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Discriminative Robust Local Binary Patterns for Effective Face Detection Using Machine Learning

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Abstract

Machine learning makes the systems to find, capture, store and analyse the facial features automatically. Face recognition has a major role in interpretations of expressions for identifying human faces. In the area of machine learning facial recognition is a challenging problem and lots of attempts were made for identifying invariant features of face but they recognize the face when it is completely visible. In this paper some of the techniques are investigated and proposed discriminative robust local binary patterns technique (DRLBP) for classification of face images with different emotional expressions and rotation variant images. For database construction GLCM with six features is applied on the output of DRLBP and multi linear regression classifier is applied for classification. The accuracy is estimated by using confusion matrix. The experimental results are calculated it's clearly observed that our proposed method shows better accuracy.

Keywords: *LBP, PCA, DRLBP, MLRM and GLCM*

INTRODUCTION

Face recognition has an extensive collection of applications in the field of security and surveillance. In recent years Smartphone vendors introduced face recognition as an authentication tool for secure authentication [1]. Face needs good computing techniques for recognition because of its multidimensional structure. Face recognition plays a very prominent role in the evolution of secured systems of an organization. The first survey on face

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recognition was published in 1991 [2], followed by several researchers [3]. Geometric-based and appearance-based methods are used to extract an image for better face recognition and classification rate [4]. Geometric-based methods specify the shape and components of a face like mouth, eyes, etc but appearance-based methods specify the texture of the face. Face detection using Appearance-based methods has made huge progress. The Most popular appearance-based methods are: local binary patterns LBP, to encode texture of an image LBP uses gray level intensity values [5].

The LBP operator is more powerful for texture description and texture classification. Texture species the content of the face image like colour, shape, size etc. based on these textures, face image features like eyes, nose, lips, mouth and skin colour are extracted. For facial expression recognition LBP examined with different region selections and in different colour channels [6]. LBP is computationally very simple to implement but one of the limitations of LBP is they recognize face when it's completely visible in high resolution [7], to overcome this limitation we proposed FRLBP fuzzy robust local binary patterns. FRLBP [8] effectively specifies difference between week contrast local regions to the small contrast local region so; contours of a human face are extracted effectively.

Raw Face image contains huge amount of pixels and it takes lot of time to recognize face, by reducing the number of pixels we can easily identify a face. This process can be achieved by dimensionality reduction technique; it's an important phase of face recognition process. In this paper we proposed PCA [9-11], high dimensional data is mapped into lower dimensional data by preserving the data samples geometry. Principle component analysis (PCA) is used for face recognition for client server application [12-14].For texture feature classification the (GLCM) method [15] is used. GLCM represented by matrix that contains relative frequencies of gray level values at a specific distance m and at a particular angle Θ, which scale in four different directions those are 0°, 90°, 45° and 135°.

Different feature values are generated from different angles in GLCM. By selecting the correct angle Θ it can easily extract the textual information from images which contains high directional characteristics. In this paper machine learning technique is proposed based on Discriminative Robust local binary pattern.

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Through classification mechanism a class of variables are predicted. Classifier is used to classify characteristics that are extracted from a face image and assigns a label to identify face. The most popular classifier used is naive bays classifier that predicts each class by learning from information [16].Main application of this classifier is face detection and sentiment prediction [17].

PROPOSED METHOD

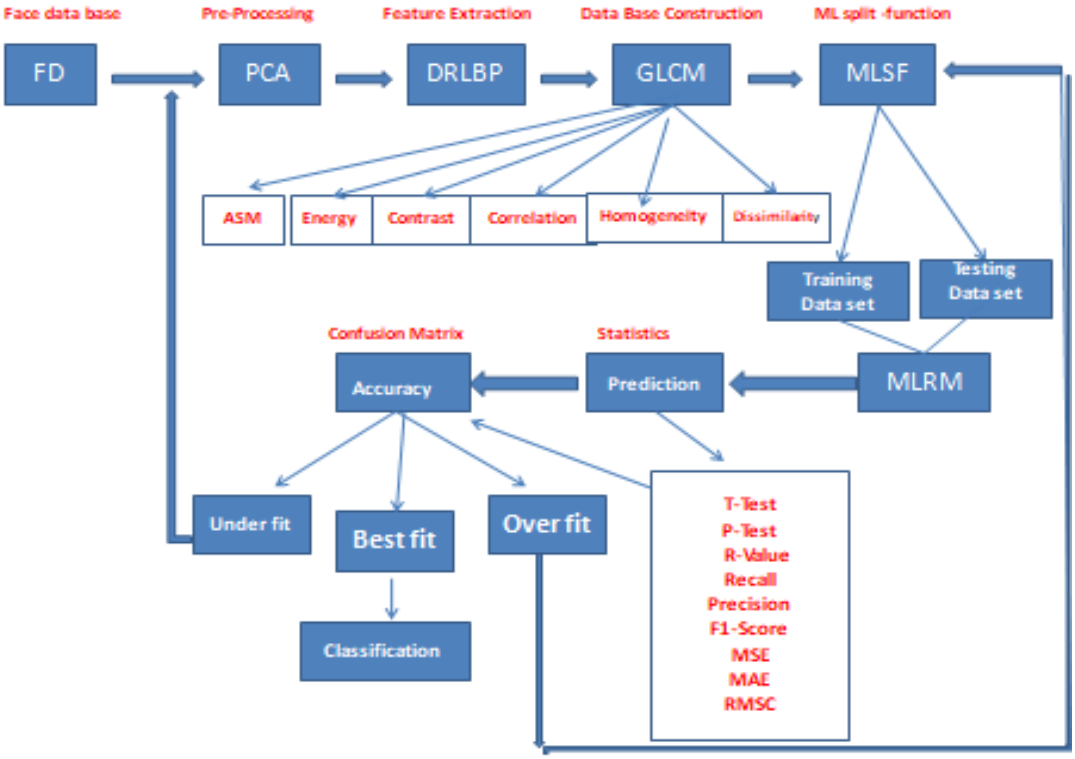


Fig1: Proposed System Block Diagram

PRE-PROCESSING

Data pre-processing is a procedure for cleaning of facial database for making suitable to machine learning model. It is the processes of improving the quality of the database by applying operations like feature extraction, feature selection, scaling, dimensionality reduction, Colour transformation, Contrast Enhancements and selection of samples. In this paper PCA is applied for dimensionality reduction to improve the execution speed and for quality database. The Principle component analysis is unsupervised learning method which contains major parts of covariance, Eigen values decomposition, transformation of principle components. The components will be

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selected in terms of variance. The major scope of PCA is to get the directions of maximum variances in high dimensional data and shows the data into new space that represented by equal or lesser dimensions compared to the original.

Let Z= [z j] be any m X1 random vector we now define m x 1 vector X = [xi], where each I the I[th] principal component of Z is xi = $\sum_{j=1}^{m} \beta ij\ zj$

Covariance=$\frac{1}{n-1}\sum_{i=1}^{n}(Xi-\bar{x})(Yi-\bar{y})$

Eigen vectors of matrix X = X □= λ □

Data Base Image



Face Detected Image



Output of PCA



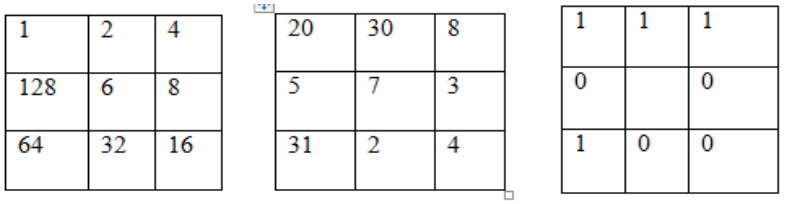
Fig2: Images Generated By PCA

FEATURE EXTRACTION

Extracting the features like mouth, nose, eyes, lips are very important in face detection and classification. The LBP operator is more powerful for texture description and texture classification. Texture species the content of the face image like colour, shape, size etc. based on these textures, face image features like eyes, nose, lips, mouth and skin colour are extracted. This technique is very useful for face identification and classification. The LBP operator considers the window size of 3×3 in the face image and with the following formula LBP value is computed.

Where P_c represents central pixel and P_g represents neighbourhood gray values correspondingly. Binary values are computed by comparing Pc value with its neighbours. This is vigorous to uneven illumination and variations in contrast. Yet this technique is high sensitive to noise and generates lengthy histograms, this may slow down the identification particularly on large-scale databases. In some cases like uneven illumination and occlusions of faces the local structure is missing and does not consider the effect of the centre pixel and the binary data generated by LBP are very sensitive to noise. To overcome these problems here RLBP is proposed.

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Pattern =01000111 LBP=1+2+4+64=71

$$LBP = \sum_{k=0}^{7} s(\text{Pc-Pg})\, 2^k \quad (4)$$

$$S(x) = \begin{cases} 1 & \text{if } x>=0 \\ 0 & \text{if } x<0 \end{cases} \quad (5)$$

Fig3:.LBP Operator

DISCRIMINATIVE ROBUST LBP OPERATOR (DRLBP)

Most of the cases for face detection intra-class variance are undesirable. Intra-class variance means classes of variances within the same face image. Intra-class variance is high face recognition rate is high and Intra-class variance is low face recognition rate is low. The LBP does not clearly separate the intra-class variance for low contrasted and uneven illuminated images.

The intra-class variance is better when dark face with bright features or vice versa. This can be achieved by using RLBP (Robust Local Binary Pattern) method. RLBP values are calculated by appealing the minimum values of Local Binary Patterns operator and one's compliment of LBP operator. This formulates RLBP to improve the recognition rate for selected features by intensities reversing.

RLBP=Minimum [LBP^{-1}, LBP]

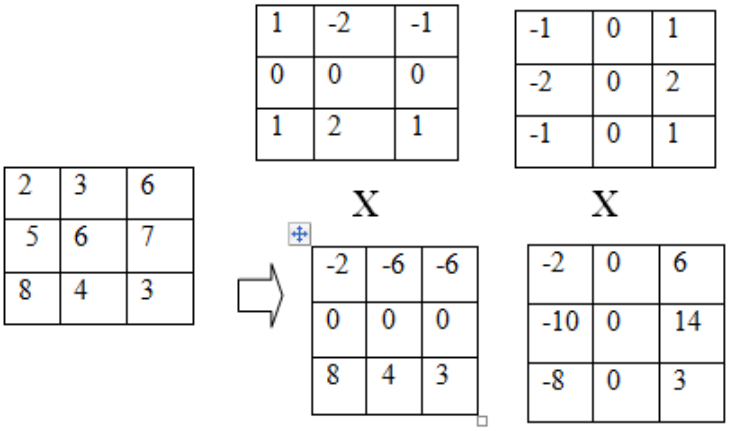
Where LBP-1 represents one's compliment of the given LBP and The RLPB is more powerful apparatus to describe colour features and however this method can produce same gray value for highest and lowest gray values. For example 11111111 and 00000000 similar value 00000000 is obtained so this is not capable to distinguish face features unmistakably. RLBP fails to recognize the edges and shape information with in the face image.

Face recognition rate is improved by adding edge information to RLBP and renamed it as discriminative robust LBP which is as follows

DRLBP =$\sum_{i=1}^{i=9} S(m,n) * RLBP(m,n)$.

Where, S (m, n) is computed by computing $\sqrt{}$ m direction and $\sqrt{}$ n direction. Discriminative robust LBP specifies texture information, shape, and edge information it's an advantage for face detection and classification.

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$Dx = 19-14=5 \qquad Dy = 20+23=3$

$$D=\sqrt{Dx^2 + Dy^2}$$

$$D=\sqrt{25+9} = 6$$

Fig4: Shows Detailed DRLBP Operator



Fig5: images generated by DRLBP

GLCM-GRAY LEVEL CO-OCCURRENCE MATRIX

The face data base image contains similar gray values for every feature. Different features have different range of gray values. These ranges are converted into similar regions by using GLCM. The Co-occurrence matrix is most classical approach for describing the spatial arrangements of colour or intensities of an image. It is referred as co occurrences distribution because it specifies how pixel values are distributed throughout the image.

The GLCM matrix is computed on the output Image of DRLBP. GLCM is a square matrix and equal to quantization gray levels of an image. GLCM can be calculated at any angle and at any offset in the diagonal GLCM matrix is symmetrical, this symmetry will be achieved if each pair of pixels is counted two times, forward once and backward once.

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This symmetrical matrix needs to be normalized to convert it into probabilities. The each GLCM is obtained based on the directions 0◦, 45◦, 90◦ , and 135◦, after that averaging these four GLCMs and Make final GLCM and created database by computing contrast, dissimilarity, homogeneity, ASM, energy, correlation, by adding similar Label component for similar type of images. This database is used in the linear regression machine learning classifiers which is simple and more powerful.

PROPERTIES OF GLCM

$$\text{Contrast} = \sum_{s}\sum_{a} |s-a|^2 p(s,a) \quad (11)$$

$$\text{Dissimilarity} = \sum_{s}\sum_{a} |s-a|^1 p(s,a) \quad (12)$$

$$\text{Homogeneity} = \sum_{s}\sum_{a} \frac{1}{1+(s-a)^2} p(s,a) \quad (13)$$

$$\text{Angular Second Moment (ASM)} = \sum_{i,j=0}^{N-1} (Ps, a^2) \quad (14)$$

$$\text{Energy} = \sum_{s,a=0}^{M-1} (Psa)^2 \quad (15)$$

$$\text{Correlation} = \sum_{s,a=0}^{N-1} p(s,a) \frac{(i-\mu i)(i-\mu j)}{\sqrt{((\sigma i2)(\sigma j2))}} \quad (16)$$

$p_x(s, a)$= normalized symmetrical GLCM elements

M= gray levels contained in an image

μ=mean value of GLCM

$\sigma 2$=variance of the intensities of all pixels

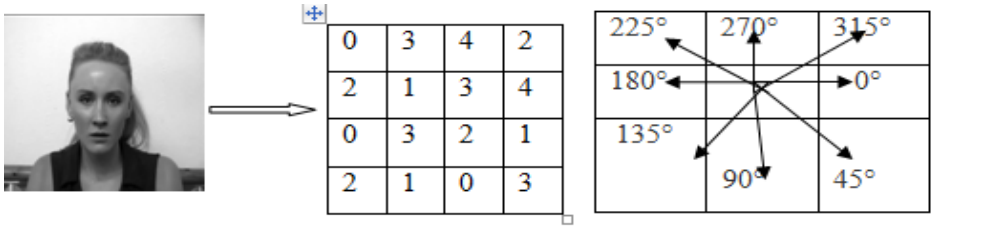


Fig6: a) Gray Image b) Gray levels c) Different angles of GLCM

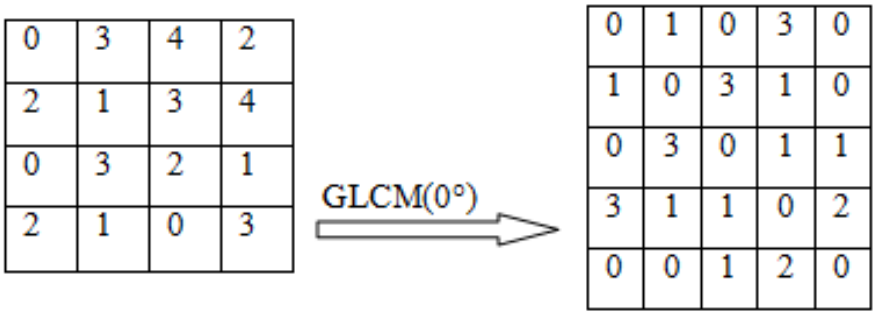


Fig7: The concurrence matrix obtained by 0°

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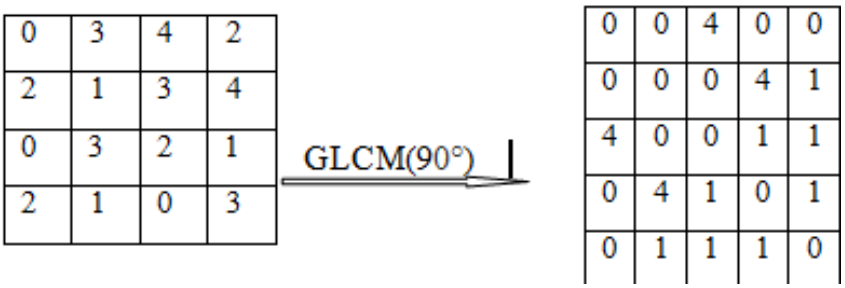


Fig8: The concurrence matrix obtained by 90°

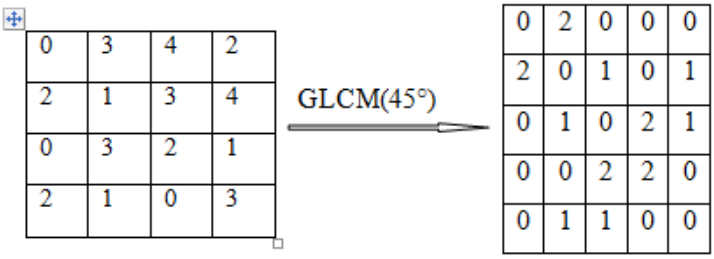


Fig9: The concurrence matrix obtained by 45°

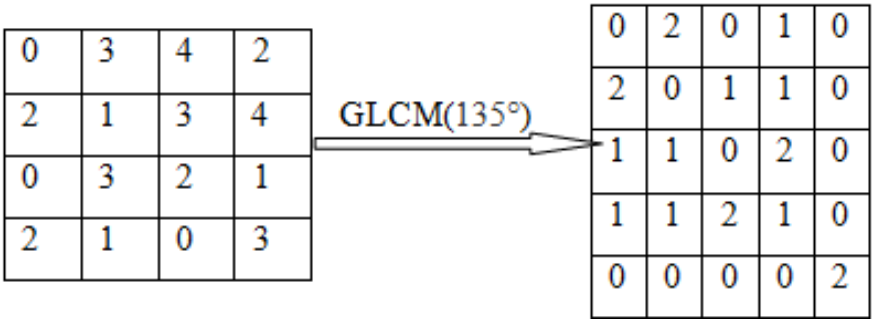


Fig. 10: The concurrence matrix obtained by 135°

0	5	4	4	0
5	0	5	6	2
5	5	0	6	3
4	6	6	3	3
0	2	3	3	3

Fig. 11: The Resultant Matrix

MLR MODEL

Machine learning is more power tool for classification of face features. Multiple linear regression models are one of the machines learning technique that trains the model to predict the accurate face

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recognition and classification rate of faces on GLCM features and on hypothesis. Multiple linear regressions create model which shows association more features and a dependent variable by fitting a linear equation to Independent variables data. The Multiple linear regression method is similar to linear Regression except in the evaluation process to detect which feature has the highest impact on the predicted result and how diverse independent variables relate to each other. The MLR formula is given below.

$$Y_i = a_1 X_{i1} + a_2 X_{i2} + \ldots + a_p Xip + a_0 + \epsilon$$

Where Yi represents dependent variable Xi represents GLCM features as independent variables, a0 is intercepting value, ap represents slope coefficients for each ai features of GLCM and ϵ represents the model's of the residuals the a1 is the coefficient that measures a change in the Yi when Xi1 changes and a2 is coefficient value that measures change in the Yi when Xi2 changes and so on. This model allows predicting result, based on information provided on all Xi features.

Multiple regression model (MLRM) is working on the hypothesis that present is a linear relationship between both on Yi and all Xi features of GLCM. This model represents that no major correlation exist among the independent variables.

EXPERIMENTAL RESULTS

In this research paper, for experimentations two data sets YALEB, ORL are considered for analysing the performance of DRLBP method. This analysis is done by applying confusion matrix with two predicted possibilities of classes "yes" or "no". True-positive: actually it's not true but predicted positive. True-negative: it's true but negatively predicted.

False-positive: it's false but predicted positively. False-negative: its false but predicted negative. Based these probabilities precision, recall, f1-score and accuracy are computed with following formulae. Precision: Precision specifies how many of correctly how many predicted correctly cases come to positive. High precision value should be better.

Precision: $\frac{truepositive}{truepositive + falsepositive}$

Recall

Recall is used to correctly retrieving true negative values

Recall: $\frac{truenegative}{truepositive + falsenegative}$

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Accuracy

Accuracy value should be high accuracy is used to measure in total number values how many values we are correctly predicted.

Accuracy=

$$\frac{truepositive+truenegative}{truepositive+falsepositive+truenegative+falsenegative}$$

F1 Score

F1-score is used to find accuracy of datasets that categorizes values into positive or negative. F-score is used to group recall and precision and it is called as mean of precision and recall. We can, adjust the f-score value for giving more importance to precision and recall.

$$\text{F1-score} = \frac{\frac{2}{1}}{recall} + \frac{1}{precision}$$

T-Test

It's a statistical measure used to specify difference between means of two groups

$$\text{T-test}=\frac{difference\ between\ sample\ mean}{estimated\ sample\ error\ of\ differences\ between\ mean} = \frac{(x1-x2)-(\mu1-\mu2)}{\sqrt{\frac{s12}{n1}+\frac{s22}{n1}}}$$

n1, n2= sample sizes; x1, x2= samples; µ1, µ2= means; s12, s22= variances

R2

It's an important statistical measure in regression model used to determine how well data will be fit into regression model.

$$r2 = \frac{\mathbf{k}\,(\sum \mathbf{ab}) - \sum \mathbf{a} \sum \mathbf{b}}{\sqrt{[\mathbf{k} * (\sum \mathbf{a2} - (\sum \mathbf{a})\mathbf{2})] * [\mathbf{k} * (\sum \mathbf{b2} - (\sum \mathbf{b})\mathbf{2})]}}$$

r = Correlation coefficient; k = number in given dataset; a = first variable; b = second variable

F-Test

It's a statistical test used for comparing the statistical models that have been fitted to data base.

$$\text{F-test} = \frac{varience\ between\ sample\ mean}{varience\ expected\ by\ error} = \frac{explained\ varience}{un\ explained\ varience}$$

Table 1: Shows Original Data Base

Contrast	Dissimilarity	Homogeneity	ASM	Energy	Correlation	Label
6600.157627	77.84957627	0.098367694	0.000456399	0.030172851	0.623078429	1
5930.236299	74.39081921	0.099299813	0.000411951	0.028695792	0.532736344	2
6385.783051	76.40621469	0.099042495	0.000433838	0.029375698	0.625785207	1
6411.721328	77.72556497	0.093715029	0.000401974	0.028353533	0.583037017	2
6583.757556	77.62408192	0.096657011	0.000447701	0.029920444	0.611835106	1

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6060.035664	74.40812147	0.099770668	0.000438793	0.029550864	0.628168449	1
5881.264689	73.53361582	0.103246992	0.000523945	0.032191265	0.613089895	2
6282.894209	75.96935028	0.097178175	0.000449476	0.029955488	0.641817331	1
5757.182062	72.46398305	0.098485075	0.000421779	0.029043129	0.515289298	2
6385.178814	76.47443503	0.096766486	0.000415103	0.028775892	0.639771439	1
6200.62048	75.04067797	0.09987253	0.000445297	0.029842814	0.511141352	2
6063.032556	75.00218927	0.092483542	0.000399949	0.028275827	0.503712997	2
6241.596822	75.26235876	0.098647129	0.000442935	0.029668563	0.655865866	1
5994.630862	73.7345339	0.097930265	0.000389959	0.027917622	0.537817386	2
6673.251624	78.41165254	0.099380003	0.000455681	0.030168209	0.619073263	1
6062.132839	75.18509887	0.099258778	0.000490455	0.031245434	0.586127255	2
6675.409958	78.27153955	0.09835464	0.000423719	0.029046716	0.61142498	1
5359.493785	68.67485876	0.103235142	0.000430073	0.029326276	0.53408367	2
4676.287288	61.94646893	0.116949049	0.000586036	0.03422722	0.616460595	1
6031.732203	74.5420904	0.097425777	0.000416856	0.028872795	0.519113105	2

Table 1 represents the database which is created by using GLCM with six parameters and table2 contains statistical parameters values.

Table 2: Experimental Results of Statistical Parameter

Sample size	Precision	Recall	F-score	MAE	MSE	RMSE	R2	T-test	F-test	Accuracy
0.05	0.44	0.67	0.53	0.3683	0.2242	0.4735	0.21	0.9077	0.52	0.67
0.1	0.64	0.8	0.71	0.3329	0.1698	0.4121	0.23	1.7961	0.58	0.8
0.15	0.9	0.88	0.87	0.3683	0.2242	0.4735	0.33	0.8047	0.6	0.88
0.2	0.86	0.8	0.79	0.3138	0.1769	0.4205	0.1576	1.053	0.6905	0.8
0.25	0.83	0.83	0.83	0.2919	0.1386	0.3723	0.4294	0.3549	0.5128	0.83
0.3	0.87	0.87	0.87	0.2597	0.1155	0.3399	0.5184	0.185	0.7617	0.87
0.35	0.88	0.88	0.88	0.2399	0.1021	0.3196	0.5899	0.1298	0.7524	0.88
0.4	0.85	0.84	0.84	0.2591	0.1274	0.357	0.488	0.3194	0.7722	0.84
0.45	0.79	0.73	0.74	0.3291	0.169	0.4111	0.3238	0.775	0.6372	0.73
0.5	0.8	0.75	0.75	0.3008	0.1524	0.3904	0.3859	0.7092	0.7088	0.75
0.55	0.81	0.77	0.77	0.3059	0.1553	0.3747	0.3747	0.809	0.8057	0.77
0.6	0.83	0.79	0.8	0.2848	0.1413	0.3759	0.434	0.7657	0.9812	0.79
0.65	0.84	0.81	0.81	0.2733	0.1333	0.3651	0.4659	0.6248	0.9538	0.81
0.7	0.85	0.82	0.82	0.2735	0.1318	0.3631	0.472	0.53	0.9153	0.82
0.75	0.36	0.47	0.39	0.5859	0.5526	0.7433	-1.21	1.1569	2.6536	0.47
0.8	0.4	0.5	0.43	0.5888	0.5598	0.7482	-1.245	1.4235	2.4141	0.5
0.85	0.63	0.65	0.62	0.4695	0.4021	0.6341	-0.608	2.004	1.42696	0.65

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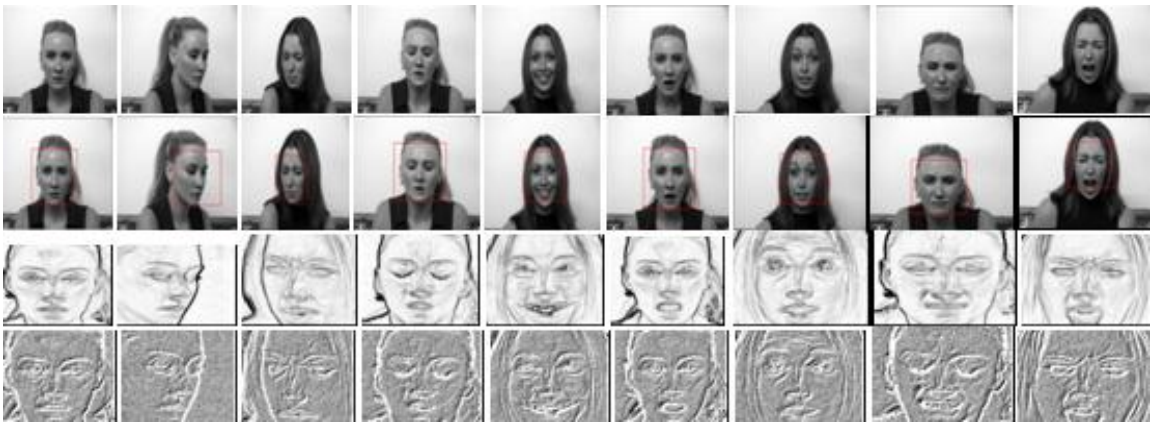
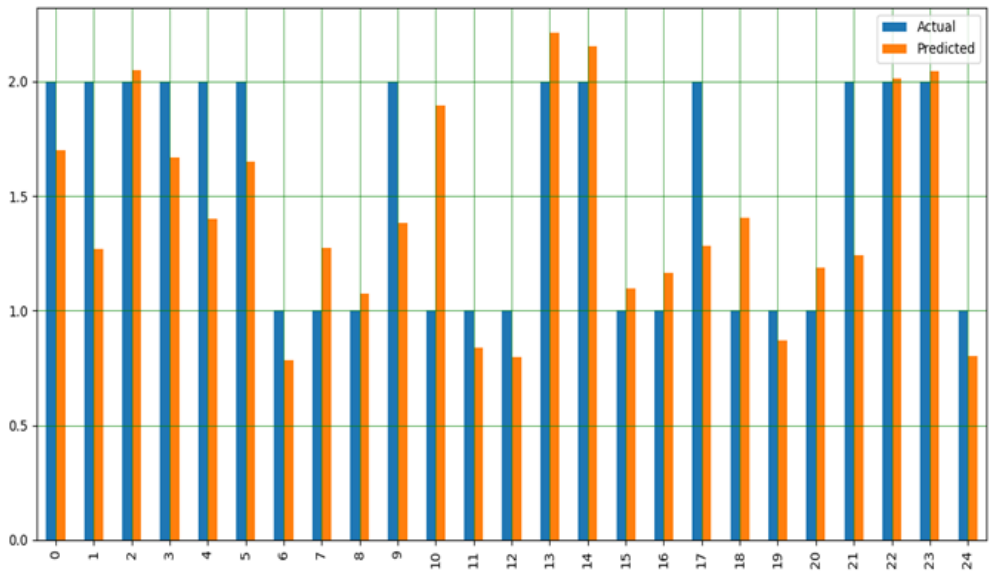


Fig 12: Sample Images from two databases

(a) Data Base image (b) face detected image (c) output generated by PCA (d) output of DRLBP

Graph1 describes the visual representation of relation between actual and predicted values of MLR model's accuracy 88% of accuracy with sample size is 35%.

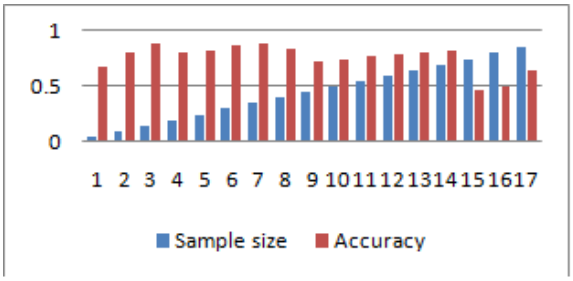


Graph 1: Actual and Predicted Values

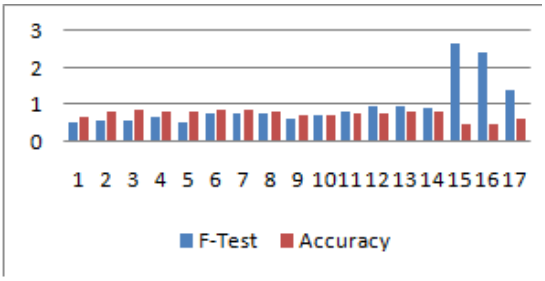
Graph 2 shows the relationship between sample size and accuracy where sample size is increasing accuracy rate is decreasing. Sample size between 15% to 40% the accuracy rates are stable so that it shows best fit of the model according to selected parameters on specified database.

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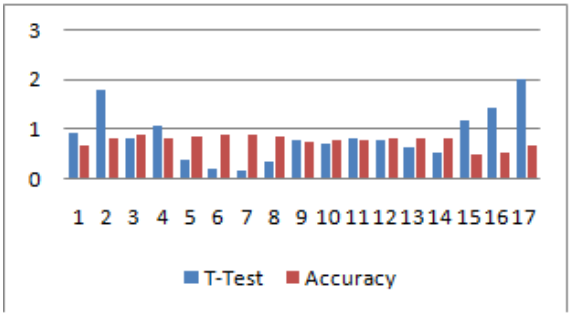
From graph 3 to graph11 show the relation between accuracy which is calculated by confusion matrix and reaming statistical parameters. These graphs show that accuracy is inversely proportional to Precision, Recall, F-Score, MAE, MSE, RMSE, R2, T-test, F-test statistical parameters.



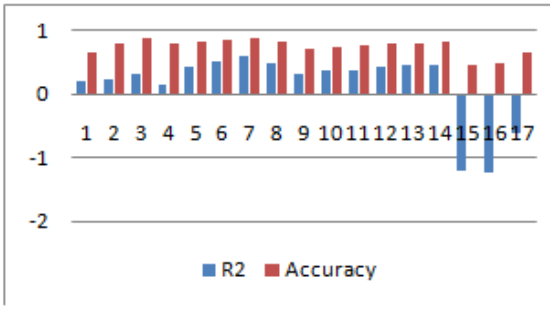
Graph2



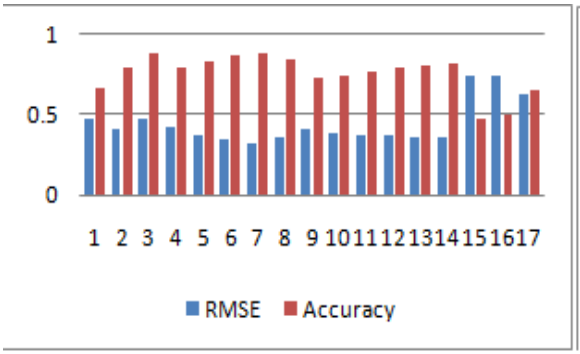
Graph3



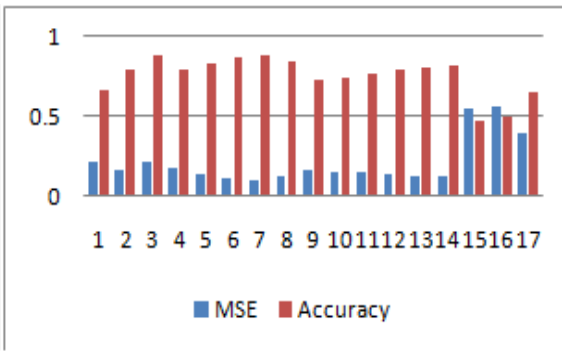
Graph4



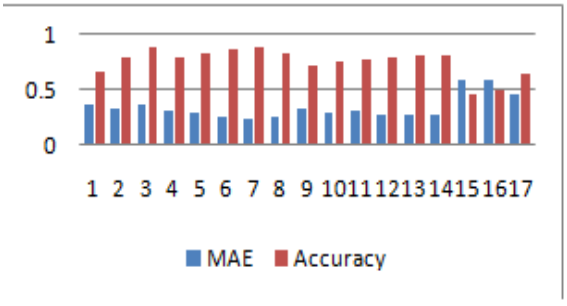
Graph5



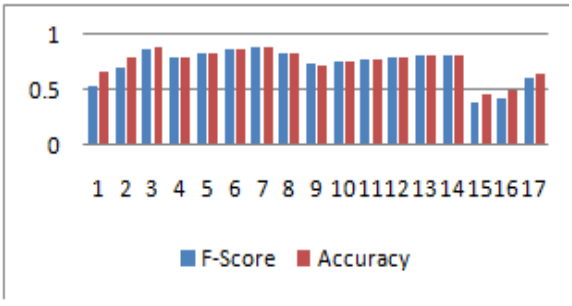
Graph6



Graph7

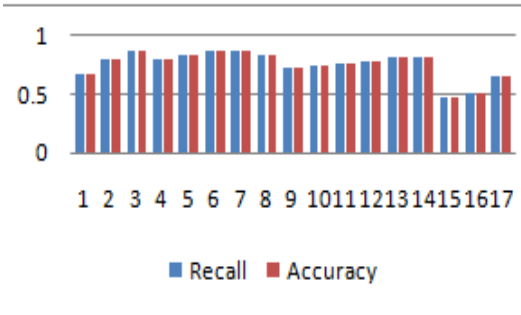


Graph8

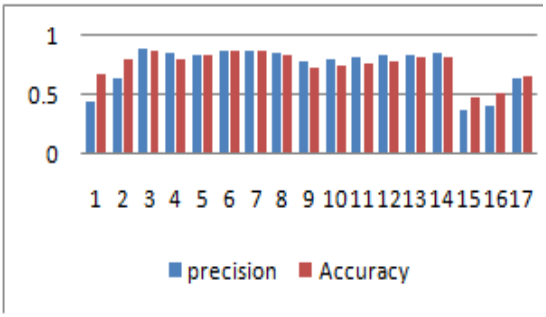


Graph9

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Graph10



Graph11

CONCLUSIONS

Face recognition has a very prominent role in the development of secured systems. In pre-processing step the data base image is converted into gray scale image and PCA is used for dimensionality decrease. Aims at eliminating noises and data with high dimensions are mapped into data with minor dimensions by protecting the data samples sizes.

The LBP operator is more powerful for face identification and classification. The data generated by LBP is very responsive to noise, for eliminating these problems, DRLBP is proposed. It is very efficient operator to get information of shape and edges in an image. GLCM is used for constructing Data Base. Final feature vectors of training data set are trained using multiple linear regressions classifier.

The output which predicted is tested by using training and test features. The experimental results are produced using various statistical parameters and confusion matrix and the results are tabulated. It's clearly observed that our proposed method has 88% accuracy.

This technique is tested with different sizes of samples and found best fit for most of the sample. For very few samples under fit, over fit are occurred because of faces with different emotions. The accuracy can be improved by applying this method on individual face features separately.

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