Design of Face Recognition System Using Viola-Jones and GLD Method

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Abstract— *Face recognition systems are the need of time. We have applied de-noising technique and GLD method in conjunction with Viola-Jones, PCA-ANN and achieved recognition rate beyond expectation.*

Keywords— PCA, Viola-Jones, GLD Method, Median Filter. (i)

I. INTRODUCTION (ii)

Face recognition consists of feature extraction and classification of the same. The system is trained using a (iii)
set of human faces and then recognition of the test images submitted as a query. PCA principal component analysis is popularly used to extract the features from human face and neural network. In the previous work back-propagation technique is applied. The performances of the system rely upon the face detection and edge detection method. Viola-Jones is seen to affect the whole of the system. The authors have fused the feature of the facial images by enforcing various feature extraction techniques. The shape of the face is used which results in higher performance rate [1] [2] [3] [4] [5].

Our present work focal point is fusion of the facial features from the trained database and facial image on the anvil under test.

II. PROPOSED WORK

The proposed methodology for the face recognition system. The higher performance and reliability is achieved in two phases.

Phase I: - Training

Phase II: - Testing (iv)

Training phase consists of teaching about a set of images which works like a template which functions as a bench (v)
marks for recognition of the unknown faces. The image (vi)
on the anvil is recognized by extracting the salient facial features and comparing the same with features already (vii)
available in the training database. The method is to fuse the two characteristics of facial images into a feature vector. PCA is applied on this vector to reduce the dimension. Proof to this is median filter is used to de-noise the image. The reduced feature is finally used by BPNN algorithm which is later used in recognition process. The same method is applied to unknown image [6].

The train network arrives at result by selecting closet images with unknown one. The bench mark is set to reject the facial images on the basis of the threshold value.

III. PROPOSED ALGORITHM

The project starts with uploading 50 images of 10 persons with five different facial expressions.

In the pre processing step use median filter for removing the noise from an image.

Feature extraction is achieved using gray level difference method.

$$hom = \sum \frac{P}{greydiff^2 + 1} \qquad (1)$$

Where greydiff=[0:1], P is probability function and hom denotes to homogeneity

$$con = \sum (PX\ greydiff^2 + 1) \qquad (2)$$

Where con is contrast of an image

$$eng = \sum (P)^2 \qquad (3)$$

Where eng denotes energy of an image

$$ent = -\sum PXlog(P + eps) \qquad (4)$$

Where ent denotes the entropy of an image

$$B1 = \sum PXgreydiff \qquad (5)$$

Detect edge of an image using the canny edge detection method on filtered image.

Detect face from an image using Viola Jones method.

Repeat step 3 to 4 until all train and test images processing is completed.

In the feature selection process, apply principal component analysis -A picture of size NXN can be represented as a point in a N2 dimensional space. Given a face picture I(x, y), be two dimensional N by cluster of (8 bit) intensity value. M training pictures are represented by I_1, I_2,…., I_N and every picture Ii is represented to as a vector Fi. Presently the normal face vector is figured utilizing the accompanying comparison.

$$\varphi = \frac{1}{N}\sum_{i=1}^{N} Fi \qquad (6)$$

Here, φ is the average face vector. Now the deviation is estimated from the mean (average) face vector for every image. The equation will be as follows:

$$\emptyset i = Fi - \varphi \qquad (7)$$

A=[$\emptyset 1, \emptyset 2 \ldots \emptyset N$]

Here, $\emptyset i$ is the deviation vector for ith image. A is the set of deviation vector of M images. We can compute the covariance using A vector as

$$D = AA^T \qquad (8)$$

Here D is an *N2xN2* matrix and A is an *N2xM* matrix. In place of matrix AA^T, we study the matrix A^TA. Remember A is a N*2xM* matrix, thus A^TA is an *MxM matrix*. If we calculate the Eigenvectors of this matrix, it would return M Eigenvectors, each of dimensions *Mx1*; let's call these Eigenvectors v_i. The best M Eigenvectors can be detected with the help of below equation:

$$\mu_i = Av_i \qquad (9)$$

(viii) Each face in the preparation set (short the mean), $\emptyset i$ can be spoken to as a straight gathering of Eigenvectors μi.

$$\emptyset i = \sum_{k=1}^{j} \omega k \mu k \qquad (10)$$

(ix) These weights can be considered as:

$$\omega_k = \mu_i^T \emptyset i \qquad (11)$$

(x) Every normalized training image is characterized on this basis as a vector

$\omega_i = \omega_1, \omega_2 \ldots \omega_j$

(xi) In classification process, apply artificial neural network to classify the data.

Gray Level Difference Method (GLDM)

The method is:

(i) The fundamental method is to achieve a uniform histogram for discrete histograms.

(ii) The gray scale is more efficient in utilization.

(iii) Treat the histogram components and group them on selective basis. This is called Gray Level Grouping.

(iv) On the basis of gray levels group the histograms.

(v) Next step is to redistribute these groups uniformly on gray scale. These image contrast increases and contrast problem is resolved [7].

Mean Squared Error

In statistics, the mean squared error or mean squared deviation of an estimator measures the average of the errors or deviation that is the difference between the estimates.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (12)$$

BPNN (Backpropogation Neural Network)

Back propagation is a multi-layer feed forward; supervised learning network based on gradient BPN is the commonly used learning algorithm in training multilayer perceptions (MLP). Network consisting of a set of source nodes that form the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input signal moves through the network in a forward direction, from left to right and on a layer-by-layer basis [8]-[9]. The advantages of the neural network are possible interactions between predictor variables, and the availability of multiple training algorithms [10].

IV. FLOW CHART

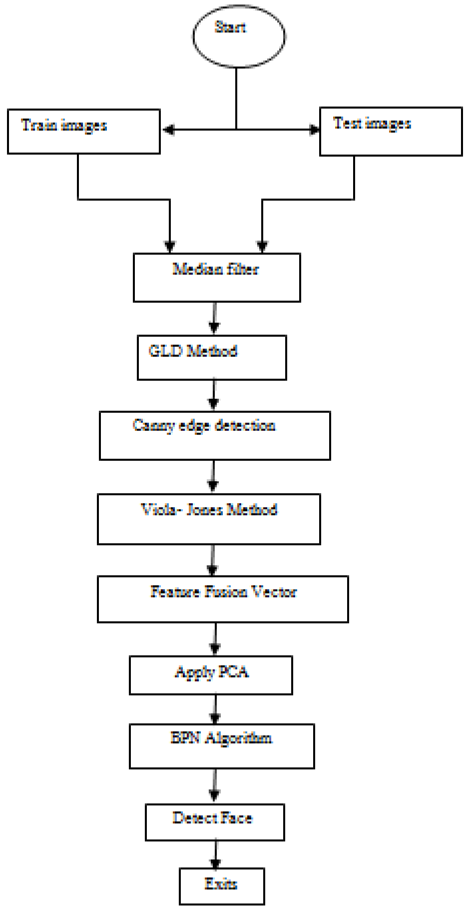

Fig. 1: Flow Chart of the Proposed Algorithm

V. SIMULATION AND RESULT

The gray image dataset is uploaded by the user to train the system. User inputs the gray images.

The median filter is applied at step 1 to de-noise the image. The human face consists of various features. These features are extracted using gray level difference method for gray images.

$$Hom = \sum \frac{P}{\text{gray diff} = [0:1],P} \qquad (13)$$

is probability function and hom stands for homogeneity .

Contrast = $\sum$ (P x gray diff ^{2} + 1) (14)

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$$\text{Energy} = \sum (P)^2 \qquad (15)$$

(a) Original image (b) Feature facial image

Fig.2: Feature is shown in figure (b)

Many a times viola – Jones detects as follows:

(a) Original image (b) Featured facial image

Fig. 3: Dimension reduction of the facial image

1. Gray Image Dataset for Train image

Fig. 4: Image Dataset (1 to 50)

2. Gray Image Dataset for Test image

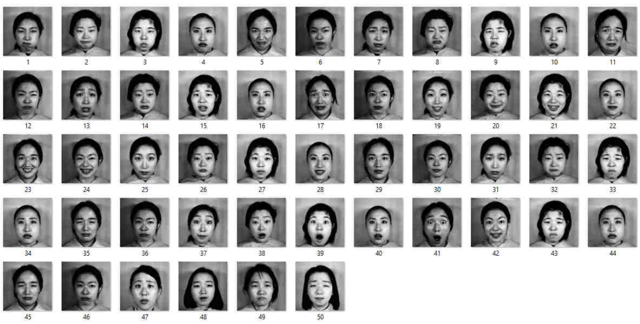

Fig.5: Image Dataset (1 to 50)

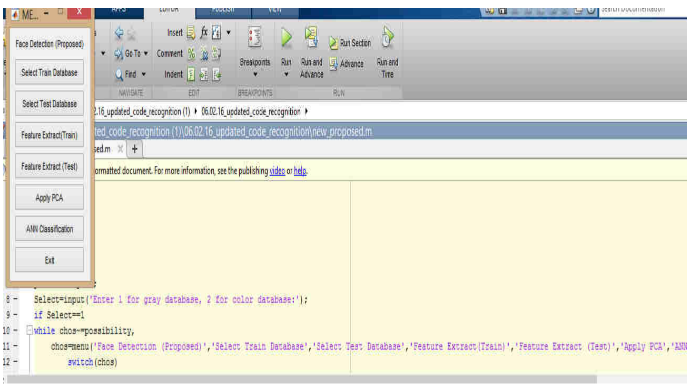

Fig. 6: select the images of Train and Test

In figure 6 graphical user interface with the choice select the train database and test image one by one.

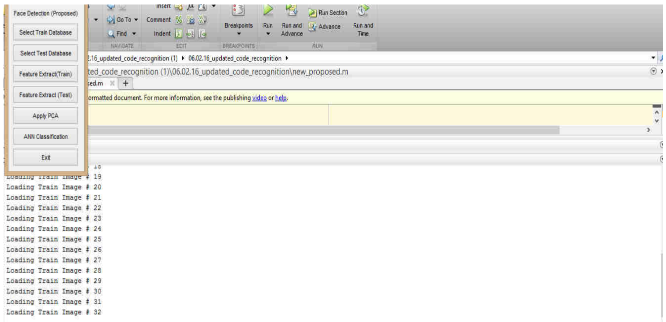

Fig. 7: Uploading the Trained images

In figure 7 the trained images are uploaded one by one.

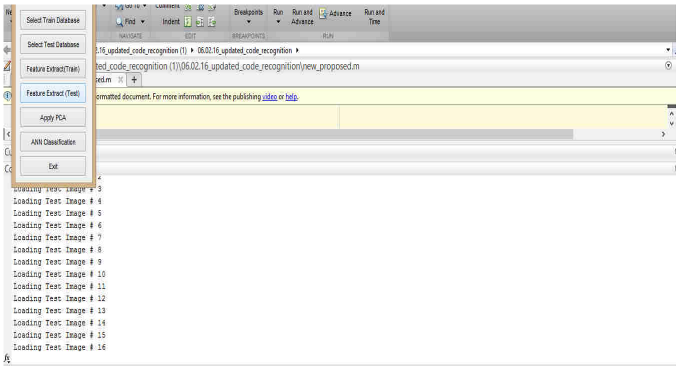

Fig. 8: Uploading the Test images

In figure 8 test images are uploaded one by one.

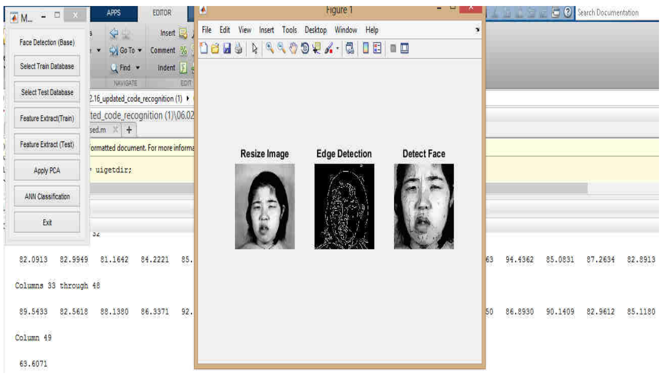

Fig. 9: Feature Fusions for Train and Test images

In figure 9 feature fusion for train and test images is done by the system by user's interference.

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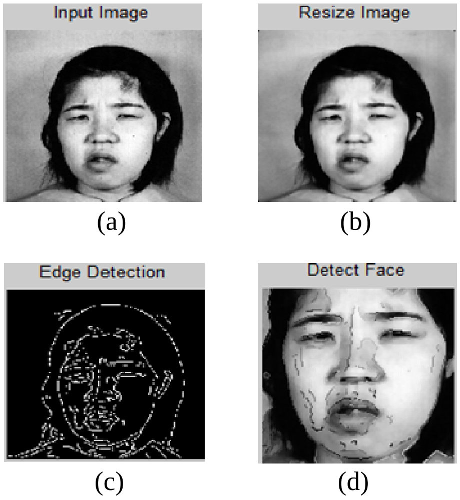

Fig. 10: Pre-processing Step for Test Images (a) Input image (b) Resized Image (c) Filtered Edge Image (d) Cropped Face

Table 1 Recognition table

No of Images	Test Image	Person Number	Euclidean Distance	Match Test Image with Train Image
1	10.tiff	Forth	13	16.tiff
2	11.tiff	Fifth	23	11.tiff
3	14.tiff	Second	58	15.tiff
4	13.tiff	First	7	21.tiff
5	36.tiff	Sixth	18	46.tiff
6	43.tiff	Third	16	3.tiff
7	8.tiff	Fifth	5	45.tiff
8	50.tiff	Tenth	12	50.tiff
9	48.tiff	Eighth	6	48.tiff
10	49.tiff	Ninth	46	49.tiff

Table explains the image under test on the basis of Euclidean distance against the matched image. This chart is genrated automatically by the system.

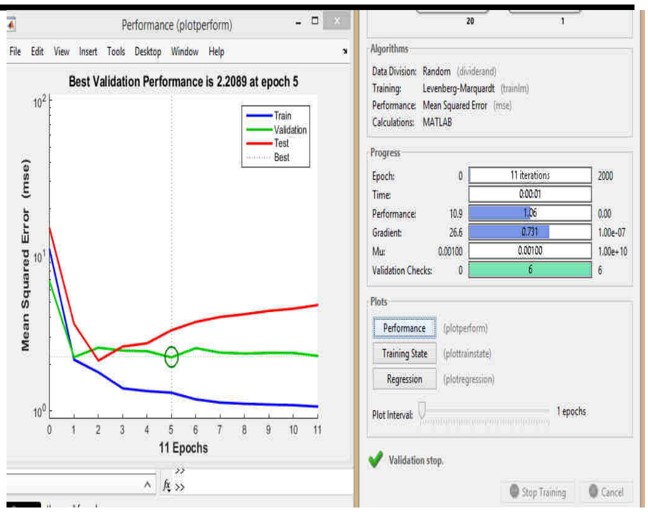

Fig. 11: Graph of Epoch (Iterations) v/s M.S.E (Base)

In figure 11 the graph is displaying Mean Square Error (MSE) with the iteration

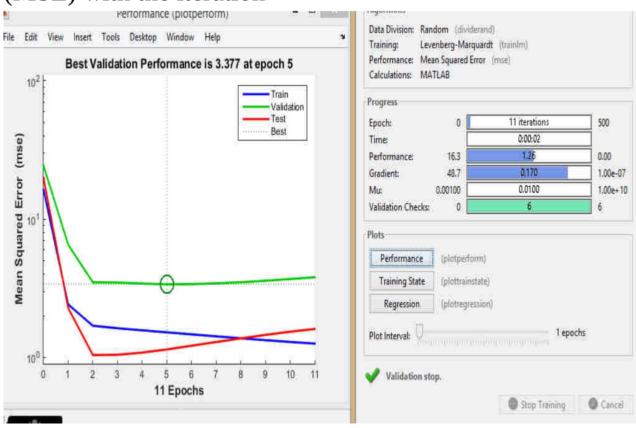

Fig. 12: Graph of Epoch v/s M.S.E (Proposed)

In figure 12 shows the Mean Square Error (MSE) for proposed system.

Table 2 Comparative Results of Learning Error

No. of Images	Image	Learning Error (Base)	Learning Error (Proposed)
1	10.tiff	1.36	0.92
2	11.tiff	0.31	0.73
3	14.tiff	0.3	1.19
4	13.tiff	0.42	0.8
5	36.tiff	1.57	1.47
6	43.tiff	2.08	1.54
7	8.tiff	0.68	1.56
8	50.tiff	2.27	1.9
9	48.tiff	0.98	2.01
10	49.tiff	1.39	2.02

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In table the learning error is shown for both the base work and proposed work for every test image.

Table 3 Comparative Results of Accuracy

No. of Images	Image	Base (%)	Proposed (%)
1	10.tiff	89.30	99.22
2	11.tiff	95.64	99.56
3	14.tiff	98.22	99.82
4	13.tiff	84.39	98.49
5	36.tiff	94.43	99.43
6	43.tiff	92.56	99.39
7	8.tiff	85.11	98.34
8	50.tiff	63.62	97.24
9	48.tiff	84.61	98.29
10	49.tiff	97.77	99.78

In table displays the performance accuracy rate for both base and the proposed works.

Table 4 Comparative Results of M.S.E (Mean Square Error)

Number of Iteration	Base	Proposed
1	11.2	7.97
2	7.44	6.41
3	6.42	6.14
4	6.46	6.07
5	6.8	6.02
6	7.44	6.06
7	7.5	6.14
8	7.61	6.15
9	7.84	6.36
10	7.97	6.5
11	8.1	6.64

In table displays the mean square error for base work and proposed work.

Table 5 Comparative Results of Validation, Recognition Rate, and Time

Algorithm	Validation Performance	Recognition Rate	Execution Time(sec)
Base	2.20	88.55%	4.78
Proposed	3.37	99.03%	2.44

The validation performance of the proposed work is more than double, recognition rate has gone up by 10 % and efficiency has increased significantly.

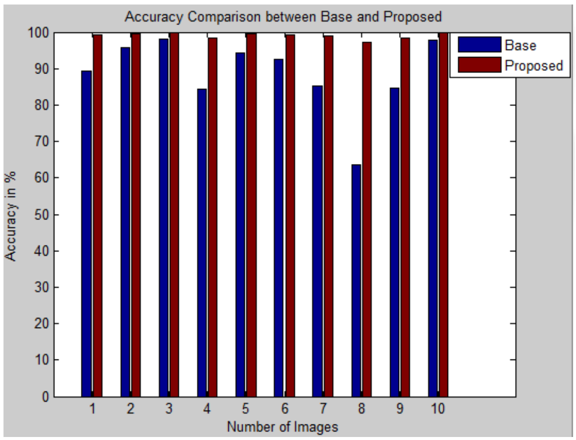

Fig. 13: Graph of Accuracy Comparison

In figure 13 bar chart displays accuracy rate for both base and proposed system.

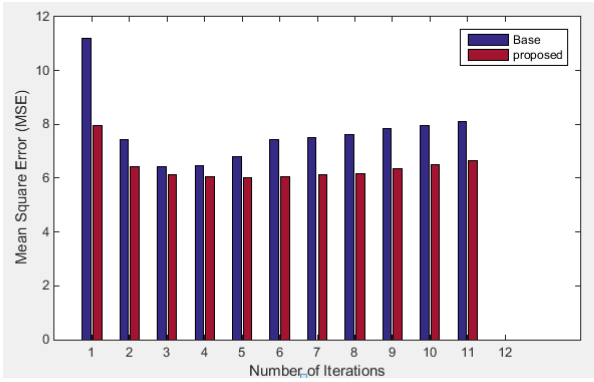

Fig. 14: Graph of MSE Comparison

In figure 14 bar graph displays mean square error for base work and proposed work over the iteration.

VI. CONCLUSION

The proposed technique is tested on 5 gray images of 10 persons with different emotions like Angry, Sad, Happy, Fear, and Disgust. The uniform size 256×256. The train data base is loaded and images are tested by both base work method and the proposed work method for accuracy. Our method is better than the previous work. Statistically performance can be found out by percentage recognition. The recognition accuracy for base work is 88.55 % while that achieved by applying Median Filter and Gray Level Difference Method (GLDM) is 99.03%.

The GLDM evolves as a very effective method applicable on low – contrast images and generates promising result. This method can be implemented automatically. The GLDM algorithm can process the image with speed. The current work methodology yields an efficient algorithm with higher accuracy recognition results proving that the previous nominal methods are not satisfactory.

VII. SCOPE FOR FUTURE WORK

Our proposed fusion method works successfully under controlled environment. The frontal upright face image and uniform ambient light is must for the better performance. The present work can be modified in such a way not the constraints are reduced to an extent like detection of the face from dynamic video. The presence of noise should not be able to affect the performance of the system. The other areas of improvement can be combination of neural network and fuzzy logic for soft computing. This may improve the performance. Other feature extraction techniques should be applied to achieve better result. The number of classifiers can be increased.

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