Multiple Mean Fuzzy LBP: A Novel Technique for face Detection

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Abstract:

LBP known as The Local Binary Pattern non-parametric descriptor which is used to investigate different local structures in an image. It is rendered as a straightforward and effective texture operator for different real-time applications. LBP generated binary data is sensitive to noise and it will identify face images when its completely Visible. To increase LBP's efficiency and resilience, in this research paper we proposed a novel multiple mean fuzzy LBP(MMFLBP)to classify facial images with different facial expressions and rotation invariant images. GLCM with six features is used for construction of Database on the outcome of MMFLBP. Confusion matrix is used for estimating the accuracy of MMFLBP. Upon calculation of the experimental results, it is obvious that our proposed method exhibits better accuracy.

Keywords: LBP, MMFLBP, AFR, RLBP, DRLBP.

Introduction:

Throughout the past several years, there has been a lot of research done on automatic face recognition (AFR). It is essential to the development of surveillance systems and the processing of biometric images, among many other computer vision applications. There are still numerous obstacles to overcome, including things like posing [1], illumination [2], and face expression [3].

The (LBP)[4-7] local binary pattern for extraction of features approach has developed a lot in recent years, making impressive growth in applications like texture analysis and face recognition [8].

LBP is not only a simple texture operatorinaddition to that being straightforward and having a low computational complexity, it also offers important advantages like rotational invariance and grayscale invariance. LBP is therefore often used in image matching, target recognition and tracking for pedestrians and cars, and medical image analysis.

Despite LBP's early uses being quite successful, its actual outcomes in several domains are not adequate. As a result, several studies have enhanced the LBP in the relevant fields and produced numerous noteworthy outcomes.

It is evidently required to outline several LBP approaches, particularly in applications for face recognition, texture analysis and, and there is a need to highlight the LBP's remaining key problems.

With the many anisotropic features present in faces, anisotropic structural information is a crucial component for face identification (e.g. eyes, mouths). To achieve this, we proposed the MMFLBP

Proposed Method:

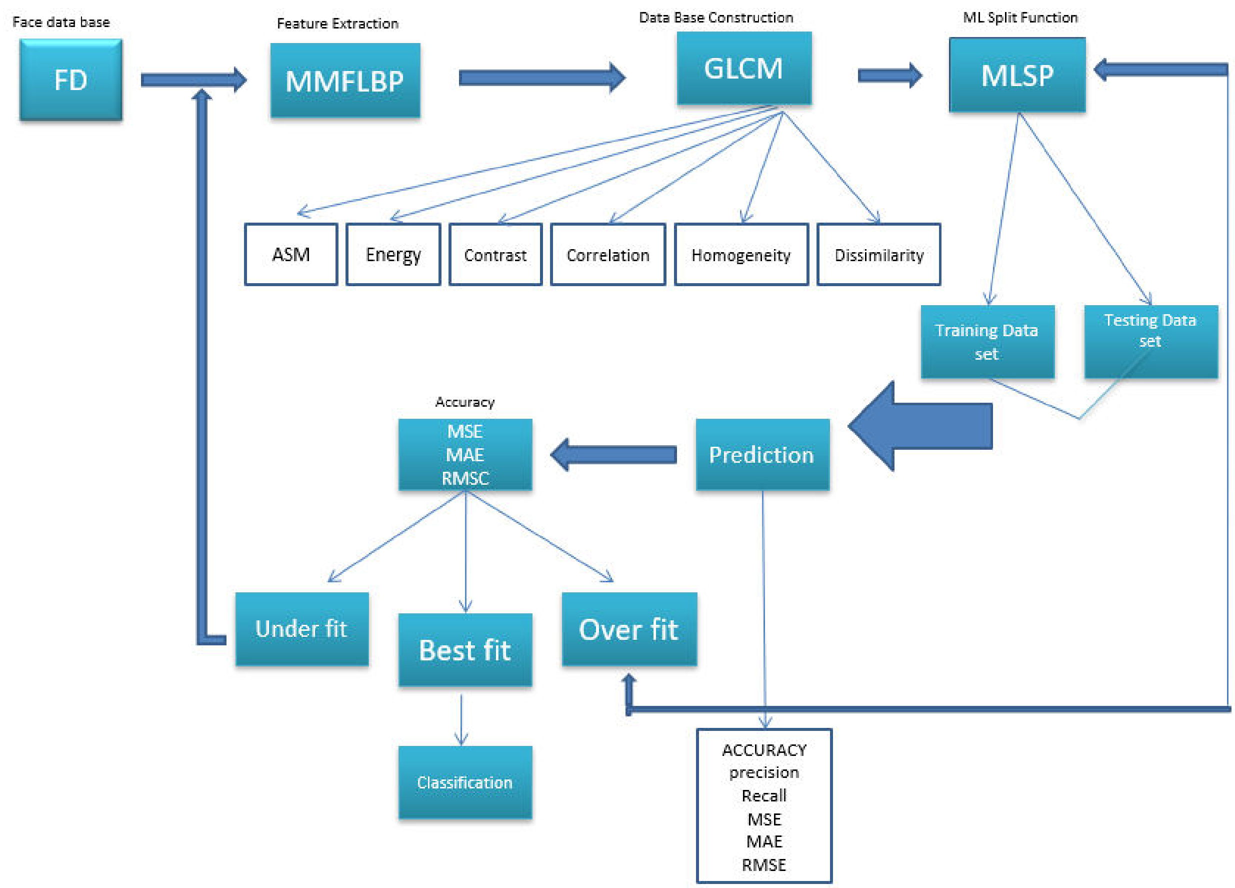


Fig: Multiple Mean Fuzzy LBP Block Diagram

The above figure explains the process of Multiple Mean Fuzzy LBP

Local Binary Patterns:

Assume I(x, y) be a grayscale image for the LBP.Consider a set of pixels (Px) that are encircled by a (Rad)-radius Rad radius shown as (Px, Rad).

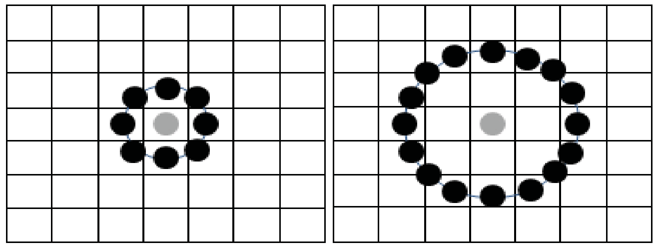


Fig: Circular (8,1) and (16,2) neighborhood's

Assume that L_c represents the center pixel's grey level intensity and L_p represents the intensity of the sampling locations (p=1, 2, P-1).

$$L_c = I\,(x, y) \qquad (1)$$

$$L_p = I\,(x_p, y_p) (2)$$

$$x_p = x + \text{Rad}\, cos\, (2\pi\, p/\, P) \qquad (3)$$

$$y_p = y + \text{Rad}\, sin\, (2\pi\, p/\, P) \qquad (4)$$

we define the texture *M* in the image by The joint distribution of grey values P(P>1)

$M = m\,(L_0, L_1 \ldots\ldots\ldots L_p\text{-}1)$ (5)

To achieve grey scale invariability, we subtract the central pixelintensity L_c from the intensities of the surrounding pixels $L_{p.}$

$$M = m\,(L_c\,, L_0\text{-}L_c, L_1\text{-}L_c \ldots\ldots\ldots L_p\text{-}1\text{-}L_c) \qquad (6)$$

The above equation can be redefined as

$$M = m\,(L_c)\; m\,(L_0\text{-}L_c, L_1\text{-}L_c \ldots\ldots\ldots L_p\text{-}1\text{-}L_c) \qquad (7)$$

Here$m$ (L_c) represents the overall intensity distribution. the above equation does not provide any information to analyze the local structure therefore the joint distribution is

$$M = m\,(L_0\text{-}L_c, L_1\text{-}L_c \ldots\ldots\ldots L_p\text{-}1\text{-}L_c) \qquad (8)$$

Changes in the image's mean intensity have no impact on signed differences. Hence, only the signals of the variations in the above equation were considered for obtaining grey level invariance:

$M = m\,(S\,(L_0\text{-}L_c), S\,(L_1\text{-}L_c) \ldots\ldots\ldots S\,(L_p\text{-}1\text{-}L_c))$ (9)

Where

$$S(Az) = \begin{cases} 1, & z >= 1 \\ 0, & z < 0 \end{cases} \qquad (10)$$

(1) They produce lengthy histograms, which reduce identification speed, particularly for Large scale face databases; (2) occasionally, they fail to recognize local structure because they ignore the impact of the center pixel; (3) The binary data they create is noise-sensitive. Aiming this RLBP proposed.

Rule Based LBP:

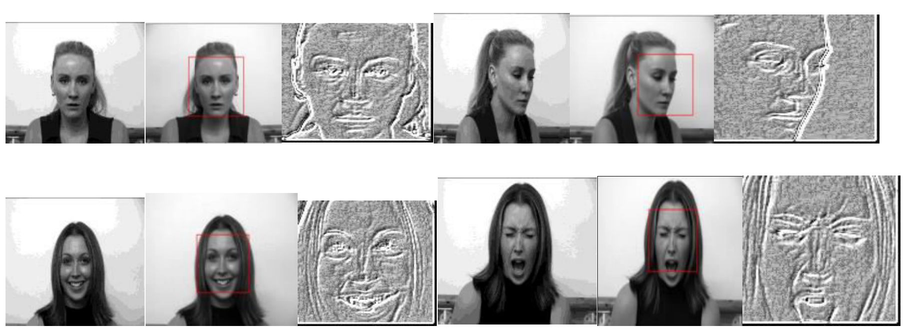
For many face recognitions tasks, the LBP increases the intra-class variance, which is undesirable. When bright characteristics contrast with dark facial features or vice versa, the intraclass variation rises. The minimal LBP code and one's complement of LBP code are combined to create RLBP code. Because the intensities of facial characteristics are reversed, LBP code is made to be the most durable.

$RLBP = \min(LBP, LBP^{-1})$ (11)

LBP^{-1} represents one's compliment of LBP. For example, if u consider LBP as 100101 then LBP^{-1} would be 011011.

The fact that this RLBP cannot distinguish between weak contrast local patterns and strong contrast local patterns is one of its drawbacks.For instance, 11111111 can be complimented as 00000000, and 00000000 can be complemented as 11111111. As a result, it cannot precisely and correctly distinguish between facial feature patterns that are weak and powerful.

Output of RLBP:



i.Original image ii. face detected image iii. RLBP image

DRLBP:

Different features don't all have the same colors and forms. The mouth, brows, and other facial characteristics have different colors. A more effective tool for describing color patterns is the RLPB but are unable to identify any edge or shape characteristics in the face image. Because RLBP only employs texture information, it is unable to distinguish between local patterns with uneven lighting, feeble contrast, and equally powerful local patterns.

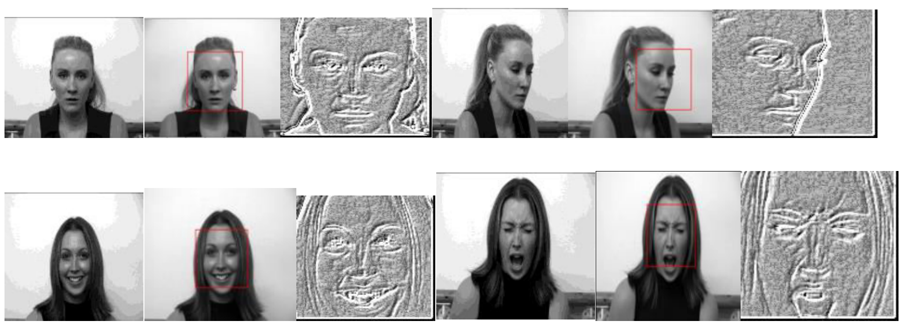
RLBP is unable to identify the facial imagine boundaries and shape features. Edge information is added to RLBP to increase the rate of face identification, and it is called discriminative robust LBP, which is as follows.

$$\text{DRLBP} = \sum_{i=1}^{i=9} K(a,b) * RLBP(a,b) \quad (12)$$

the vectors of √a and √bis used to calculate K (a, b).For recognizing and categorizing features, DRLBP specifies border, outline, and texture information.

Output of DRLBP:

(i) (ii) (iii) (i) (ii) (iii)



i.Original image ii. face detected image iii.DRLBP image

Local Orientation Gradient XOR Patterns LBP POP:

The definition of the LOGXORP has been modified from that of RLBP, LBP, and LGXP. Gradients (n=8) are calculated as follows using a starting point pixel in the center of the image:

$$I^{G}_{kc} = k1 - k9$$

$$I^{v}_{kc} = k3 - k7 \quad (13)$$

the neighbors' grey values for a specified center pixel kc are "k1, k2, k3, k4, k5, k6, k7, and k8" |n=8.

The calculations for orientation and gradient are

$$I^{G}_{gc} = \sqrt{((I^{h}_{gc})^2 + (I^{v}_{gc})^2) \div 2}$$

$$\theta_{gc} = \tan^{-1}\left(\frac{(I^{v}_{gc}}{I^{h}_{gc}}\right)$$

$$\left(I^{G}_{g0}\right) = \begin{cases} 0^\circ + \theta gc & I^{h}_{gc} \geq 0 \; and I^{v}_{gc} \geq 0 \\ 180 - \theta gc & I^{h}_{gc} < 0 \; and I^{v}_{gc} \geq 0 \\ 180^\circ + \theta gc & I^{h}_{gc} < 0 \; and I^{v}_{gc} < 0 \\ 360^\circ - \theta gc & I^{h}_{gc} \geq 0 \; and I^{v}_{gc} < 0 \end{cases} \quad (14)$$

$$\mathrm{LGXORP} = \begin{bmatrix} \{Q(I^{G}_{g1}) \otimes (I^{G}_{gc})\}, \\ \{Q(I^{G}_{g2}) \otimes (I^{G}_{gc})\}, \\ \vdots \\ \{Q(I^{G}_{gp}) \otimes (I^{G}_{gc})\} \end{bmatrix}$$

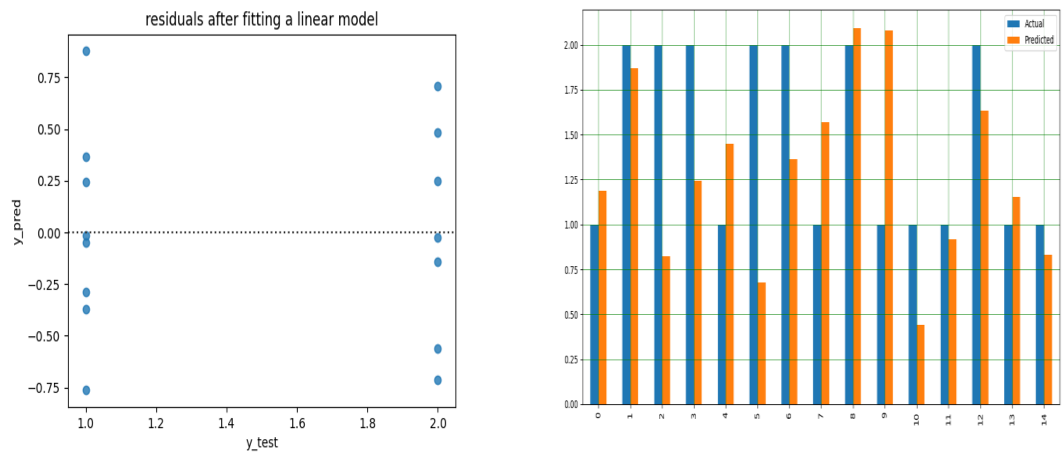
$$\mathrm{LOXORP} = \begin{bmatrix} \{Q(I^{O}_{gc}) \otimes (I^{G}_{gc})\}, \\ \{Q(I^{O}_{gc}) \otimes (I^{G}_{gc})\}, \\ \vdots \\ \{Q(I^{O}_{gc}) \otimes (I^{G}_{gc})\} \end{bmatrix}$$

(15)

Output of LBP-POP:

(x) (y) (z) (x) (y) (z)

x. Original image y.face detected imagez. LBPPOP image



Graph1: actual and predicted values

MM Fuzzy LBP:

multi-valued logic is called as Fuzzy logic that accepts true/false values or values between 0 and 1.In this Multiple Mean Fuzzy LBP for representation of texturefuzzy binary patterns are used.

$$\mu_{A}: x \in X \to \mu_{\dot{A}}(x) \in [0,1] \qquad (16)$$

here$\mu_{\dot{A}}(x)$ –The membership function determines how much element $x \in X$ is a part of the fuzzy set A.

$$\mu_{\dot{A}}(x) \begin{cases} \text{if } \mu_{\dot{A}}(x) = 1 & \text{x completely belongs to the fuzzy set A.} \\ \text{if } \mu_{\dot{A}}(x) = 0 & \text{then x is not a member of the fuzzily defined collection A.} \\ \text{if } 0 > A > (x) > 1 & \text{then x is partially a member of the ambiguous set A.} \end{cases}$$

A membership function only needs a group of values that are within the closed range [0, 1] in order to be valid.

Fuzzy Logic is a branch of fuzzy set theory that allows for many degrees of inclusion (between 0 and 1).

As a result, a $\mu_{\dot{A}}(x)$‘membership function’ is linked with a fuzzy set and maps every component of the discourse universe X to the range [0,1].

$$\mu_{\dot{A}}(x): X \to [0,1]. \qquad (17)$$

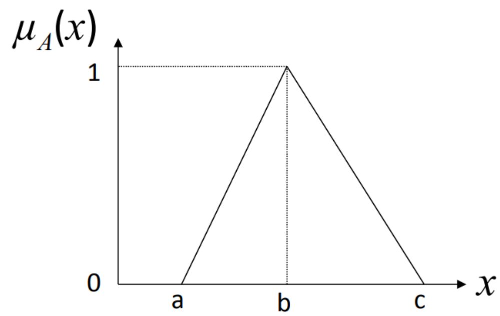
Fuzzy logic can handle ideas that are inherently inadequate (vague or inexact, rough, or incorrect).

a three-parameter triangle membership function with the letters a, b, and c. The three fuzzy set

μA (x) edges' x values are denoted as A, b, and c, respectively.

Membership degree-lower boundary-a: Membership degree-1-b: Membership degree-0-c

$$\mu_A(x) = \begin{cases} 0 & if\ x \le a \\ \frac{x-a}{b-a} & if\ a \le x \le b \\ \frac{c-x}{c-b} & if\ b \le x \le c \\ 0 & if\ x \ge c \end{cases}$$



The four factors a, b, c, and d that make up a trapezoidal membership function are as follows.

$$\mu_A(x) = \begin{cases} 0 & if\ x \le a \\ \frac{x-a}{b-a} & if\ a \le x \le b \\ 1 & if\ b \le x \le c \\ \frac{d-x}{d-c} & if\ c \le x \le d \\ 0 & if\ d \le x \end{cases} \tag{18}$$

Fuzzy LBP (FLBP) (Iakovidis et al., 2008) combines fuzzy logic with LBP to mitigate the impact of noise on LBP and improve its capacity to discriminate between different objects.

The Multi Mean Fuzzy LBP histogram contains multiple bins because each pixel in MMFLBP can be recognized by multiple LBP codes, which is a distinction between LBP and Fuzzy LBP.

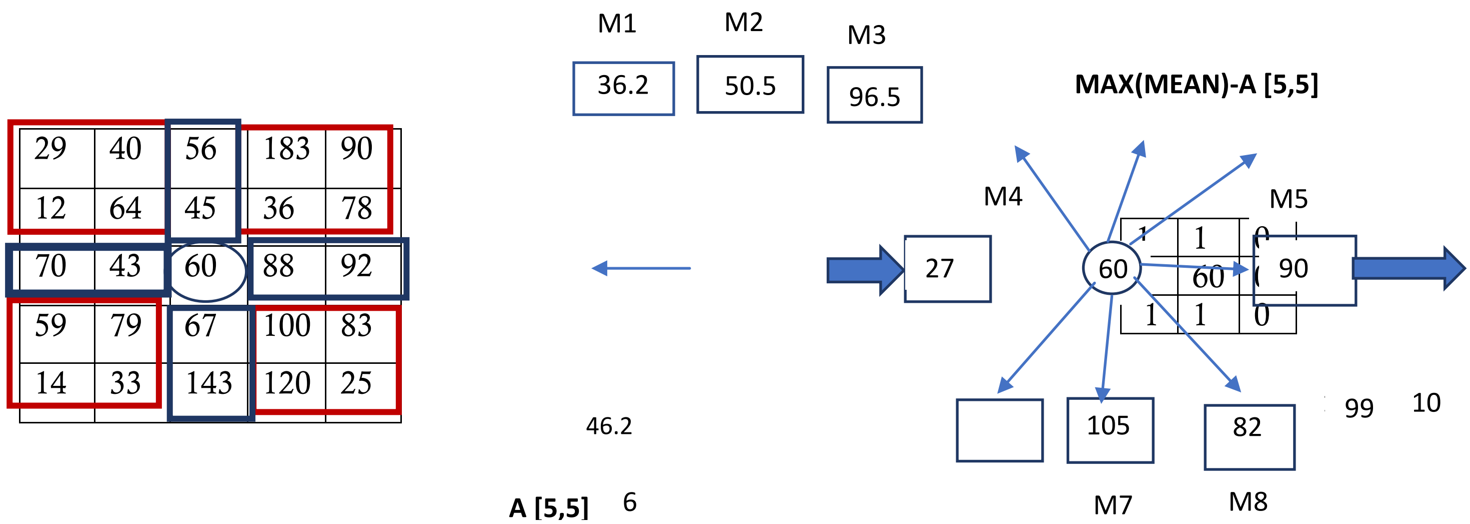


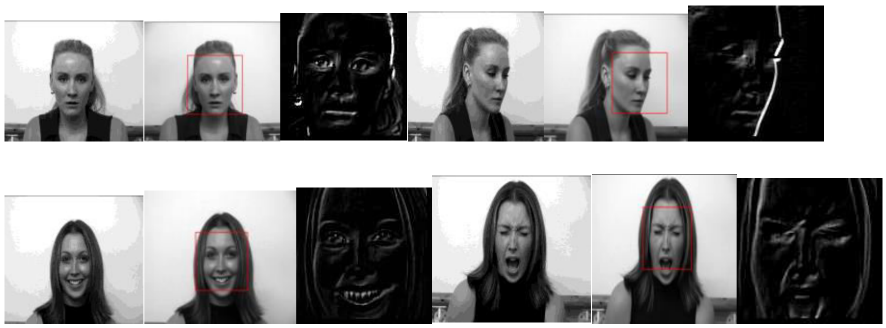
Fig: Multiple Mean Fuzzy LBP

Here considering 5x5 matrix, we are dividing this matrix into 8 regions based on location of the pixels. Among these 8 mean values significant mean value is considered and subtracted from the center pixel. We are considering maximum of mean among all the regions because if that it can extract the features effectively from the face images. Low pass filter removes noise effectively form the images.

$$\mathrm{Max}(f(x)) = \left\{ \begin{array}{ll} M_1 & \text{if } i<2 \;\&\; j<2 \\ M_2 & \text{if } i<2 \;\&\; j>2 \\ M_3 & \text{if } i>2 \;\&\; j<2 \\ M_4 & \text{if } i>2 \;\&\; j>2 \\ M_5 & \text{if } i<2 \;\&\; j=2 \\ M_6 & \text{if } i>2 \;\&\; j=2 \\ M_7 & \text{if } i=2 \;\&\; j<2 \\ M_8 & \text{if } i>2 \;\&\; j>2 \end{array} \right\} \qquad (19)$$

Output of MMFLBP:

(x) (y) (z) (x) (y) (z)



x. Original image y. face detected image z. MMFLBP image

Experimental Results and Discussions:

In this study, for experiments— 'YALEB' and 'ORL'—two data sets are used for evaluating the performance of the Multiple Mean Fuzzy LBP operator, these data sets include noisy, rotation-invariant, and unevenly illuminated face images.

These data sets are subjected to the use of MMFLBP technique, and the accuracy, precision, and recall are evaluated using confusion matrices. Three data are acquired and utilized for error detection: "(MSE)mean square error, (MAE)mean absolute error, and (RMSE)root mean square error". We used a variety of machine learning classifiers, including SVM, LR, DTC, RF-Reg, KNN, and K-Means classifiers, for classification.

To solve regression and classification issues, SupportVectorMachine is a machine learning approach used. The random forest classifier divides this dataset into subsets'*-means* is an unsupervised classification algorithm.Based on predefined conditions, decision Tree employs every possible solution to a problem. K-means, also known as clustering method, divides objects into k groups according to their traits. Table 2 and Graph1 shows accuracy of SVM, DT, **RF Tree,KNN,K-Means**for MMFLBP, it is clearly noticed that the MMFLBP technique shows better accuracy with SVM classifier than RLBP AND DRLBP method.

This analysis employs a confusion matrix with two expected categories containing "yes" or "no" options. True-positive: In reality, it's false but a positive outcome was expected. accurate-negative: It's accurate but as anticipated, it's negative. untrue-positive: It's untrue, but it was correctly anticipated. untrue-negative: It's untrue but an expected negative. The following formulas are used to calculate precision, recall and accuracy.

Accuracy: The accuracy value has to High accuracy is used to determine how many predictions of the total number of values were accurate.

$$\text{Accuracy}=\frac{truepositive+truenegative}{truepositive+falsepositive+truenegative+falsenegative} \quad (20)$$

Precision: Precision describes the number of accurately anticipated situations that really turn out to be positive. A high accuracy number ought to be preferable.

$$\text{Precision: } \frac{truepositive}{truepositive+falsepositive} \quad (21)$$

Recall: Used to retrieve true negative values in the proper way.

$$\text{Recall: } \frac{truenegative}{truepositive+falsenegative} \quad (22)$$

Mean absolute Error: It is used to evaluate the efficacy of a regression model.

$$\mathbf{MAE = (1/n)\ \Sigma\ (i{=}1\ to\ n)\ |y_i - \hat{y}_i|} \quad (23)$$

MSE -Mean Square Error: Measures the similarity of a regression line to a group of data points.

$$\mathbf{MSE = (1/n) * \Sigma\ (actual - predicted)2} \quad (24)$$

RME-Root Mean Square Error:calculated by

$$\text{RME}=\sqrt{\frac{\Sigma(i{=}1\ to\ n)\ |y\_i - \hat{y}\_i|}{N}} \quad (25)$$

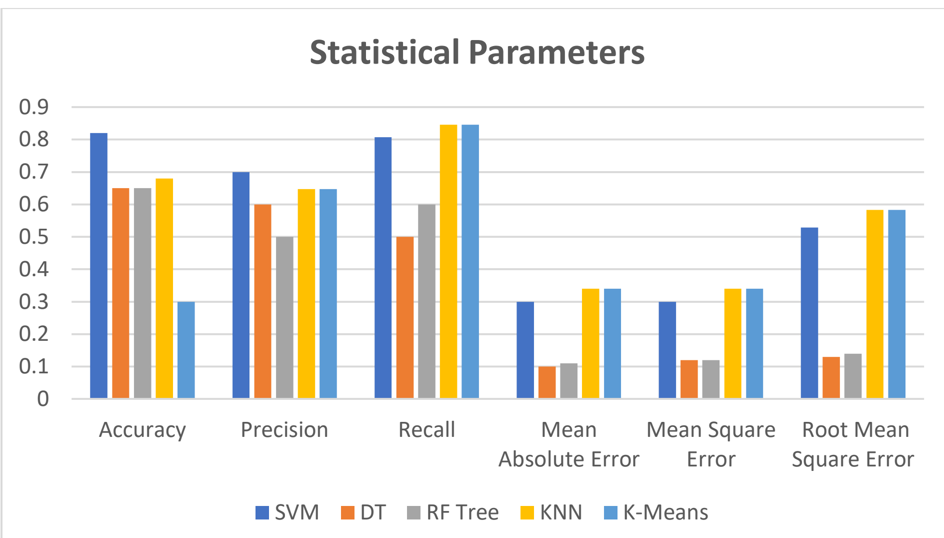
Contrast	Dissimilarity	Homogeneity	Energy	Correlation	Label
335.218927	9.341384	1.047871	0.687184	1.143495	1
210.508192	6.909463	1.240168	0.909869	1.217941	2
326.855014	9.896963	1.015580	0.666057	1.103021	1
311.488771	9.754590	1.013046	0.669441	1.104733	2

214.456850	8.172811	1.045480	0.679350	1.131389	1
290.538206	9.020975	1.045937	0.707541	1.135037	1
93.353884	5.309958	1.263550	0.934706	1.239325	2
267.933192	8.778531	1.063154	0.713181	1.107327	1

Table1: shows original Database values

Parameters	**SVM**	**DT**	**RF Tree**	**KNN**	**K-Means**
Accuracy	0.82	0.65	0.65	0.68	0.3
Precision	0.7	0.6	0.5	0.647	0.647
Recall	0.8076	0.5	0.6	0.8461	0.8461
MSE	0.3	0.1	0.11	0.34	0.34
MSE	0.3	0.12	0.12	0.34	0.34
RMS-Error	0.5291	0.13	0.14	0.5831	0.5831

Table2: Statistical Parameters of Different Classification Methods



Graph1: Statistical Parameters

Conclusions:

LBPis a straightforward and effective texture operator for different real-time applications. LBP generated binary data is sensitive to noise and it will identify face images when its completely Visible. To increase LBP's efficiency and resilience, in this research paper we proposed a novel multiple mean fuzzy LBP(MMFLBP) to classify facial images with different facial expressions and rotation invariant images.Various statistical parameters and a confusion matrix are used to obtain the experimental results, and the results are tabulated. It is evident that our proposed approach has an accuracy rate of 82% because this method is unable to recognize the face images which has high emotional expressions like instead of smiling if u have laughing face image it can't able to recognize face images accurately .In our data set most of the images are having high emotional expressions to overcome this draw back if u combine this Fuzzy technique with speeded up robust features (SURF)technique it will increase the rate of accuracy. This method was tested with samples of various sizes and was found to fit most of the samples the best. Due to faces with various emotions, underfit and overfit are seen in a relatively small number of samples. Applying this technique to distinct facial characteristics can increase accuracy.

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