International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-4, February 2019

Electroencephalography and Physiological Signals for Emotion Analysis

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Abstract: ***A novel method for Electroencephalography (EEG) based emotion analysis using Gray Level Co-occurrence Matrix1 (GLCM) features contrast, correlation, energy, and homogeneity has been discussed with peripheral physiological signals. Emotions are classified using Linear Discriminant Analysis (LDA) and obtained an accuracy of 93.8. The proposed novel method discussed the effect of distances, and direction on GLCM features for different emotions. This paper concluded that GLCM features are an effective measure to discriminate the emotions and give significant knowledge for each emotion. The proposed novel methodology can be used as a tool for emotion analysis and it can also be useful for observing brain lobe variation globally.***

Index Terms: ***Electroencephalography, Gray Level Co-occurrence Matrix1, physiological signals, Linear Discriminant Analysis***

I. INTRODUCTION

An affective Computing (AC) system can detect emotions by analyzing the pattern of physiological changes associated with each emotion. There are various methods used for the emotion analysis such as speech [1], facial expression [2, 3], body gestures [4], and physiological signal [5]. Electroencephalography signals provide more insight into emotional responses and are mostly used for emotion recognition. EEG is a noninvasive method to measure the electrical activity of the brain with temporal resolution in milliseconds. It is very complex and less understood function, primarily responsible for emotion processing. The spatial variation of pixel intensity in an image is known as texture [6]. Gray Level Co-occurrence Matrix1 is a well-known second-order mathematical method for texture analysis. A benchmark DEAP [7] dataset is used in this experiment. The preprocessed EEG signals, GSR, pulse rate and respiration rate are used for analysis. The emotions relax, happy, sad and angry are isolated in view of valence-excitement esteems given with DEAP dataset. The novel approach of this proposed work is to use the GLCM features and physiological signals for EEG-based emotion analysis. In GLCM features set contrast, correlation, energy, and homogeneity and 3 physiological signals are used for classification of emotions. Each emotion EEG signals are represented as texture. The spacial and temporal variations are observed using EEG and texture feature combination. To the best of our insight, nobody has endeavored to actualize this technique previously.

Manuscript published on 28 February 2019.
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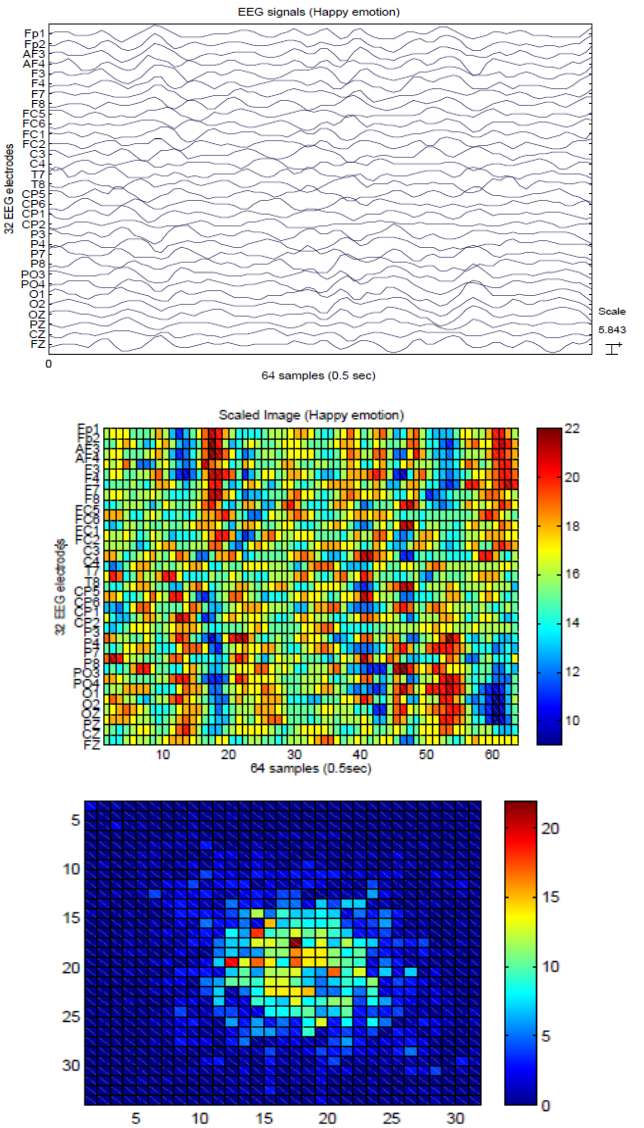

Fig. 1. Variation in 32 electrodes for happy emotion of one subject. a) EEG signals, b) Scaled Image (SI), c) Co-occurrence matrix

Each emotion matrix is formed by 32 electrodes x 8064 samples. The amplitude of EEG signal varies at each electrode and these electrode sample variations are nothing but a type of texture per emotion. The 0.5 sec (64 samples) EEG signals of 32 electrodes are shown in Fig. 1(a). The scaled image and co-occurrence matrix is shown in Fig.1(b) and Fig.1(c) respectively. The scaled image (SI) is represented as texture. The different colors in SI represent the variations in the EEG signals amplitude. The SI and co-occurrence matrix is obtained by the 32 gray levels, distance one and direction zero. The SI and GLCM matrix is different for each emotion.

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The SI represents the texture of emotion which gives the global view of the effect of emotion on each EEG electrode (frontal, temporal, parietal, and occipital) represented by different color shades. In this paper, an analysis of the effect of GLCM parameters (distances and directions) on all four emotions; an analysis of the effect of peripheral physiological signals on all four emotions; comparison of LDA classification results based on GLCM features and peripheral physiological signal features is presented. In the proposed method a pre-processed DEAP dataset is used for experimentation. The 40 emotion videos are separated based on the ground truth of valence and arousal values are given by dataset. The detail about DEAP dataset and the Valance-Arousal plane is discussed in section II as methods and materials. An EEG signal of 32 electrodes for one emotion is given as input for co-occurrence matrix calculation. Then GLCM matrix is calculated in four directions using five distances for each emotion: happy, angry, sad and relax. Calculation of GLCM features and parameters are discussed in section III. An effect of GLCM parameters, effect of peripheral physiological signals on emotions and classifier performance are discussed in the result and discussion section IV. The paper is concluded in section V.

II. PROPOSED METHOD

In the proposed method, the dataset considered is pre-processed DEAP EEG [7]. In this paper GSR, pulse rate and respiration rate as peripheral physiological signals for emotion analysis. A set of 50 participants' (25 men and 25 women) of age between 20 and 40 are considered for experimentation. Their EEG and peripheral physiological data have been recorded using 32 EEG electrodes and eight physiological electrodes. Each participant watched 40 music videos and the length of the music video is one-minute long. The participants self- assessment manikin (SAM) rating of valence and arousal values of 40 music videos is also available.

A. The Emotion Elicitation Materials

Dimensional scales of emotion have been proposed by 2-D Russells valence-arousal plane [8]. In DEAP dataset, 40 emotions have been scaled by 50 subjects using valence and arousal plane. The scale is from 1 to 9. The high and low scale for arousal and valence are defined as positive or high valence (HV) scale is more than 5 to 9 and negative or low valence (LV) scale is 1 to less than 5. Excited or high arousal (HA) scale is more than 5 and calm or low arousal (LA) scale is less than 5. The EEG data is available for each 50 participants in 3-D format means array shape of 40 (Video/trial) x 40 (32 EEG electrodes and 8 peripheral electrodes) x 8064 (data samples). The videos/trials are reordered from presentation order to video order.

B. EEG Data Recording

The EEG data is recorded at 512 Hz frequency. A preprocessed EEG dataset filtered at 4 to 45 Hz and down sampled at 128Hz is used. The 32 electrodes are placed according to the international 10-20 system. The 32 EEG electrodes are used for EEG signal recording with 128 sampling frequency for 63 seconds (8064 samples).

GLCM Features

In benchmark DEAP dataset, there are two EEG data available: raw data and pre- processed data. In this work, pre-processed EEG data is used. The contaminated EEG artifacts were removed using EEGlab toolbox. EEG signals of one emotion are 32 electrodes and 8064 samples (32 x 8064). A GLCM is created by calculating how often a gray-level value i occurs adjacent to a gray-level value j. The offsets parameter specifies the spatial relationships between gray levels. EEG signals amplitude value is scaled using different quantization levels such as 8, 16, 32, 64, 128. In this work 32 quantization level is used i.e., the values of EEG signal amplitude scales between 1 and 32. The number of gray levels determines the size of the GLCM, here 32 gray level creates 32 x 32 matrix and each element (i, j) in matrix specifies the occurrence of value i adjacent to value j. The Scaled Image (SI) acted as a texture of each emotion and used for GLCM matrix calculation. Here the size of SI is 8064 x 32. The co-occurrence matrix is a symmetrical two-dimensional matrix of the same size as the Grey levels used as shown in Fig.1 (c).

The GLCM matrix can be defined by equation 1. An input I for GLCM calculation is matrix of EEG signals of 8064 electrode samples 32 electrodes of one emotion.

$$CM(i,j) = \sum_{r=1}^{8064}\sum_{c=1}^{32}\begin{Bmatrix} 1\ if I(r,c) = i\ and \\ I\ (r+\Delta_r, c+\Delta_c) = j, \\ 0\ otherwise \end{Bmatrix} \quad (1)$$

where CM is co-occurrence matrix, Δ_r and Δ_c are offset [0 d; -d d; -d 0; -d -d] used for direction (0^0, 45^0, 90^0, 135^0) respectively, d is the electrode distance, *c* is EEG electrodes and *r* is electrode samples, *i* and *j* are coordinates of the co-occurrence matrix (number of Grey levels). The texture features are calculated by using Haralick techniques [9]. The GLCM features are used for characterizing the co-occurrence matrix contents. The GLCM features are calculated by GLCM matrix obtained by using distances 1 to 5 and directions 0^0, 45^0, 90^0, 135^0. The GLCM features can be calculated by using the following equations [2-5].

$$contrast = \sum_{i,j}|i-j|^2 p(i,j) \quad (2)$$

$$correlation = \sum_{i,j}\frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j} \quad (3)$$

$$energy = \sum_{i,j} p(i,j)^2 \quad (4)$$

$$Homogeneity = \sum_{i,j}\frac{p(i,j)}{1+|i-j|} \quad (5)$$

Where p(i, j) is the normalized co-occurrence matrix by the sum of all elements to yield a probability matrix, are used to calculate GLCM features. The contrast represents the difference between the two electrode samples. The less value of contrast represents the two electrode samples are approximately same. The correlation value shows the closeness of two electrode samples. Energy feature detects the electrode sample value distribution. This shows the sample value uniformity between brain lobes. Homogeneity measures the closeness of the distribution of sample value of each electrode.

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GLCM feature contrast and homogeneity are inversely proportional to each other.

μ and σ represent means and standard deviations of probability matrix pr and pc for a selected distance d and direction. The mean is equation 6.

$$\mu_{(r,c)} = \sum_{i=1}^{N_g} i p_{(r,c)}(i) \quad (6)$$

Where, $p_{(r,c)}(i)$ are probability matrix and standard deviation is equation 7

$$\sigma_{(r,c)} = \sqrt{\sum_{i=1}^{N_g} p_{(r,c)}(i)(i-\mu_{(r,c)})^2} \quad (7)$$

All features are normalized by equation 8 to the range from 0 to 1 before classification.

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (8)$$

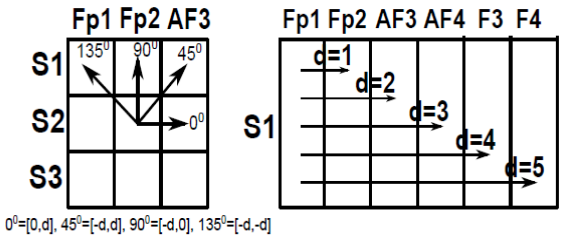

Fig. 2. The direction and distance between electrodes. a) 4 directions with off- sets: 0^0=[0,d], 45^0=[-d,d], 90^0=[-d,0], 135^0=[-d,-d] where d is distance between electrodes; b) the 5 distances (1 to 5) between electrodes. S represents electrode samples

The distances and directions are the major parameters for GLCM matrix calculation. GLCM features are determined separately for direction 00, 450, 900 and 1350, as well as distances d = 1 to 5 for each emotion. The direction represents the relation between sample values of left and right brain lobe electrodes. The 00 direction represent the changes occurred in left and right brain lobe electrodes during the same sample value, the 450 and 1350 directions shows the changes in both brain lobe electrodes during the previous sample values and 900 direction represent the changes occurred in the same electrode during the neighboring sample values as shown in Fig. 2. The distance d=1 shows the brain asymmetry (e.g. FP1 and FP2), d=2 shows the relation between same lobe electrodes (e.g. FP1 and AF3) and d=3 represents the relation between two lobes electrodes (e.g. FP1 and AF4) and so on. All five distances are represented at 00 directions. The same process repeated for all remaining electrodes. Classification The LDA classifier [10] is used in this experiment. LDA is a linear classification method which separates two classes by searching for a linear combination of features. LDA uses the statistical properties of the data. Here LDA is used for classification of two emotions using different features and combinations of features. Combinations of GLCM, Galvanic Skin Response (GSR), Plethysmograph (Ple), and Respiration (Res) are used as features for classification. In confusion matrix the true classes and the estimated classes are distributed over rows and columns, respectively. The overall performance is calculated by using accuracy. The classification accuracy is calculated using confusion matrix. All 32 electrodes are used for the features calculations using equations (9-11). The four features for four directions give 16 features for each distance d = 1to5. The each GLCM feature vector is defined as Vi,j,32, where i is contrast (con), correlation (cor), energy (en), and homogeneity (ho) feature, j is distance d=1 to 5, and 32 is quantization level. For each emotion, combined four GLCM features V is given as equation 9.

$$feat_{GLCM} = [V^k_{con,j,32}, V^k_{cor,j,32}, V^k_{en,j,32}, V^k_{ho,j,32}] \quad (9)$$

Where, k is used for considered emotions. From peripheral physiological signals, we calculated mean, standard deviation, first difference and peak amplitudes. The feature vector of GSR, pulse rate (Ple) and respiration rate (Res) are separately used and combined with GLCM features to check their effectiveness by classification results using equation 10.

$$feat_{Physio} = [V^k_{GSR,j}, V^k_{Res,j}, V^k_{Ple,j}] \quad (10)$$

Where, j is mean, standard deviation, first difference and peak amplitudes, k for emotions. The combined GLCM and physiological features are represented as equation 11.

$$feat = [feat_{GLCM}, feat_{Physio}] \quad (11)$$

III. Results and Discussions

In this section, the effect of GLCM parameters and peripheral physiological signals on four emotions is presented.

A. Analysis of Effect of Distances and Directions using GLCM features

Experimentation was conducted with four GLCM features (contrast, homogeneity, energy, and correlation) using four directions (00, 450, 900, 1350) and three distances (1, 3 and 5). The effect of directions and distances using GLCM features on four emotions is presented in the following section.

B. Analysis of the Effect of Direction

The effect of direction using GLCM features on four emotions is shown in Fig.3.

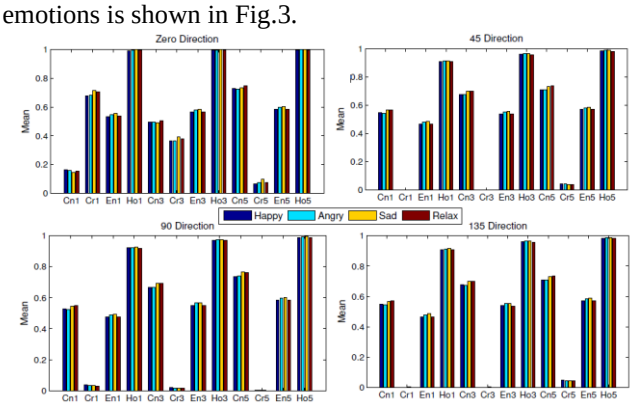

Fig. 3. Analysis of the effect of distances and directions for all four emotions using GLCM features: Contrast (Cn),Correlation (Cr), Energy (En), Homogeneity (Ho) for distance one (1), three (3) and five (5).

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All four directions are compared by considering distance one of contrast feature using mean (standard deviation) values. The contrast feature of happy emotion for four directions are [00 = 0.164 ± 0.28,450 = 0.549 ± 0.78,900 = 0.527 ± 0.77,1350 = 0.549 ± 0.78]. The result shows that the variation in 450 and 1350 directions is almost same while in 900 directions slight variation is observed for all features. The 00 direction gives the significant emotion discrimination value than the other direction using all GLCM features.

At 00 direction for distance one, the contrast feature is lower[happy=0.152±0.23,angry=0.161±0.33,sad=0.146±0.43, relax=0.151±0.43], and correlation [happy=0.675± 0.16, angry=0.680 ± 0.15,sad=0.713 ± 0.11, relax=0.703 ± 0.12], energy [happy=0.534 ± 0.26, angry=0.548±0.33,sad=0.556±0.36, relax=0.538±0.46]and homogeneity [happy=0.991± 0.02, angry=0.994 ± 0.04,sad=1.00 ± 0.04, relax=0.996 ± 0.08] feature is higher. This result indicates that variations in left and right brain lobe electrodes are less. The variation in homogeneity value is less which shows the closeness of the distribution of sample value of each electrode. The average value of all directions is used for classification. The GLCM features vary with the distances as discussed below.

C. Analysis of the Effect of Distances

All three distances are compared by considering direction zero of all features using mean (standard deviation) values. All four features of happy emotion for three distances are: for distance 1 [Contrast=0.164±0.28, Correlation=0.675±0.16, Energy=0.534±0.26, Homogeneity=0.991±0.02], for distance 3 [Contrast=0.494±0.85, Correlation=0.362±0.09, Energy=0.563±0.26, Homogeneity=0.993±0.03] and for distance 5 [Contrast=0.727±0.84, Correlation=0.067±0.03, Energy=0.585±0.23, Homogeneity=0.993±0.06]. The result shows that as distance increases, the contrast, energy and homogeneity feature increases except correlation feature for four emotions. As distance increases, the closeness of the distribution of sample value of two electrodes decreases and hence the contrast feature increases and correlation decreases.

The analysis of the effect of distances and directions using GLCM features is discussed using 32 quantization levels. When the number of quantization levels is higher, EEG signal values are approximately same and vice versa. If a high number of quantization levels are chosen, the information is found to be preserved but calculation complexity increases. The quantization levels are needed to represent a set of textures.

D. Analysis of Effect of Peripheral Physiological Signals on Four Emotions

Analysis of the effect of peripheral physiological signals such as GSR, pulse rate and respiration rate on four emotions is discussed in this section. The three peripheral physiological electrodes (GSR: electrode 37, respiration: electrode 38 and pulse rate: electrode 39) along with 32 EEG electrodes is used for emotion analysis. The mean value, standard deviation (std), first difference and number of peaks are used as features for all physiological signals. The effect of physiological signals on four emotions is compared with these feature values.

The arousal of emotion induces a sweat reaction due to the large concentration sweat at that location. The resistance of the skin using middle and index fingers measure the GSR. The emotion arousal is measured by the average value of the GSR of an individual. The range of GSR between 0.2 to 20 µS (10k to 500k resistances). The GSR is linearly correlated with the intensity of stimuli considered to be useful for emotion analysis. The average effect of GSR signal on four emotions is shown in Fig. 4. The four emotions are compared using number of peaks [happy: 3.83e+03 angry: 5.75e+03, sad: 5.66e+03 relax:4.63e+03] and mean (std.) values [happy: 2.26e+03 (±4.29e + 03), angry: 4.41e+03 (±4.51e + 03), sad: 3.13e+03 (±4.29e + 03), relax: 2.81e+03 (±4.15e + 03)]. The result indicates that the maximum GSR is observed for angry emotion.

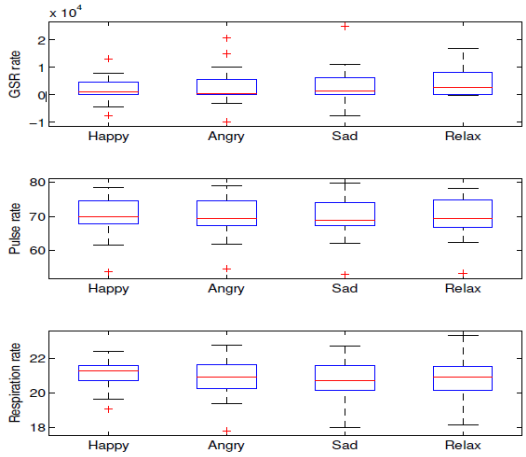

Fig. 4. Analysis of average effect of GSR, respiration and pulse rate on four emotions using number of peaks feature

An optical technique is used to measure pulse rate (Ple) is known as Photoplethysmograph. A pulse oximeter measures oxygen saturation level (SpO2) of arterial blood. The thumb is used for blood volume measurement with each pulse rate. The pulse rate varies with emotions due to increase or decrease blood pressure. The normal pulse rate at rest is between 60 to 100 beats/min. The average effect of the pulse signal on four emotions is shown in Fig. 4. The four emotions are compared using number of peaks [happy: 70.16, angry: 70.09, sad: 69.60, relax: 69.94] and mean (std.) values [happy: 5.38e+03 (±8.57e + 03), angry: 4.38e+03 (±8.61e + 03), sad: 1.99e+03 (±7.82e + 03), relax: 5.37e+03 (±8.11e + 03)]. The maximum pulse rate is observed for the happy emotion. The pulse rate can be seen to increase for stress or happy emotion [11].

The respiration rate (Res) is measured by the respiration belt. The respiration rate varies with different emotions. The respiration rate was longest for relax and happy emotion, slightly shorter for the sad emotion, and much shorter in the anger emotion [12]. The happy breathing induced more positive feeling than any other condition.

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The same is true for anger emotion in opposite i.e. induced more negative feeling. The average effect of respiration signal on four emotions is shown in Fig.4. The four emotions are compared using number of peaks [happy: 20.89, angry: 21.13, sad: 20.80, relax: 20.82] and mean (std.) values [happy: -1074.4 (±1.54e +03), angry: -952.3 (±1.49e + 03), sad: -635.5 (±1.67e + 03), relax: -1113.3 (±1.58e + 03)]. The result indicates that the maximum respiration rate is observed for the angry emotion.

E. Two Emotions Classification

In this section classification of two emotions using LDA are discussed. The features used for the classification process are GLCM (all four features), GLCM + GSR, GLCM + Ple, GLCM + Res, GLCM + all 3 physiological signals. The results in fig. 5 showed that classification accuracy of the combination of GLCM features along with physiological features is more as compared to GLCM features only. Also among the three physiological features combination of GLCM and Ple gave more classification accuracy. So for classification, physiological signals are efficient in emotion recognition. For different combinations of emotions, the classification accuracy is more for low and high valence emotions.

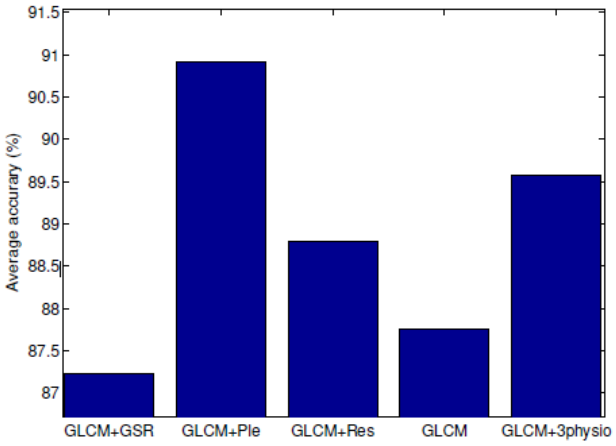

Fig. 5. Average accuracy of two emotions using LDA classifier Ple is pulse rate, Res is respiration rate, 3physio is 3 physiological signals

IV. Conclusion

In this paper a novel technique for Electroencephalography (EEG) based feeling investigation utilizing Gray Level Co-occurrence Matrix1 (GLCM) highlights differentiate, connection, vitality, and homogeneity has been talked about with fringe physiological signs. Feelings are grouped utilizing Linear Discriminant Analysis (LDA) and got a precision of 93.8. The proposed novel strategy speaks about the impact of separations, and heading on GLCM features for various feelings. This paper presumed that GLCM highlights are a powerful measure to segregate the feelings and give critical learning for every feeling. The proposed novel strategy can be utilized as a device for feeling examination and it can likewise be helpful for watching mind projection variety universally.

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