Facial expression classification using Cross Diagonal Neighborhood Pattern

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Abstract: Facial Expression Recognition has significant applications in the field of Affective Computing. FER has its significant contribution in the fields like human computer interaction, neurology, psychiatry, image processing, computer vision, affective computing, and information security. This work gives unique and robust FER System by extracting unique and robust face features. This work proposes Cross Diagonal Neighborhood Patterns (CDNP) for unique feature extraction. The CDNP features are further processed by Gray Level Co-occurrence Matrix (GLCM). The derived CDNP-GLCM features are sent to Convolutional Neural Network (CNN) to train various expressions.

Index terms: Affective Computing, Cross Diagonal Neighborhood Patterns (CDNP), Convolutional Neural Network (CNN).

1. Introduction
Affective Computing[1][2] is the field of computer science which moves human computer interaction to the next level by imparting emotional interaction between humans and the machines. The motive of affective computing is to simulate empathy, so that the human computer interaction becomes more efficient i.e., the machine should adapt to the human emotions and react accordingly. Affective computing[1][2] is multi-disciplinary course which deals with psychology, physiology, cognitive sciences and computer sciences. Affective computing has various applications like virtual reality, perpetual interfaces, smart surveillance, emotional healthcare. An “affect model”[3] is built by capturing information using various sensors, for example knowing the heart beat rates and blood pressure of a person, to develop a personalized computing system which is able to perceive and interpret human feelings and also is able to give intelligent, friendly and sensitive responses.

Humans have various ways of expressing emotions like facial expressions, body movement, gestures, voice tone and also through physiological signals such as heart rate, sweat, hormone changes in the body etc. Progresses in development incite the enhancement of all the more amazing HMI structures which never again rely upon typical devices, for instance, support, mouse and shows anyway take summons particularly from customer's voice and duplicates. Such structures intend to impersonate human-human collaboration by simply using correspondence channels used among individuals and not requiring counterfeit equipment.

In spite of the fact that people can distinguish and translate articulation in a scene with next to zero exertion, same errand will be very trying for machines. Changes on face and body ought to be displayed utilizing legitimately picked highlights and those highlights ought to be followed, arranged progressively. FER can be thought as a between disciplinary issue of picture video preparing, design acknowledgment, brain
science and concentrates to expand precision and speed has been completed throughout the previous 20 years.

An essential issue with acknowledgment errand is the quantity of articulations separated from regular ones, for example, outrage, delight and dread. A few different messages ought to be perceived in such a framework. A grinning mouth and cocked eyebrows signifying "I don't know" can be considered as an instance to such messages. There are moreover articulations ordinarily utilized by a particular individual however extremely uncommon out in the open. This makes the issue particular for every individual and requires a versatile arrangement system in translation expression.

Aside from HMI frameworks video communication and conferencing is another application of facial component extraction. High data transfer capacity required to transmit facial pictures brings utilizing a symbol which recreates changes in clients confront. Changes on facial element directions can be coded and transmitted on low data transfer capacity stations empowering video conferencing and video communication while securing client's protection.

Human robot communications (HRI) have pulled in numerous scientists as of late to contribute in growing adroitly controlled social insurance frameworks. People all the time utilize nonverbal prompts in their everyday lives where the signs incorporate hand motions, outward appearances express sentiments. Subsequently, frameworks ought to incorporate these to make full profit of characteristic connection with the clients. In an omnipresent automated medicinal services framework, HRI frameworks could be significantly enhanced if robots could comprehend people groups' feelings in light of dissecting outward appearances and respond as neighborly as conceivable concurring to their current enthusiastic states.

Giving passionate medicinal services bolster utilizing robots could likewise be critical to make strides the personal satisfaction. People's psychological states are uncovered through feelings in their everyday circumstances where constructive feelings speak to sound mental states via conveying positive outward appearances (e.g., joy and joy). Then again, negative feelings can speak to undesirable mental states via conveying negative outward appearances, for example, outrage and trouble.

Along these lines, both constructive and pessimistic feelings can nearly influence people groups' passionate wellbeing in their day by day lives. To enhance passionate wellbeing, a strong outward appearance acknowledgment (FER) framework assumes discernment of psychological states after some duration by examination enthusiastic personal conduct standards. Essentially, vision-based FER frameworks, classified into 2 principle composes: present based and unconstrained. Posture based FER frameworks normally perceive counterfeit outward appearances where articulations are created by individuals by asking them to express a choice of articulations in succession. Despite what might be expected, unconstrained FER frameworks perceive the outward appearances that individuals do suddenly in day by day life, for example, amid preservation and keeping in mind that watching motion pictures.

Through physical contact devices: Emotions which are physically visible are captured through physical contact devices like Camera, Microphone.

Contactless devices: Emotions which are intrinsic i.e., not exposed physically are captured through certain “sensors” like galvanic skin response sensors, electrocardiogram, blood volume pressure, respiration sensors.

Capturing of human affective states: Human affective states[3] are captured by facial expressions(FEs), body temperature, body gesture and heart rate pulse.
Among these various kinds of emotion analyzing methods, this project deals with facial expressions of human beings.

Emotions are detected using certain features like the shape of the mouth, formation of the lips and eyebrows. Analyzing all these features FEs can be determined. These features are extracted by image processing techniques like gray-scale, thresholding and edge detection.

FEs results from different movements or places of the muscles of the face. These developments delineate the passionate condition of the people. Outward appearances are one kind by which people's express feelings. The 7 kinds of FEs are as follows.

Figure 1: Basic 7 kinds of expressions of emotion.

Human emotional states could be revealed through nonverbal cues like gestures, facial expressions. Human Robot Interaction[4] system could be improved if robots could understand emotional behavior of human beings. Healthy mental states carry positive emotions (eg: happiness and pleasure) unhealthy mental states carry negative mental states (eg: anger, sadness).

FER systems are classified into two types:
A) Pose based expressions[4]
B) Spontaneous expressions[4]

A) Pose based expressions:
These are the expressions caught by making people to implicate an expression, could be considered as artificial facial expressions.

B) Spontaneous expressions:
These are the expressions which are produced by the humans resonating in life, like daily conversations, etc.

A colossal measure of work is done in developing enhanced FER frameworks for effective utilization in picture preparing, and design characterization [11][12][13]. An extremely difficult issue to tackle in these is the capacity of the processing frameworks to distinguish human appearances to perceive hidden articulations. Consequently, exact acknowledgment outward appearances is as yet thought to be a noteworthy test because of a few parameters, for example, nearness of commotion from the situations because of light. Henceforth, strong FER needs huge regard for various apps. Geometric framework extract features from component vectors. Appearance framework extract features from edges.

The viability exceedingly subject to exact recognition of facial parts in the pictures, which can be an extremely difficult assignment in unconstrained situations and dynamic situations. Thus, stronger FER framework is required. FER techniques based on appearance center with respect to facial appearance to do distinctive examination. Speaking outward appearance includes in a video, Principal Component Analysis
(PCA) was generally connected in Expression frameworks [13][11][12]. In [12][11], PCA was attempted to perceive activity units to speak to and perceive diverse outward appearances.

In addition, LBP is brisk in computation. LBP could not consider angle data, modified version called as LDP is developed. LDP highlights in light of inclination data in eight conspicuous encompassing headings of a pixel [10]. While separating average LDP highlights, the double qualities are allotted. LDP overgoes directional signs. In the wake of getting directional edge qualities for a profundity pixel with respect to the normal LDP, top edge qualities are sorted out in dropping request and afterward their signs are thought about individually to speak to strong highlights. Essentially, dull pixels for the most part speak to negative directional qualities and splendid pixels indicate positive qualities. To resolve this, we follow a new approach called CDNP (Cross Diagonal Neighborhood Patterns). RGB confront pictures can uncover a man's personality effortlessly which can prompt issues identified with protection. With depth pictures individual's personality can be covered up.

### 1.1 LOCAL BINARY PATTERNS (LBP)

LBP is a strong means of texture description. LBP method is implemented by Ojala[14] used for texture analysis, is tolerant for illumination, known for brisk computation. LBP[7][8][9] value is computed based on following function.

$$f(x) = \begin{cases} 
0, & x < 0 \\
1, & x \geq 0 
\end{cases} \quad (1)$$

![Image showing the neighboring 8 pixels of the central pixel](image)

If central pixel is higher, result is "1". Else "0". Giving an 8-digit binary number.

The LBP code is determined for all the pixels of an image.
Figure 3: local binary pattern representation. (a) 3x3 neighborhood (b) Difference with respect to central pixel (c) Binary pattern.

The LBP code of a pixel \((x, y)\)

\[
LBP^{S,T}_{x,y} = \sum_{S=1}^{T} (g_S - g_c) 2^S
\]

\[
f(x) = \begin{cases} 
0, & x < 0 \\
1, & x \geq 0 
\end{cases}
\]  

2. Proposed Framework

The motive of this research is to design and implement FER system by using statistical methods like GLCM, LBP\([7][8][9]\), ULBP for feature extraction. Machine learning methods like SVM \([10]\), Decision tree, Logistic regression to classify FEs. Deep neural networks like Convolutional Neural Networks(CNN)\([8]\) is used for the classification of expressions as CNN proved to be the best in image classification.

This system uses a unique method called cross diagonal neighborhood pattern (CDNP) with GLCM, and CNN for efficient FER. The LBP method is enhanced to create Cross Diagonal Neighborhood Patterns. The CNDP features along with GLCM features are trained using various machine learning algorithms. The features are sent into the CNN to determine facial expressions.

![Figure 4: Frame work of proposed method.](image)
FEATURE EXTRACTION

The Cross-Diagonal Neighborhood Patterns (CDNP) features are obtained for each expression image. CDNP is the modification of Local Binary Patterns (LBP) considering the neighborhood cross pixels for a central pixel as one unit and the neighborhood diagonal pixels as another unit.

In Cross Diagonal Neighborhood Patterns, there are two patterns.

Cross Neighborhood Pattern

In a cross-neighborhood pattern, the central pixel of a 3x3 matrix is compared with the crossneighborhood pixels. If central pixel is higher, result is “1”. Else, "0". Giving a 4-digit binary number. The Cross Neighborhood Pattern code is determined for all the pixels of an image.

ILLUSTRATION OF CROSS NEIGHBORHOOD PATTERN

| 5 | 7 | 8 | 1 | 5 |
|---|---|---|---|---|
| 7 | 8 | 1 | 6 | 7 |
| 6 | 7 | 8 | 1 | 6 |
| 9 | 6 | 7 | 8 | 1 |
| 8 | 7 | 6 | 7 | 8 |

Cross pixels

Diagonal pixels

Figure 5: Cross and diagonal pixels representation.

In the above illustration, consider the first 3x3 matrix which is as follows

In the above illustration, 8 is the centre pixel to which the cross neighborhood pixels are compared. The cross neighborhood pixels marked in red are 5,8,6,8. Now, if central pixel is higher or equal to surrounding pixel, Cross Neighborhood pattern would be ‘1’ else, if the centre pixel is less than the cross neighborhood pixel then its value would be ‘0’.

Now after obtaining the binary values of each and every pixel, multiply the binary values with powers of 2 and add the values to get a decimal value.

The CNP code of a pixel \((x, y)\) is given by

\[
\text{CNP}_{x,y} = \sum_{s=0}^{S} s(g_s - g_c)2^s
\]  

\[
f(x) = \begin{cases} 
0, & x < 0 \\
1, & x \geq 0 
\end{cases}
\]

CNP Code : Multiply by powers of 2 and add them

\[0 \times 1 + 1 \times 2 + 1 \times 4 + 0 \times 8 = 6\]

'6' is the DNP Code for the above example. Similarly, DNP code is to be calculated for all the pixels of an image.
CALCULATION OF HISTOGRAM

The number of possible outcomes for a diagonal neighborhood pattern is from 0 to 15.

|   | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| 1 | 1 | 0 | 1 | 0 | 2 | 0 | 3 | 1 | 1 | 4 | 0  | 0  | 0  | 0  | 0  | 1  |

The histogram is calculated by taking into account of the frequency of the output in the range of 0 to 16 values. For example, while calculating Cross neighborhood pattern code if a particular value 9 has occurred 4 times, then the frequency of that value is noted down as '4'. Similarly for all the other possible values of Cross neighborhood pattern values. The Diagonal Neighborhood Pattern code is determined for every pixel in an picture. In the above illustration, 8 is the centre pixel to which the cross neighborhood pixels are compared. The cross neighborhood pixels marked in red are 7,7,1,7. Now, if the centre pixel is higher or equal to surrounding pixel, then Diagonal Neighborhood pattern would be ‘1’ otherwise, if the centre pixel is less than the cross neighborhood pixel then its value would be ‘0’.

Now after obtaining the binary values of each and every pixel, multiply the binary values with powers of 2 and add the values to get a decimal value.

3. Results and Discussions

3.1 GRAY LEVEL CO-OCCURANCE MATRIX (GLCM)

GLCM[19][20] is a factual strategy to extricate highlights from the pictures, as it looks at surfaces thinking about spatial connection of the pixels in a picture. The GLCM capacities depicts the unmistakable highlights of the surface of a picture by figuring recurrence of pixel sets with recognized qualities and in a specific spatial relationship that exist in a picture, making a GLCM, and after that extricating factual measures from this framework. GLCM is the traditional second-arrange measurable strategy utilized for surface investigation. A picture is made out of pixels each with a power (a particular dark dimension), the GLCM is an organization of how frequently unique blends of dimensions co-happen in a picture or picture area. GLCM surface assesses the connection between two pixels at any given moment, one is the reference pixel and the other is neighbor pixel. Each pixel has eight neighboring pixels permitting eight options for θ, which are 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°. According to the meaning of GLCM, the co-happening sets which are acquired by choosing θ equivalent to 0° is like that of θ equivalent to 180°. This idea stretches out to 0°,45°, 90° and 135° too. There are four decisions to choose the estimation of θ. Coming up next are the insights inferred utilizing GLCM. Insights, for example, differentiate, connection, vitality and homogeneity are resolved utilizing GLCM.

For characterizing attributes of a picture surface is a standout amongst the most vital factor. In GLCM, surface is described by thinking about the spatial conveyance of dim dimensions in an area. With the end goal to catch the spatial reliance of dim dimension esteems which add to the impression of surface, a two dimensional reliance surface examination grid are talked about for surface thought.
Since surface demonstrates its qualities by both every pixel esteems and its neighborhood. There are numerous methodologies utilized for surface grouping. The dim dimension co-event lattice is a mainstream factual system for highlight extraction. Haralick [18] recommended the utilization of dark dimension co-event frameworks (GLCM) for meaning of textural highlights. Where one of them has dark dimension I and another j. Such grid is symmetric and furthermore an element of the precise connection between two neighboring pixels. To lessen the computational complexities the co-events network are figured in a little window. The beneath model shows co-event lattice related with every pixel. Above networks are 4x4 on the grounds that the picture in Figure 4.1 has 4 dark dimensions 0, 1, 2, 3. Similarly for a 256 dark dimensions picture one ought to figure 256x256 co-event networks at all places of the picture. It is realized that grids of such kind are too substantial, and their calculation devours much memory. In this way, it is comprehended to utilize a less number of dark dimensions like 64 or 32. There is no unmistakable method to pick estimations of edge, separation and window as they are connected with a size of example. In this model, the separation d=1 and point θ=45 degrees are chosen.

\[
\begin{array}{cccc}
0 & 0 & 1 & 1 \\
0 & 0 & 1 & 1 \\
0 & 2 & 2 & 2 \\
2 & 2 & 3 & 3 \\
\end{array}
\]

\[
\begin{array}{cccc}
0 & 1 & 2 & 3 \\
0 & P(0,0) & P(0,1) & P(0,2) & P(0,3) \\
1 & P(1,0) & P(1,1) & P(1,2) & P(1,3) \\
2 & P(2,0) & P(2,1) & P(2,2) & P(2,3) \\
3 & P(3,0) & P(3,1) & P(3,2) & P(3,3) \\
\end{array}
\]

\[
\begin{array}{cccc}
4 & 2 & 1 & 0 \\
2 & 4 & 0 & 0 \\
1 & 0 & 6 & 1 \\
0 & 0 & 1 & 2 \\
\end{array}
\]

\[
\begin{array}{cccc}
6 & 0 & 2 & 0 \\
0 & 4 & 2 & 0 \\
2 & 2 & 2 & 2 \\
0 & 0 & 2 & 0 \\
\end{array}
\]

\[
\begin{array}{cccc}
2 & 1 & 3 & 0 \\
1 & 2 & 1 & 0 \\
3 & 1 & 2 & 0 \\
0 & 0 & 2 & 0 \\
\end{array}
\]

\[
\begin{array}{cccc}
4 & 1 & 0 & 0 \\
1 & 2 & 2 & 0 \\
0 & 2 & 4 & 1 \\
0 & 0 & 1 & 0 \\
\end{array}
\]

**Experimental Results**
JAFFE DATASET

The following table gives Classification rate for 7 kinds of expressions for JAFFE Dataset using various machine learning classifiers.

Table 1: Classification rate(%) of existing and proposed method.

| Classifier       | LR     | KNN    | SVM    | Naïve Bayes | Decision Trees | Random Forest | CNN    |
|------------------|--------|--------|--------|-------------|----------------|---------------|--------|
| GLCM             | 79.86  | 80.12  | 81.36  | 78.26       | 81.41          | 82.62         | 86.42  |
| GLCM + LBP       | 79.99  | 80.56  | 81.86  | 79.21       | 81.98          | 83.62         | 87.81  |
| Proposed CDNP    | 90.23  | 81.26  | 82.14  | 81.68       | 81.89          | 84.65         | 94.51  |
| Proposed CDNP + GLCM | 91.54  | 83.24  | 84.16  | 82.91       | 83.45          | 85.96         | 96.62  |
Figure 6: Comparison of proposed and existing methods.

**MS CELEBS DATASET**

The following table gives Classification rate for 7 kinds of expressions for MS CELEBS Dataset using various machine learning classifiers.

| Classifier          | LR   | KNN  | SVM  | Naïve Bayes | Decision Trees | Random Forest | CNN   |
|---------------------|------|------|------|-------------|----------------|---------------|-------|
| GLCM                | 78.86| 79.12| 80.36| 77.26       | 80.41          | 80.62         | 85.42 |
| GLCM + LBP          | 76.29| 81.42| 80.62| 78.21       | 80.98          | 81.32         | 86.81 |
| Proposed CDNP       | 89.23| 80.26| 81.14| 80.68       | 80.89          | 83.65         | 93.45 |
| Proposed CDNP + GLCM| 90.54| 82.24| 83.16| 82.21       | 82.45          | 84.96         | 94.32 |
Figure 7: Comparison of proposed and existing methods.

FEI DATASET

The following table gives Classification rate for 7 kinds of expressions for FEI Dataset using various machine learning classifiers.

Table 3: Classification rate(%) of existing and proposed method

| Classifier       | LR  | KNN | SVM  | Naive Bayes | Decision Trees | Random Forest | CNN    |
|------------------|-----|-----|------|-------------|----------------|---------------|--------|
| GLCM             | 76.86 | 78.12 | 79.16 | 78.26       | 80.21          | 80.24         | 84.42  |
| GLCM + LBP       | 75.29 | 80.42 | 80.23 | 79.21       | 81.98          | 81.29         | 86.21  |
| Proposed CDNP    | 91.23 | 81.26 | 82.24 | 80.28       | 81.89          | 83.24         | 94.25  |
| Proposed CDNP + GLCM | 90.24 | 83.24 | 84.26 | 82.51       | 83.45          | 84.78         | 96.12  |
Figure 8: Comparison of proposed and existing methods.

CK+ DATASET

The following table gives Classification rate for 7 kinds of expressions for CK+ Dataset using various machine learning classifiers.

| Classifier | LR    | KNN   | SVM   | Naïve Bayes | Decision Trees | Random Forest | CNN    |
|------------|-------|-------|-------|-------------|----------------|---------------|--------|
| GLCM       | 73.86 | 76.12 | 78.16 | 77.26       | 80.21          | 78.24         | 83.20  |
| GLCM + LBP | 74.29 | 75.42 | 77.23 | 78.21       | 80.98          | 81.92         | 84.33  |
| Proposed CDNP | 90.35 | 81.25 | 81.57 | 80.38       | 81.76          | 81.44         | 93.21  |
The following table gives Classification rate for 7 kinds of expressions for CASME Dataset using various machine learning classifiers.

Table 5: Classification rate(%) of existing and proposed method

| Classifier       | LR     | KNN    | SVM    | Naïve Bayes | Decision Trees | Random Forest | CNN     |
|------------------|--------|--------|--------|-------------|----------------|---------------|---------|
| GLCM             | 74.16  | 77.12  | 76.16  | 78.26       | 81.21          | 79.44         | 81.2    |
| GLCM + LBP       | 77.29  | 75.42  | 74.23  | 78.39       | 77.11          | 81.32         | 84.33   |

Figure 9: Comparison of proposed and existing methods.

CASME DATASET
| Method                  | 87.35 | 83.25 | 80.57 | 81.38 | 83.76 | 84.44 | 91.21 |
|------------------------|-------|-------|-------|-------|-------|-------|-------|
| Proposed CDNP          |       |       |       |       |       |       |       |
| Proposed CDNP + GLCM   | 86.21 | 83.22 | 82.61 | 81.11 | 81.34 | 84.70 | 92.23 |

Figure 10: Comparison of proposed and existing methods.

4. Conclusion

This paper proposed Cross Diagonal Neighborhood Patterns (CDNP) method to extract unique and robust face features for FER. We have applied CDNP with Gray Level Co-occurrence Matrix (GLCM) to extract expression features and CNN for classification of expressions. The proposed approach achieved maximum classification rate of 96.62%. Thus, in future we will consider improving our approach and developing robust models to classify dynamic facial expressions.
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