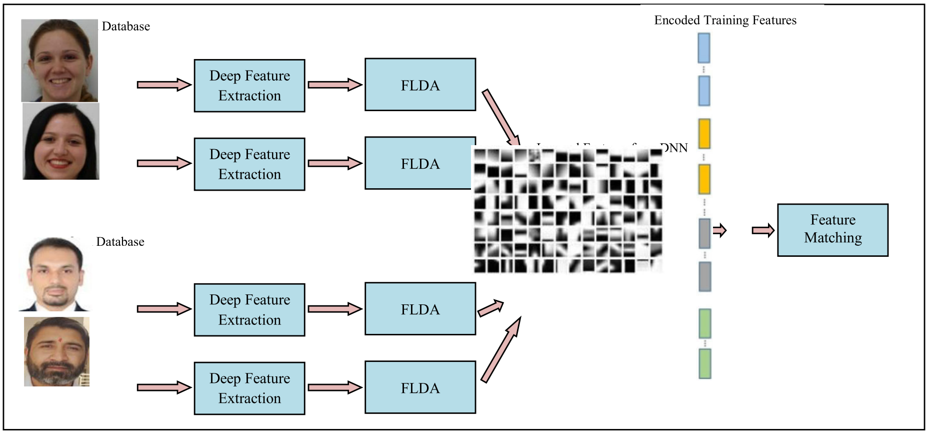

Fig. 4 Testing Stage of Proposed Methodology on Complete Face

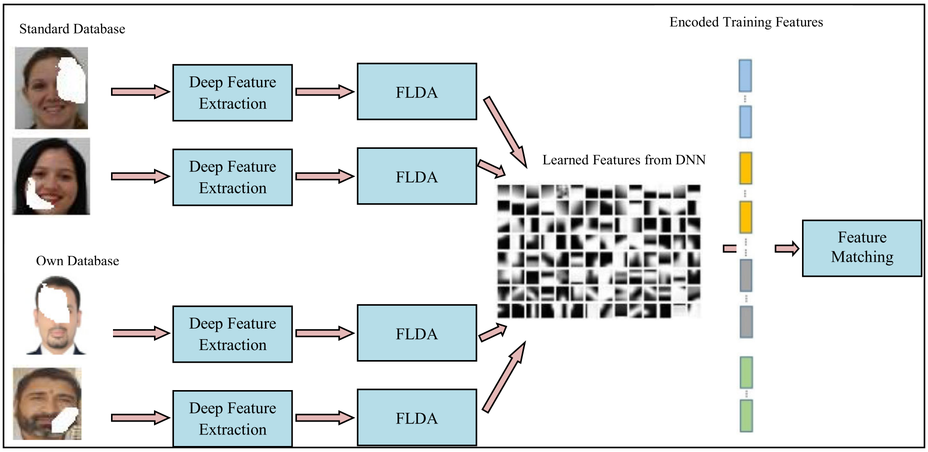

Fig. 5 Testing Stage of Proposed Methodology on Destructive Face

Fig. 6 Original picture, Image of Case 1, Image of Case 2, Image of Case 3

Fig. 7 Image of Case 1, Image of Case 2, Image of Case 3

Algorithm for Recognizing the Reconstructed Face Image

The methodology adopted in the present work has been depicted below.

Algorithm 1 Recognition algorithm called RRFI

Step1. Read an unknown plant image

Step2. Convert into grayscale image, say R.

Step3. Filter the image using DCT

Step4. Get the Cropping counter, say, n

Step5. Set the counter for Objsel = m

Do while Objsel> 0

Select the Object of Interest (OOI) for each Objsel

Crop the selected object

Scale the Cropped and Selected object using 2D transformation technique (Scaling technique)

Segment the OOI using connected component method

Employ Flood fill algorithm for image rectification

Re-segment the filled object image

Extract the features of the object rectified

And store in the form of face model

Objsel = Objsel - 1

End Do

Step6. Store in a template and map the data with corpus for the classification process and recognition of reconstructed face image using Naïve classification method, SVM, GA.

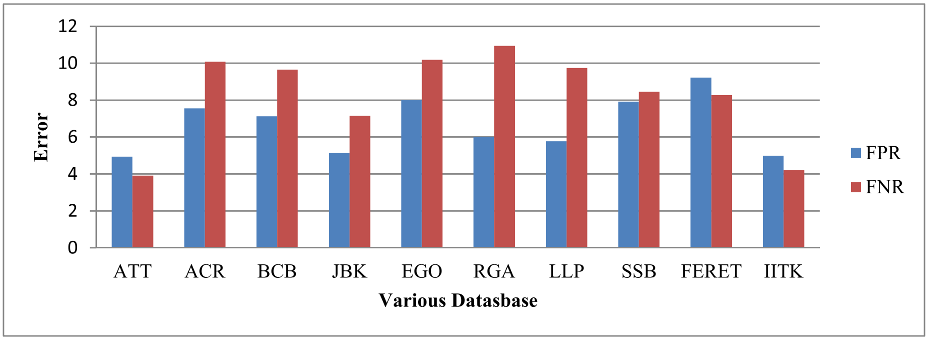

Fig. 8 Comparison of FPR and FNR on Various Database with Proposed Methodology

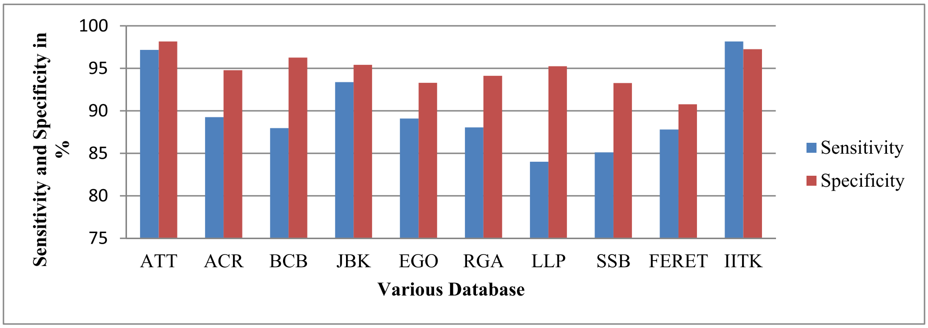

Fig. 9 Comparison of Sensitivity and Specificity on Various Databases with Proposed Methodology

4 Results and discussions

In the present work an algorithm is developed for the reconstruction of destructed human face has been represented in Fig. 3. It represents the original face image and almost all possible combination of destruction in 2d face image. The proposed work is carried out in two parts, in first part destructed face image is read and preprocessing techniques is performed after that segmentation is perform, from segmented face image the mirror image part is crop which is almost similar to the destructed part (Table 2). After that the face image will be used for recognition and performance is measured as shown in Fig. 4.

The Table 3 illustrates the achieved percentage for different methods for different datasets (Fig. 11).

The feature clusters used for the identification of behavioral patterns of human face have been drawn by adopting fuzzy c-means clustering and the outcome is visualized in Fig. 12.

False positive rate (FPR) The percentile of cases where an image was segmented to the shape, but in fact it did not (Fig. 13).

$$FPR = \frac{FP}{FP + TN} \tag{20}$$

Table 1 Statistics for various datasets

Sr. No.	Dataset Name	No. of Person	Total Images
1.	ATT	40	400
2.	ACR	10	282
3.	BCB	22	839
4.	JBK	65	4009
5.	EGO	148	7950
6.	RGA	215	12,394
7.	LLP	264	17,602
8.	SSB	222	18,599
9.	FERET	329	3290
10.	IIT-Kanpur	40	400

Table 2 Comparison of Accuracy, FPR, FNR, Sensitivity and Specificity on all standard datasets (Fig. 10)

Datasets	FPR	FNR	Sensitivity (in %)	Specificity (in %)	Accuracy (in %)
ATT	4.9511	3.9222	97.1888	98.1589	98.9957
ACR	7.5504	10.0836	89.2484	94.7996	95.1185
BCB	7.1283	9.6467	87.9713	96.2767	95.4705
JBK	5.1306	7.1463	93. 3756	95.4134	97.4006
EGO	7.9959	10.191	89.0829	93.2941	94.4491
RGA	6.0173	10.9402	88.0512	94.1127	93.4955
LLP	5.7689	9.7401	84.0111	95.2611	90.1226
SSB	7.9147	8.4565	85.1005	93.2863	91. 1126
FERET	9.2179	8.2678	87.7902	90.7721	90.1939
IITK	4.9852	4.2191	98.1589	97.2597	97.3251

False negative rate (FNR) The percentile of cases where an image was segmented to the shape, but in fact it did.

$$FNR = \frac{FN}{FN + TP} \tag{21}$$

Sensitivity The sensitivity is defined as the rate of proportions of true positive that are correctly identified. It correlates the ability of the test to obtain positive outcomes.

$$Sensitivity = \frac{Number\ of\ TP}{Number\ of\ TP + Number\ of\ FN} X100 \tag{22}$$

Specificity The specificity is defined as the rate of proportions of true negative that are correctly identified. It correlates the ability of the test to obtain negative outcomes.

$$Specificity = \frac{Number\ of\ TN}{Number\ of\ TN + Number\ of\ FN} X100 \tag{23}$$

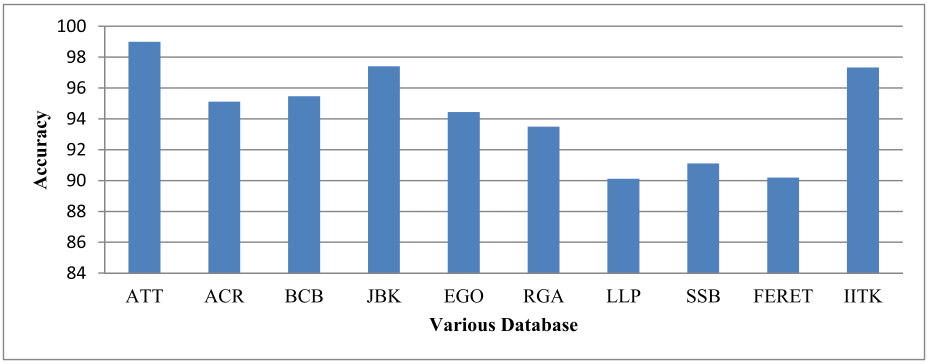

Fig. 10 Comparison of Accuracy on Various Databases with Proposed Methodology

Table 3 Accurate percent measures of datasets & approaches (in %)

	ATT DB	ACR DB	BCB DB	JBK DB	EGO DB	RGA DB	LLP DB	SSB DB	FERET DB	IITK DB
PCA	94.1	70.7	58.2	57.5	53.8	51.0	48.1	57.2	90.2	93.3
IPCA	95.4	66.1	57.0	57.2	52.6	50.9	47.9	56.6	92.4	94.3
Ind. IPCA	94.1	70.7	60.3	51.9	49.3	44.4	39.9	45.1	90.2	93.3
ICA	92.3	73.5	57.9	52.4	51.1	46.5	42.0	49.9	89.1	91.3
ILDA	97.3	71.6	67.7	60.4	56.6	53.4	50.3	58.6	93.3	96.3
PCA/VM	96.5	73.5	72.3	65.0	62.7	59.1	54.5	63.4	94.2	96.6
ILDA/SVM	95.3	73.5	64.6	63.3	63.3	62.3	58.4	68.5	93.5	96.3
SVM	97.9	71.6	71.9	67.6	65.3	61.2	59.2	67.0	94.2	96.8
Proposed	98.9	95.1	95.4	97.4	94.4	93.4	90.1	91.1	90.1	97.3

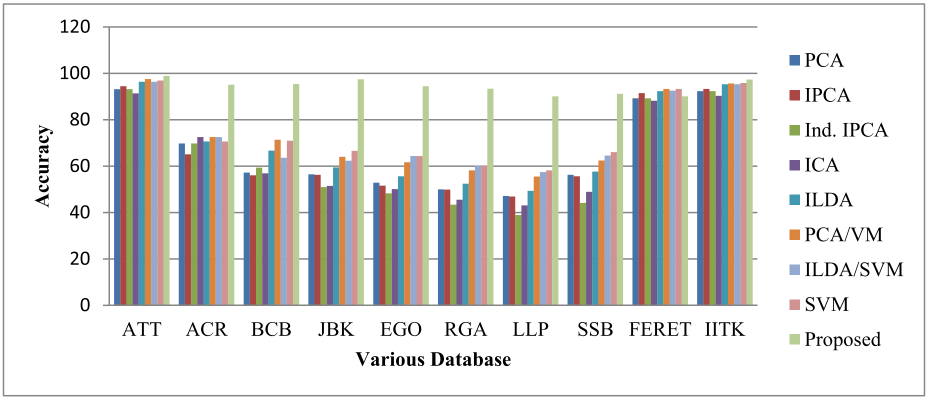

Fig. 11 Comparison of Accuracy on Various Database with different Methodology

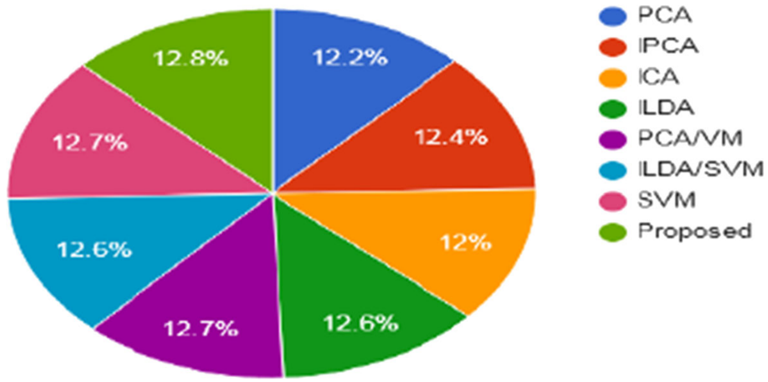

Fig. 12 Statistical analysis in papers with numerical results

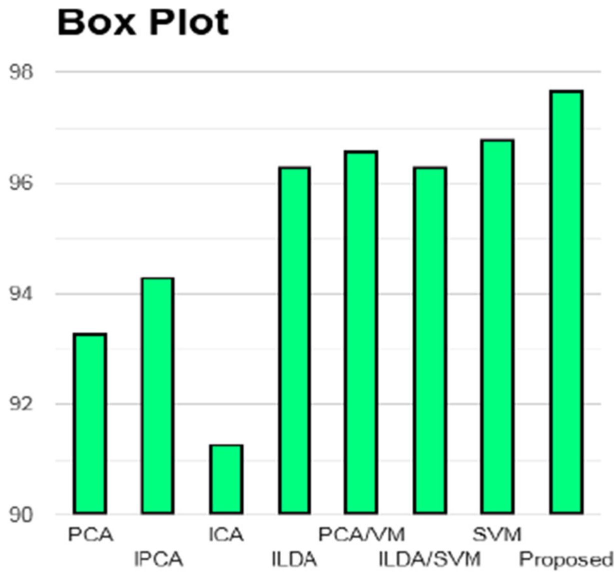

Fig. 13 Box plot analysis in paper with numerical results

Accuracy The weight percentile of pose varied facial images is exactly categorized by measuring the accuracy. It can be expressed as given in Eq. (14).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} X100 \tag{24}$$

5 Conclusion

The present research work we have discussed the results obtained. In this research work knowledge-based model has been formed by considering the relevant features of human face image as case study. After that knowledge-model has been mapped with test reconstructed face image for recognition and classification, The feature clusters used for the identification of behavioral patterns of human face have been drawn by adopting fuzzy c-means clustering and the outcome is visualized, From the experimental results, the application of proposed algorithm has been found very satisfactory.

Data availability Various facial image database is collected and the proposed technique is applied for automatic generation of seven numerous facial datasets. Table 1 shows the statistic comparison of each database with various Database Faces given in [14]. The samples facial images of several dataset are presented.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

References

1. Bhattacharyya S, Chakraborty S (2014) Reconstruction of Human Faces from Its Eigenfaces. International Journal of Advanced Research in Computer Science and Software Engineering. 4(1)
2. Chang YS, Ahn SY (2008) Side view face detection using geometrical characteristics of nose and chin in color image. Journal of the Research Institute for Computer and Information Communication 11(3):23–28
3. Choubey DK, Paul S (2016) GA_MLP NN: a hybrid intelligent system for diabetes disease diagnosis. Int J Intel Syst Appl 8(1):49–59
4. Choubey DK, Paul S (2016) Classification techniques for diagnosis of diabetes: a review. Int J Biomed Eng Technol 21(1):15–39
5. Choubey DK, Paul S (2017) GA_RBF NN: a classification system for diabetes. Int J Biomed Eng Technol 23(1):71–93
6. Choubey DK, Paul S, Dhandhenia VK (2017) Rule based diagnosis system for diabetes. Int J Med Sci 28(12):5196–5208
7. Choubey DK, Kumar M, Shukla V, Tripathi S, Dhandhania VK (2020) Comparative analysis of classification methods with PCA and LDA for diabetes. Curr Diabetes Rev 16(8):833–850
8. Choubey DK, Kumar P, Tripathi S, Kumar S (2020) Performance evaluation of classification methods with PCA and PSO for diabetes. Network Model Analy Health Inform Bioinfor 9(1):1–30
9. Choubey DK, Tripathi S, Kumar P, Shukla V, Dhandhania VK (2021) Classification of diabetes by Kernelm based SVM with PSO. Recent Adv Comput Sci Commu (Formerly: Recent Patents Comp Sci) 14(4):1242–1255
10. Devireddy SK, Siva Nagireddy K, Ramsaswamy G, Ravikiran D, Sireesha P, Suresh Babu Y (2008) A study of Unimodel multimodel and soft biometric recognition. IJCSNS Int J Comput Sci Netw Sec 8(8):36–46
11. Jangir SK, Joshi N, Kumar M, Choubey DK, Singh S, Verma M (2021) Functional link convolutional neuralnetwork for the classification of diabetes mellitus. International journal for numerical methods in biomedical engineering. e3496
12. Kemelmacher-Shlizerman I, Basri R (2011) 3D face reconstruction from a single image using a single reference face shape. IEEE Trans Pattern Anal Mach Intell 33(2):394–405. https://doi.org/10.1109/TPAMI.2010.63
13. Kumar S (2018) Health care monitoring based on internet of things" the (Springer) International Conference on Artificial Intelligence & Cognitive Computing (AICC), 2nd -3rd Feb 2018 Hyderabad (Scopus Indexed-Published)
14. Kumar S, Singh S, Kumar J (2017) A study on face recognition techniques with age and gender classification. In: IEEE international conference on computing, Communication and Automation (ICCCA). pp 1001–1006
15. Kumar S, Singh S, Kumar J (2019) Gender classification using machine learning with multi-feature method. In: IEEE 9th annual computing and communication workshop and conference (CCWC), Las Vegas, USA, January 7th–9th
16. Kumar S, Singh S, Kumar J (n.d.) Live Detection Of Face Using Machine Learning with Multi-Feature Method in Wireless Personal Communication Springer Journal (SCI) Published https://doi.org/10.1007/s11277-018-5913-0
17. Kumar S, Singh S, Kumar J (n.d.) Automatic Live Facial Expression Detection Using Genetic Algorithm with Haar Wavelet Features and SVM. In Wireless Personal Communication Springer Journal (SCI) Published https://doi.org/10.1007/s11277-018-5923-y
18. Kumarc S, Singh S, Kumar J (2017) A comparative study on face spoofing attacks. In IEEE international conference on computing, Communication and Automation (ICCCA), pp 1104–1108
19. Raja R, Sinha TS, Dubey RP (2015) Recognition of human-face from side-view using progressive switching pattern and soft-computing technique, Association for the Advancement of modelling and simulation techniques in enterprises, AMSE journals 2015 series 58(1):14–34
20. Raja R, Sinha TS, Dubey RP (2015) Biometrical authentication of twins from side-view using hybrid approach, (BJSTH) Bharat journal of science technology and humanities, Vol. I (1), 2015
21. Raja R, Sinha T, Dubey RP (2015) An Empirical Analysis for Detection of Occlusion for face image parallel to the surface plain using Soft-Computing technique. MATS J Eng Appl Sci 1(2):97–104 ISSN No 2394–0549
22. Raja R, Sinha TS, Dubey RP (2016) Soft computing and LGXP techniques for ear authentication using progressive switching pattern, published in international journal of engineering and future technology 2(2)
23. Raja R, Sinha TS, Dubey RP (2016) Orientation Calculation of human Face Using Symbolic techniques and ANFIS. Published Int J Eng Future Technol 7(7):37–50
24. Scholkopf B, Smola A, Muller K (1998) Nonlinear component analysis as a kernel eigenvalue problem. Proc Neural Comput 10(5):1299–1319

25. Shafiee S Kamangar F Ghandehari LS (2014) Cluster-based multi-tasking sparse representation for efficient face recognition, IEEE image analysis and interpretation (SSIAI) on 6-8 April at san Diega, CA, pp 125–128.
26. Shah JD, Patil SH (2008) Biometric authentication based on detection and recognition of multiple face in image" in the proceeding of IC-3. pp 87–95
27. Shan T, Lovell BC, Chen S (2006) Face recognition robust to head pose from one sample image. In Proc 18th IEEE Int Conf Patt Recog Hong Kong 1:515–518. https://doi.org/10.1109/ICPR.2006.527
28. Sharma A, Al Haj M, Choi J, Davis LS, Jacobs DW(2012) Robust pose invariant face recognition using coupled latent space discriminant analysis, Elsevier Journal on Computer Vision and Image Understanding 116:1095–1110
29. Shuang L (2014) A novel face Dectection algorithms based on PCA and Adaboost, 6th IEEE international conference on measuring technology and Mechantronics automation on 10-11 Jan at Zhangjjajie. pp 38–41
30. Singh G, Chhabra I (2014) Human face recognition through moment descriptors, proceeding of IEEE RAECS UIET Panjab University Chandigarh on 6-8 may at Chandigarh, pp 1–6
31. Singh S, Vatsa M, Singh R, Shukla KK (2003) A comparative study of various face recognition algorithms (feature based, eigen based, line based, neural network approaches), IEEE international workshop on computer architectures for machine perception on 12-16 may at New Orleans LA. pp 160–171. https://doi.org/10.1109/CAMP.2003.1598161
32. Singh R, Vatsa M, Ross A, Noore A (2007) A Mosaicing scheme for pose-invariant face recognition, IEEE transactions on systems, man, and Cybernetics. Part B: Cybernetics 37(5):1212–1225. https://doi.org/10.1109/TSMCB.2007.903537
33. Singh R, Vatsa M, Ross A, Noore A (2007) A Mosaicing scheme for pose - invariant face recognition, in IEEE transactions on systems. MAN and CYBERNETICS 37(5):1212–1225. https://doi.org/10.1109/TSMCB.2007.903537
34. Sinha TS, Patra RK, Raja R (2011) A comprehensive analysis of human gait for abnormal foot recognition using neuro-genetic approach. Int J Tomog Stat (IJTS) 16(W11):56–73 http://ceser.res.in/ceserp/index.php/ijts
35. Siraj F Yusoff N Kee LC (2006) Emotion classification using neural network, International Conference on Computing & Informatics (ICOCI '06) on 6–8 June at Kuala Lampur. pp 1–7 https://doi.org/10.1109/ICOCI.2006.5276419
36. Suikerbuik R Tangelder H Daanen H Qudenhuijen A (2004) Automatic feature detection in 3D human body scans, Proceeding of the Conference SAE Digital Human Modeling for design and Engineering
37. Sun X Zhang Q, Wang Z (2009) Face recognition based on NMF and SVM, IEEE Second International Symposium on Electronic Commerce and Security on 22–24 May at Nanchang, (ISECS'09) 1:616–619 https://doi.org/10.1109/ISECS.2009.98
38. Takallou HM, Kasaei S (2014) Multiview face recognition based on multilinear decomposition and pose manifold, IET image processing 8(5):300–309
39. Tan X, Chen S, Zhou Z, Zhang F (2005) Recognizing Partially Occluded, Expression Variant Faces from Single Training Image Per Person with SOM and Soft kNN Ensemble. In Proceedings of IEEE Transaction on Neural Networks 16:1–13
40. Tan N Huang L Liu C (2008) Face Recognition Based on a Single Image and Local Binary Pattern, International Symposium on Intelligent Information Technology Application,(IITA) on 20–22 Dec at Shanghai 2:366–370 https://doi.org/10.1109/IITA.2008.332
41. Tan X, Chen S, Zhou Z, Liu J (2009) Face recognition under occlusions and variant expressions with partial similarity. IEEE Trans Inform Foren Sec 4(2):217–230
42. Tan H Yang B Ma Z (2014) Face recognition based on the fusion of global and local HOG features of the face images, IET comput. 8(3):224–234
43. Tanaka HT Ikeda M Chiaki H (1998) Curvature-based face surface recognition using spherical correlation, proceedings 3rd IEEE international conference on principal directions for curved object recognition, automatic face and gesture recognition on 14-16 Apr. pp 372–377 https://doi.org/10.1109/AFGR.1998.670977
44. Tenenbaum JB, De Silva V, Langford JC (2000) A global geometric framework for nonlinear dimensionality reduction. Sci Mag 290:2319–2323
45. Terzopoulos D, Waters K (1993) Analysis and synthesis of facial image sequences using physical and anatomical models. IEEE Trans Pattern Anal Mach Intell 15(6):5690–5579. https://doi.org/10.1109/34.216726
46. Vidanapathirana M, Rajapakse RN, Madugalla AK, Amarasinghe PIU, Padmathilake VH, Dharmaratne AT, Sandaruwan KD (2013) A novel semi-automated approach for forensic facial reconstruction in Sri Lanka. Galle Med J 18(1):16–25. https://doi.org/10.4038/gmj.v18i1.5517

47. Wang S (2011) Hubei “research of 3D face reconstruction based on one image”, International Conference on Image Analysis and Signal Processing, Hubei. pp 533–537. https://doi.org/10.1109/IASP.2011.6109100
48. Yoshiki K, Saito H, Mochimaru M (2006) Reconstruction of 3D Face Model from Single Shading Image Based on Anatomical Database. 18th International Conference on Pattern Recognition (ICPR'06), Hong Kong. pp 350–353. https://doi.org/10.1109/ICPR.2006.982