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Facial Expression Recognition based on Local Binary Patterns (LBP)

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Abstract: A tough however exciting challenge is that the analysis of expressions of face be done automatically. Deriving effective facial representative features from face pictures being a significant step towards flourishing expression recognition is concentrated throughout this paper. Local features called Local Binary Patterns (LBP) are enforced for empirical analysis of face expression recognition. In depth experiments prove that this feature extraction is effective. The Uniform-LBP is employed and therefore the high performance is achieved.

***Keywords**:* Facial Expression Recognition, Local Binary Patterns, Neural Network

I. INTRODUCTION

Expressions delineated on a one's face remains an awfully powerful, natural and fast mean for us as individuals to speak out our feelings and emotions. So this potential capability results in myriad applications, such as:

- ✓ Human-computer interaction (HCI)
- ✓ Retrieving image and video knowledge and understanding those images
- ✓ Artificially Intelligent animated faces
- ✓ Interactive video
- ✓ Security
- ✓ Emotion analysis
- ✓ Medical help and Behavioral science etc. [7] [10]

Automatic face expression recognition (FER) accounted with appropriate accuracy will facilitate within the development of robots and machines that are very like humans and it'll move machine generation a step closer to humans. Although humans can acknowledge each other's expressions at once and without much needed effort, however reliable and correct expression recognition by intelligent automaton continues to be a challenge.

To date, many FER strategies have been planned. The essential steps of the face expression recognition procedure includes: first of all the acquisition of the face expression pictures, second the detection of faces for the face expression feature extraction and eventually comes the recognition of face expression. The steps are shown in **Figure 1**.

Recognition of facial expressions is done to perceive the distinction among emotions like sadness (disappointment), happiness, disgust, surprise, fear and anger. These expressions will vary in each individual. Mehrabian [2] indicated that spoken words (7%), voice (38%) and facial expressions (55%) are accustomed to convey messages by humans. Extraction of face expression is the core step of derivation of expression recognition. The two necessary forms of approaches to extract features vectors are: appearance based strategies and geometric based strategies. In this paper, we introduce Local Binary Patterns (LBP) that is an appearance-based methodology for recognition of face expression. At the earliest LBP was used for texture analysis [4, 5] and Ahonen *et al.* [16] conferred LBP based strategies for detection and recognition of face and we are enhancing it further to acknowledge facial expressions person independent. My motivation is that face images can be seen as a composition of smaller patterns on that LBP can be applied.

Input face image is split into a group of smaller regions from that LBP histograms are drawn and fashioned into a one feature histogram. While for classification several classifier styles are available like neural network (NN), SVM, Self-Organizing Map (SOM) etc. Neural Network is adopted by me. In depth experiments are done to point out through empirical observation that the LBP features are economical for recognition of facial expressions.

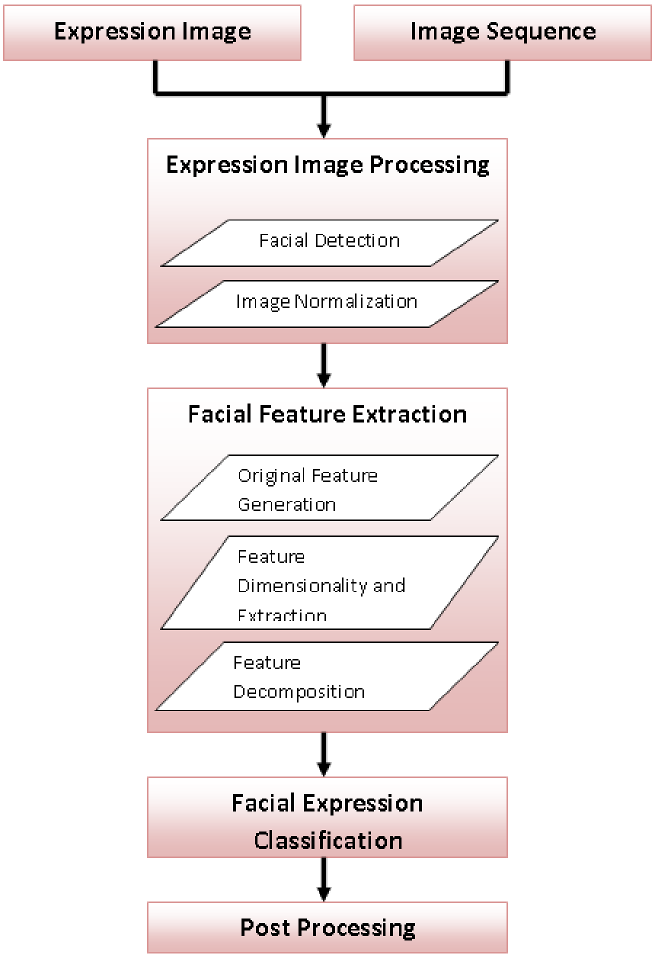


Figure 1: Organizational Model (FER)

II. PREVIOUS WORK

The face expression analysis has been a vigorous analysis topic for behavioural scientists since the work of **Darwin** in 1872 [4]. **Suwa** *et al.* [15] bestowed an early endeavor to efficaciously analyze facial expressions. After the moment, a lot of progress has been done.

Automatic face expression recognition involves 2 important aspects: facial illustration and classifier style. Facial illustration is to derive a group of features from original face pictures to effectively represent faces. The optimum features ought to minimize within-class variations of expressions whereas maximize between class differences. If inappropriate features are employed, even the most effective classifier might fail to attain correct recognition.

Ekman and Friesen [5] represent six basic face expressions (emotions): Happy, Surprise, Disgust, Sad, Angry, and Fear. As per **Meharabian** [2], 55% communicative cues can be decided by facial expression; thence recognition of facial expressions became a serious modality.

A. Colmenarez *et al.* [1] introduced that faces sculpturesque as a group of regions containing sub-groups of face features. Model was bolstered upon the belief that the facial features can be accurately located. The looks of every facial feature is provided by the image sub-window set around its position and thence the feature position is normalized with reference to the outer eye corners.

X. Feng *et al.* [19] projected a completely unique approach to acknowledge facial expressions from static pictures. At the very first, LBP are accustomed to expeditiously represent the facial images requiring linear programming methodology to adopt the classification of 7 face expressions: neutral, happy, sad, fear, anger, disgust, surprise. 21 classifiers are made supported by linear programming technique and classification is enforced with a binary tree tournament theme.

T. Ahonen *et al.* [16] used template matching to execute face expression acknowledgement employing the LBP-based facial representation: a template is made for each category of face images and then a nearest-neighbor classifier is employed to match the input image entailed to nighest template.

Recently Local Binary Patterns are brought in as effectual appearance features for facial-analysis [8, 15 and 18]. Completely different techniques have been projected to classify facial expressions, akin to Neural Network, Support Vector Machine (SVM) and rule-based classifiers.

Caifeng Shan *et al.* [3] gave a comprehensive study. In that they judge LBP features for person-independent face expression recognition. **Donato** et al. [7] explored exclusively different methodology to present face images that embody PCA, ICA, Local Feature Analysis (LFA), LDA and local schemes akin to Gabor-wavelet representation and PCA. Top notch execution was obtained employing Gabor-wavelet representation and ICA.

The LBP operator produces 2P completely different output values, equivalent to the 2P total different binary patterns which can be fashioned by the P pixels within the neighbor set. It's been shown that some bound bins contain additional information than others [17]. Therefore, it's attainable to use solely a subset of the 2P Local Binary Patterns to explain the texture of pictures. **Ojala** et al. [17] referred to these basic patterns as uniform patterns. It's ascertained that uniform pattern scores for c. 90% of all patterns within the (8, 1) neighborhood and for c. 70% within the (16, 2) neighborhood in texture images [17].

Pantic and Rothkrantz adopted rule-based reasoning to acknowledge action units and their combination [11]. To use the temporal behaviors of facial expressions, completely different techniques were acquainted for face expression recognition in image sequences. There have been many tries to trace and acknowledge facial expressions over time supported by optical flow analysis.

Tian *et al.* [20] posed a Neural Network primarily based approach to greet facial action units in image sequences. **Cohen** *et al.* [9] projected a multi-level HMM classifier that permits not solely to perform expression classification on a video phase, bust additionally to automatically phase a protracted video sequence to the various expressions segments while not resorting to heuristic ways of segmentation. However HMMs cannot handle dependencies in observation.

M. Pantic *et al.* [11] presented Local binary Patterns, that powerful entails texture description. Most vital properties of LBPs are its lustiness to alter in illumination and procedural expressions. The powerful classifiers those are typically applied in face expression recognition systems are: Multi Layer Perceptron (MLP3), NN, SVM etc.

III. OVERVIEW OF THE PROPOSED APPROACH

This paper explores LBP approach of extraction of features for recognition of expression. The input is partitioned into 16 equally placed sub-blocks, each of size 64 × 64. Then extract uniform LBP features (dimension 59) from each of the sub-blocks using the neighbourhood of eight points in unit radius tallying for each and every pixel. These are

simplicity. A face expression recognition system wants a classifier which may perform well to classify 6 basic facial

concatenated so as to result into 944 dimensional feature vector that retains location and structural information of facial expression and dimensionality is reduced by employing PCA. Thus obtained feature vector is rendered to train our neural network based classification method.

The remainder of the paper is structured as follows: Section IV and Section V illustrate LBP methodology that is to be applied on image domain given in Section VI. Expressions' recognition utilizing neural network for pattern recognition and the thence experimental results are followed up in Section VII and Section VIII.

IV. LOCAL BINARY PATTERNS

The goal of facial expression recognition is to see the emotional state of the face, let's say, happy, sad, fear, anger, surprise, neutral, and disgust, notwithstanding the identity of the face.

The original LBP operator was introduced by Ojala et al. [17], and was proved a robust means of texture description. Several features such as gray-scale invariance and no normalization in a neighbor window make it favorable to be used in texture recognition. The true LBP operator points the pixels of a picture with decimal numbers, that are known as LBPs or LBP codes that inscribe the native structure around every single pixel. It goes forward as illustrated in Figure 3. Every pixel is compared with its eight neighbours in a 3×3 neighborhood by subtracting the core pixel value. Within the result, negative values are staged as 0 and therefore the others with 1. For every given pixel, a binary number is obtained by merging of these binary values in a right-handed direction that starts from the one amongst its top-left neighbor corner value. The equivalent notation in decimal of the generated binary set is then put-upon as label for the given pixel and therefore the 256-bin histogram of the LBP labels computed over vicinity is employed as a texture-descriptor. Thus the inferred binary numbers (called Local Binary Patterns or LBP codes) systematize local primitives together with different kinds of curved edges, spots, flat areas, etc (as shown in Figure 2.).

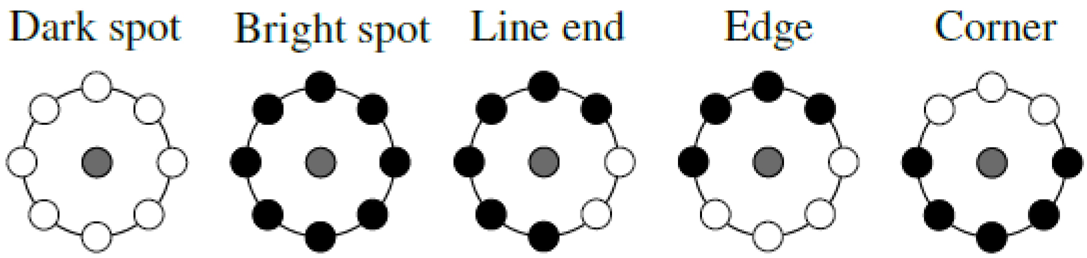


Figure 2: Samples of textures which may be acknowledged by LBP (white circles represent 1 and black circles 0) [30]

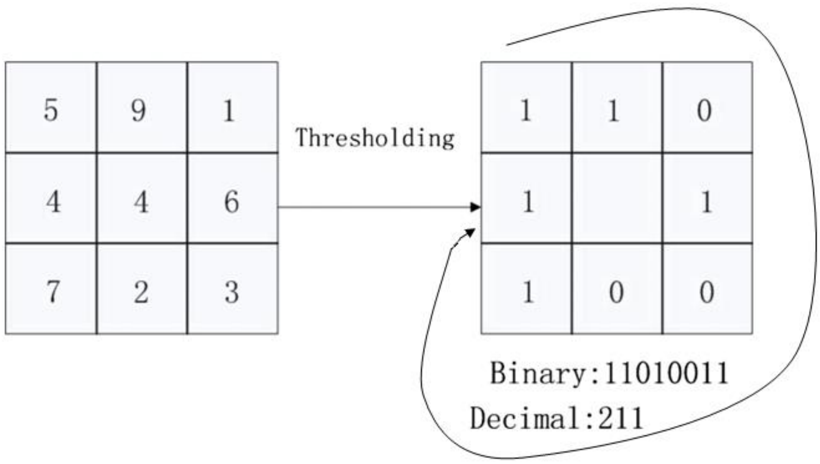


Figure 3: The fundamental LBP 3x 3 operators

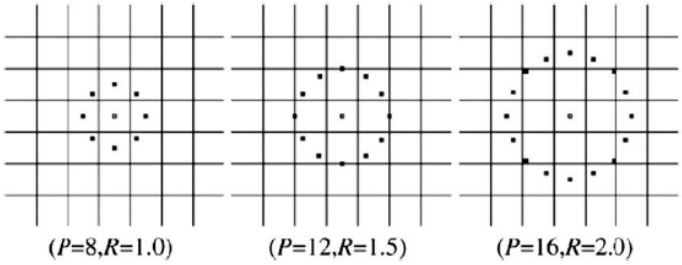


Figure 4: Extended LBP: circular (8, 1), (12, 1.5), (16, 2) neighbourhood respectively

One limitation of the fundamental LBP operator is that they're unable to capture some dominant features. So as to handle with the texture at completely different scales, hence the operator needed to be worked upon and thus emerged the use of the neighbourhoods of various sizes. A local neighbourhood is outlined as a group of sampling points equally spaced on a circle, that is focused at inside the pixels are interpolated utilizing bilinear interpolation, therefore allowing for any radius and any variety of sampling points within the neighbourhood.

See Figure 4. For samples of the extended LBP operator, where the notation (P, R) denotes a vicinity of P within which the points are equally spaced on a circle of radius of R that forge a circularly symmetric neighbor set.

The LBP operator $LBP_{P,R}$ produces 2^P completely different output values, resembling the 2^P totally different binary patterns that may be fashioned by the P pixels within the neighbor set. It's been shown that bound bins contain a lot of info than others [17]. Therefore, it's certain to use solely a subset of the 2^P Local Binary Patterns to explain the texture of images. Ojala et al. [17] presented these basic patterns as uniform patterns thus a pattern is named uniform if it contains at the most 2 bitwise transitions from 0 to 1 or the other way around once the binary string is taken into account circular. It's discovered that uniform patterns account for nearly 90% of all patterns within the (8, 1) neighborhood and for circa 70% in the (16, 2) neighborhood within texture images. Accumulating the patterns that have over 2 transitions into a single bin yields an LBP operator, denoted $LBPu2_{P,R}$ with lower than 2^P bins. To illustrate, the amount of labels for a neighbourhood of eight sampling points is 256 for the standard LBP but 59 for LBPu2.

Hence after tagging an image with the enhanced LBP operator, with following equation it's histogram i.e. of the tagged image $f_l(x, y)$ may be outlined as

$$H_i = \sum_{x,y} I\,(f_l(x, y) = i), \qquad \text{eq1.}$$

Where i has values from zero to n-1 and n is the range of different labels made by the LBP operator and

$$I\,(A) = \begin{cases} 1 & A \text{ is true} \\ 0 & A \text{ is false} \end{cases}$$

For a gray scale image $I(x, y)$, assume that the gray level at an arbitrary location (x, y) be given as g_c.

$$g_c = I(x, y).$$

For an evenly space circular neighborhood with P sampling points and R radius around the center pixel (x, y), the gray value of pixel at p^{th} sampling point is g_p, given by

$$g_p = I\,(x_p, y_p), \quad p = 0...P-1 \qquad \text{eq2.}$$

And the coordinate values of the sampling point is outlined as

$$x_p = x + R\cos(2\pi p/P) \qquad \text{eq3.}$$

$$y_p = y - R\sin(2\pi p/P) \qquad \text{eq4.}$$

The thresholding binary operator $S\,(g_p - g_c)$ can be given as

$$S\,(g_p - g_c) = \begin{cases} 1 & \text{if } gp \geq gc \\ 0 & \text{otherwise} \end{cases} \qquad \text{eq5.}$$

In basic LBP, the *LBPP R*, decimal equivalent of the *P* bit binary operator is computed by applying a binomial factor to every $S\,(g_p - g_c)$. It's calculated as

$$LBP_{P,R}\,(x_c, y_c) = \sum_{p=0}^{P-1} S\,(g_p - g_c)\,2^p \qquad \text{eq6.}$$

The main motivation behind using LBP patterns is its robustness to change in illumination and computational simplicity.

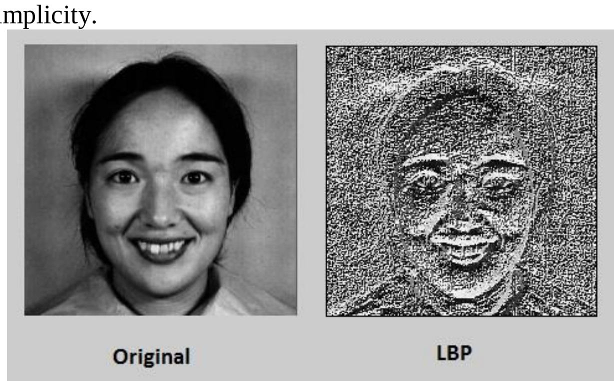


Figure 5: LBP (8, 1) transform

In this work we take advantage of uniform patterns instead of basic LBP patterns. A uniformity criterion of a local binary pattern *U* is the number of bit-wise transitions from 0 to 1 for a circular bit pattern. The uniformity measure of *U* pattern is at most 2. As an example, for *LBP*(8, 1) the patterns 00000000, 11111111 falls under category of zero transition and patterns 00001111 falls under category of one transition and patterns 00111000 falls under two transition. The total number of labels in uniform *LBPu*2 (8, 2) is 59 (58 labels for uniform patterns with at most transition 2 and rest are assigned to a single label, totally 59 labels).

The histogram of the LBP image $LBP(x, y)$ can be computed as

$$H_k = \sum_{x,y} S\,(LBP(x, y) = k), \quad k = 0 \ldots n-1 \qquad \text{eq7.}$$

Where n range up to exclusively different labels produced by LBP operator. In this case n is equal to 59 for uniform LBP.

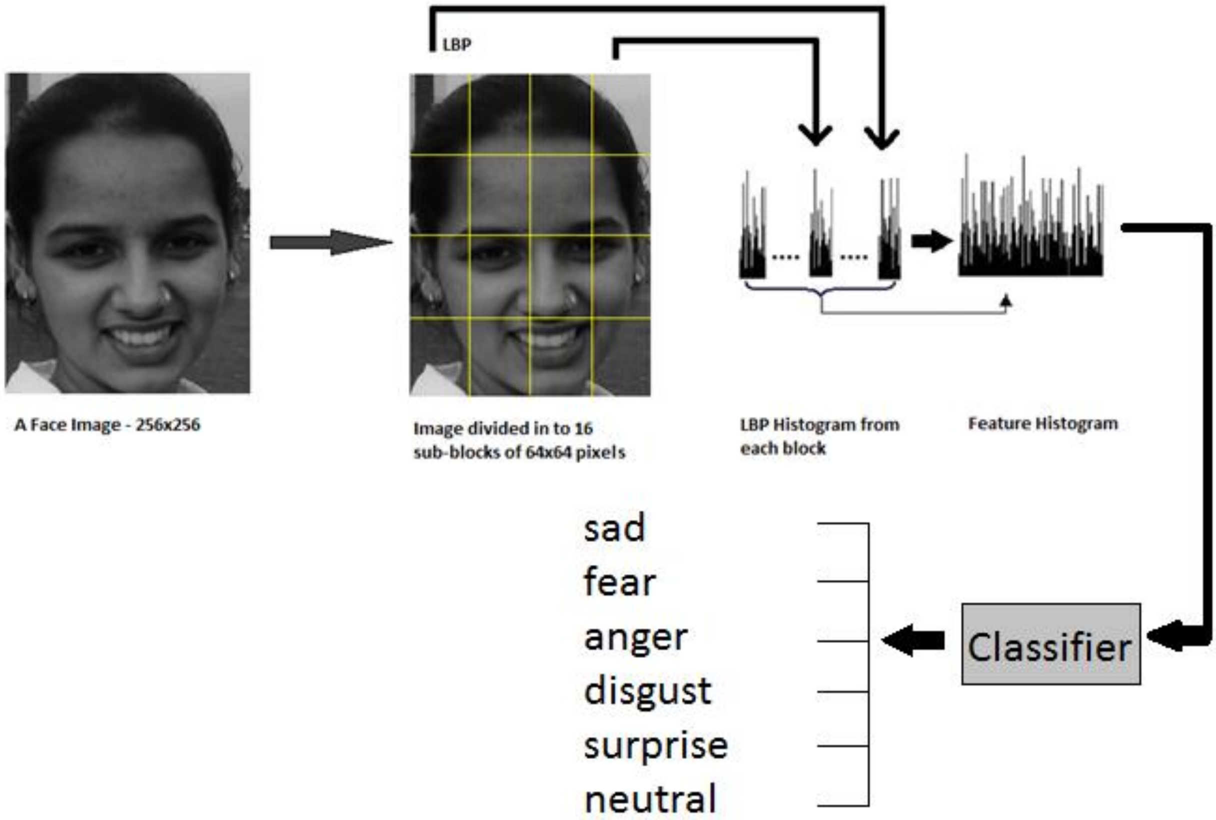


Figure 6: An example of sub-block classification technique using concatenated LBPs obtained from each sub-block

V. SUB-BLOCK BASED LBP FEATURES EXTRACTION

When LBP histogram of dimension 59 is extracted from the complete face image, the features encodes solely the presence of micro patterns. The patterns contain no data concerning it's location. Face image of size 256 × 256 is equally sub-divided into blocks of size 64 × 64, totally 16 sub-blocks. Each sub-block ($R_1 \ldots R_{15}$) contributes uniform LBP feature vector of dimension 59. Once all the feature vectors square measure concatenated so as, there is a tendency to get a replacement feature vector of dimension 944, that preserves location and shape data of the facial region.

The concatenated histogram can be outlined as

$$H_{k,r} = \sum_{x,y} S\{LBP(x,y) = k\} \qquad LBP\{(x,y) \in R_j\}$$

Where $k = 0 \ldots 58$, $j = 0 \ldots 15$.

VI. IMAGE DATABASE

We have considered each 6-class archetypical expression recognition as well as 7-class expression recognition by adding the neutral expression.

The data supply comes from Japanese Female Facial Expression (JAFFE) database that is an open face image database. It contains 10 women's expressions, including individuals KA, KL, KM, KR, MK, NA, NM, TM, UY and YM. Everybody has given 7 different expressions as AN, DI, FE, HA, NE, SA and SU. Every expression has 3 or 4 samples and therefore the total range is 213. Every image has been rated by 60 subjects on scale of 6.

- **Purpose:** This database is primarily accustomed for acknowledgement of face expression
- **Properties:** See Table I

Table I. Properties of JAFFE Database

Properties	Descriptions
# of subjects	10
# of images/videos	213
Static/Videos	Static
Single/Multiple faces	Single
Gray/Color	Eight-bit gray
Resolution	256* 256
Face pose	Frontal-view
Facial expression	7 facial expressions: neutral, sadness, surprise, happiness, fear, anger, and disgust
Description of facial expression	Posed facial expressions
Frame rate	N/A
Ground truth	Facial expression label, Identifications of subjects

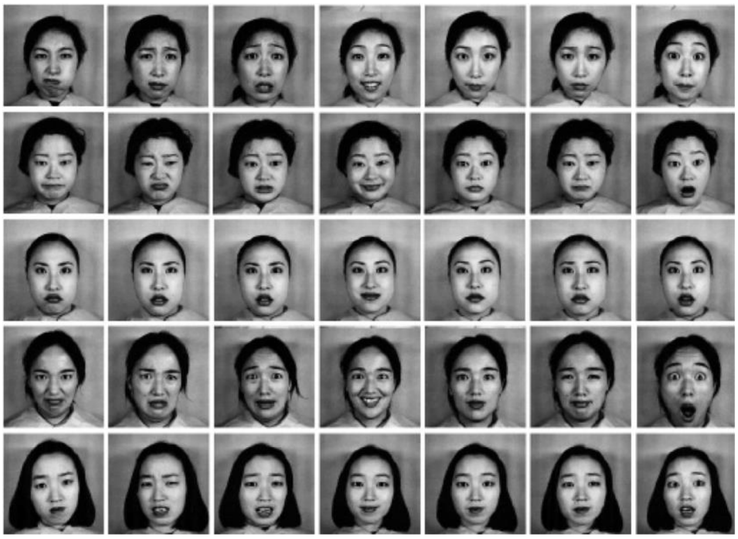


Figure 7: Shows some sample pictures from the JAFFE database.

VII. EXPRESSIONS RECOGNITION

On the input image sub-divided into sixteen equal non-overlapping blocks with every block size 64 × 64 pixels, LBP filter (P,R)-(8,1) is applied on every block and corresponding LBP features are concatenated so as to obtain 944 dimensional feature vector. The feature vector after spatiality reduction is fed as input to the neural network of size 20×7. Since I'd like seven distinct categories as output classes (Happy, Sad, Surprise, Anger, Disgust, Fear and Neutral), we set the specified output to be either 1 or 0 format. That means if the specified output is happy expression, we set it as {1, 0, 0, 0, 0, 0, 0}. 1 represents true state of the class prevalence and 0 represents the false state. Subsequent to extraction, classification step follows. For this a two-layer feed-forward network utilizing sigmoid function each in the hidden layer and the output layer, is employed to distinguish vectors. Thus we employed a neural network to classify inputs into a group of target classes.

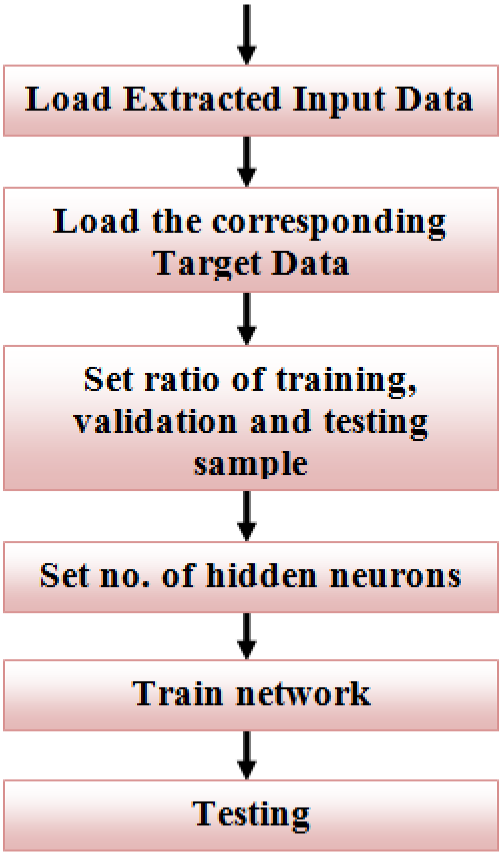
After loading the extracted classification information, a network is created: The network has 7 output neurons, because there are 7 categories associated with each input vector. Each output neuron represents a category. Once an input vector of the apt class is applied to the network, the corresponding neuron should result a 1 and the alternative neurons ought to output a 0. Network therefore created is trained to classify the inputs keeping with the targets by arbitrarily dividing the input vectors and target vectors into three sets: coaching, validation and testing.

Coaching (Training): These are given to the network throughout coaching and therefore the network is adjusted in keeping with its error.

Validation: These are employed for network generalization and to halt coaching once generalization stops up.

Testing: These have no impact on coaching and hence give an independent measure of network performance throughout and after coaching.

Figure 8: Classification Model



VIII. EXPERIMENTAL RESULTS

Among the provided data, 70% of the data is taken for coaching, 15% for validation and remaining 15% is employed for testing. LBP features extracted are of dimensions 944. The features are passed through PCA to get rid of the unessential or redundant information. The reduced LBP features are used for coaching neural network. Table II shows the confusion matrix for all the seven basic emotions: (happiness, sadness, disgusted, angry, surprised, fear, Neutral). It's discovered that the average recognition accuracy obtained during this case is 82.08%. Table III shows the confusion matrix for six emotions except neutrality and highest resultant accuracy of 6-class is 88.5% using original features and average accuracy being 80.66%. However after reduction it shows a dip with average accuracy being near 70.7%.

The only criterion followed was that a sequence could be labeled as one of the seven basic emotions. To gauge the normalized functioning to distinct subjects, a ten-fold validation testing theme is adopted in experiments. Thence the average recognition result on the test groups is reported. Overall, the planned Neural Network based technique performs with highest recognition accuracy 94.1% and average accuracy 82.08% for seven archetypical expressions.(1–H, 2–SA, 3–SU, 4–A, 5–D, 6–F, 7–N)

Table II. Confusion matrix using LBP - highest resultant accuracy 94.1% (7 class features)

OUTPUT CLASS	1	2	3	4	5	6	7	
1	29 14.1%	1 0.5%	1 0.5%	0 0.0%	2 1.0%	0 0.0%	0 0.0%	87.9% 12.1%
2	0 0.0%	27 13.2%	0 0.0%	1 0.5%	1 0.5%	0 0.0%	0 0.0%	93.1% 6.9%
3	0 0.0%	0 0.0%	27 13.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	27 13.2%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	2 1.0%	0 0.0%	0 0.0%	25 12.2%	1 0.5%	0 0.0%	89.3% 10.7%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	29 14.1%	0 0.0%	100% 0.0%
7	1 0.5%	0 0.0%	0 0.0%	1 0.5%	0 0.0%	1 0.5%	29 14.1%	90.6% 9.4%
	96.7% 3.3%	90.0% 10.0%	96.4% 3.6%	93.1% 6.9%	89.3% 10.7%	93.5% 6.5%	100% 0.0%	94.1% 5.9%
	1	2	3	4	5	6	7	

TARGET CLASS

Table III. Confusion matrix using LBP - highest resultant accuracy 88.5% (6 class features)

OUTPUT CLASS \ TARGET CLASS	1	2	3	4	5	6	
1	30 16.4%	1 0.5%	0 0.0%	0 0.0%	0 0.0%	1 0.5%	93.8% 6.3%
2	0 0.0%	25 13.7%	1 0.5%	2 1.1%	0 0.0%	0 0.0%	89.3% 10.7%
3	0 0.0%	2 1.1%	25 13.7%	0 0.0%	0 0.0%	1 0.5%	89.3% 10.7%
4	0 0.0%	1 0.5%	0 0.0%	28 15.3%	0 0.0%	0 0.0%	96.6% 3.4%
5	1 0.5%	2 1.1%	1 0.5%	0 0.0%	26 14.2%	2 1.1%	81.3% 18.8%
6	0 0.0%	0 0.0%	3 1.6%	0 0.0%	3 1.6%	28 15.3%	82.4% 17.6%
	96.8% 3.2%	80.6% 19.4%	83.3% 16.7%	93.3% 6.7%	89.7% 10.3%	87.5% 12.5%	88.5% 11.5%

IX. CONCLUSIONS

The paper presents a novel pattern recognition neural network based facial expression recognition system utilizing solely 59 dimensional uniform LBP features extracted from facial image. 16 non-overlapping sub-blocks, each of size 64 × 64 is placed over the facial region. 944 dimensional LBP feature vector is obtained after sequentially concatenating LBP vectors extracted from the every sub-block and so after dimensionality reduction it’s fed to NN leading to efficacious 94.1% highest recognition accuracy rate and 82.08% on the average.

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