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Efficient EEG Based Emotion Recognition Using Mean Threshold Based Graph Classification

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Abstract Recent advancements in human computer interaction research have led to the possibility of emotional communication via brain computer interface systems for patients with neuropsychiatric disorders or disabilities. In this paper, emotional states are efficiently recognized by utilizing mean threshold based graph classification of EEG signals. The proposed technique is described in following stages are, at first the input signal is taken from the EEG signal database and the input EEG signal is normalized using Gabor filtering in the pre-processing stage. Then the effective features such as energy and entropy are extracted from the pre-processed EEG signals and subsequently correlation is estimated based on the extracted energy and entropy features. Mean value is calculated for the estimated correlation results and the estimated mean value is taken as a threshold. Finally, utilizing the mean threshold based graph approach emotions are classified as positive and negative classes of emotions. Here, the class of positive emotions are calmness, surprise, amusement, excitement, happiness and negative emotions are anger, fear, sadness, disgust. The experimental outcomes demonstrate that our proposed strategy outperforms other existing methods.

Key words: - Normalization, Gabor filtering, Features extraction, Classification, Emotion recognition.

I. Introduction

Electroencephalogram (EEG) signal is the account of electrical possibilities of neurons in the cerebrum [1]. The signs from the cathodes put on the scalp are for the most part used to secure EEG chronicles. By referring to the 10–20 anode positioning framework, a non-intrusive estimation of EEG signals is used [2]. Brain computer interface (BCI) [3] is a standout amongst the most prevalent applications accomplished by the investigation of EEG signs to control external gadgets or actualize a few activities. Notwithstanding rationally controlling gadgets by utilizing EEG signals, evaluating the psychological and passionate states is mainstream thinks about too [4, 5].

Emotion recognition ought to be conceivable from the substance, talk, facial appearance or movement. Starting late, more investigates were done on acknowledgment of emotions in EEG [6, 7]. Usually, EEG-based development has been used in healing applications. A new remote headsets that meet client criteria for wearability, esteem, versatility and ease of use are setting off to the market [8]. It makes possible to spread the development to the zones, for instance, preoccupation, e-learning, virtual universes, digital universes, et cetera. Customized emotion recognition from EEG signals is tolerating more thought with the headway of new kinds of human-driven and human-driven relationship with mechanized media [9].

There are distinctive feeling classifications proposed by scientists. We take after two-dimensional Arousal-Valence show. This model permits mapping of the discrete feeling names to the Arousal-Valence facilitate framework. One of feeling definitions is as per the following: "The real changes take after straightforwardly the view of the energizing certainty, and that our sentiment of the progressions as they happen is the emotion"[10-12]. Our theory is that the sentiment of changes can be seen from EEG as fractal measurement changes. We concentrated on investigation of fractal measurement model and calculations, and proposed a fractal based way to deal with emotion recognition [13].

Customarily, EEG-based innovation has been utilized in medical applications and at present, new remote headsets that meet customer criteria. Emotion recognition calculations in perspective of EEG have been introduced as of late. The stage space heading of the signal using the non-straight calculation, particularly Recurrence Plot examination is used as a component [14], where KNN is used as a classifier. Generative models as Hidden Markov Models (HMM) instead of feature extraction is accounted in [15]. In any case, emotion recognition (ER) of different estimations is still remains a go up against [16]. There are various calculations for perceiving feelings. The fundamental issue of such calculations is an absence of exactness. Research is should have been done to assess diverse calculations and propose calculations with the enhanced precision [17].

The outline structure of the paper is organized as follows: Section 2 reviews the related works with respect to the proposed method. In sections 3, a brief discussion about

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the proposed methodology is presented, section 4 analysis the experimental results and section 5 concludes the paper.

II. Related Work

Qinghua Zheng et al. [18] have exhibited a novel group sparse correlation analysis (GSCCA) technique for concurrent EEG channel determination and feeling acknowledgment. GSCCA was a group sparse augmentation of the conventional canonical correlation analysis (CCA) technique to display the direct correlationship between enthusiastic EEG class name vectors and the relating EEG feature vectors. A noteworthy favourable position of GSCCA strategy was the capacity of taking care of the group feature determination issue from crude EEG features, that makes it extremely appropriate for at the same time adapting to both EEG feeling acknowledgment and programmed channel choice issues where every EEG channel was related with a group of raw EEG highlights.

John Atkinson and Daniel Campos [19] have shown a novel feature based emotion acknowledgment appear for EEG based BCIs. Not under any condition like distinctive philosophies, has their technique explored a more broad plan of feeling forms and circuits additional highlights that were essential for signal pre-processing and recognition arrangements, in light of a dimensional model of feelings: Valence and Arousal. That hopes to improve the precision of the feeling grouping errand by joining normal information based component assurance methods and bit classifiers.

Debashis Das Chakladar and Sanjay Chakraborty [20] have displayed a "Connection based subset choice" framework introduced for length reducing in EEG flag based feeling location. By then they proceed with course of action process using "Higher Order Statistics" features of the diminished arrangement of channels. Nevertheless, they have assembled four classes of sentiments, for example, positive, negative, irate and concordance in their research.

Raja Majid Mehmood and Hyo Jong Lee [21] have presented a feature extraction procedure for feeling affirmation in EEG-based human personality signals. In the research; fundamental cerebrum signals were pre-arranged using independent component analysis (ICA) to remove old rarities. They exhibited a feature extraction system using LPP, and realized a benchmark in light of quantifiable and repeat territory highlights. The LPP-based results exhibit that the most astonishing precision while using SVM in the all-chose feature set.

Hossein Shahabi and Sahar Moghimi [22] researched the effective cerebrum systems related with blissful, melancholic, and impartial music. Network designs among EEG terminals in various recurrence groups were extricated by multivariate autoregressive demonstrating while 19 non-musicians tuned in to chosen traditional and Iranian melodic passages. Melodic determinations were sorted by the members' normal self-appraisal results. Availability matrices were dissected to recognize distinct varieties in the network files identified with the sorted extracts.

III. Proposed Methodology

This paper presents efficient mean threshold graph based emotion recognition and the proposed method classifies the EEG signals into positive and negative emotions. Here, the positive emotions includes calmness, surprise, amusement, excitement, happiness and negative emotions includes anger, fear, sadness, disgust. First the input EEG signals are pre-processed using normalization and Gabor filtering. After the pre-processing of EEG signals, entropy and energy feature are extracted and then correlation is estimated using the extracted features. Finally mean of correlation is taken as an threshold value for the classification emotions and by the mean threshold based graph effectively classifies the positive and negative emotions. The Proposed work flow is shown in figure 1.

A. PREPROCESSING

Normalization Using Gabor Filtering

Normalization process is fundamentally utilized for diminishing or expanding the sound signs abundance. By doing normalization the undesirable noise accessible in the EEG signal can be expelled. The normalization concept can be clarified plainly utilizing the underneath condition.

$$N_G = \frac{\hat{Z}}{\sqrt{\sum_{i=1}^{N} \left|B_i\right|^2 / n}} \tag{1}$$

Where, $\hat{Z}$ the set of EEG signals in the dataset N_G is the normalization factor and n is the number of records.

To make the feature extraction effective the pre-preparing is performed previous to the feature extriction step. Pre-processing mainly consists of two steps they are windowing and framing. Windowing is specifically in co-worked with the Fourier transform function. The windowing and framing concept applied directly to the Gabor function. The normalization concept is associated along with the Gabor function technique. Gabor function is mainly applied to the music signals in the database. Using Gabor function the music signals in the database are filtered. The Gabor function filter esteem is gotten utilizing the underneath formula.

$$G(f) = N_G \exp\left\{-\pi\left(\frac{f-\omega}{l}\right)^2\right\}\cos\{\alpha(f-\omega)+\varphi\} \tag{2}$$

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Where, l is the scale factor, ω is the translation, α is the frequency modulation, φ is the phase angle $\varphi \in [0, 2\pi]$ .From the equation the Gabor filter value is obtained. That value is considered as the normalization value. Once the normalization is completed, in order to carry out the feature extraction process the signal obtained from normalization is given as a contribution to the feature extraction process.

B. FEATURE EXTRACTION

Feature extraction is utilized with the end goal of signal discrimination. The features associated in timbral feature extraction are spectral centroid and spectral flux is explained below.

Entropy:

Entropy is the average of information content. he sum of information of each data creates a random variable for which expected value or average is the entropy. Entropy is estimated for the data sets by using equation (3),

$$E_y(set) = -\sum_{j=1}^{M} P(v_j)\ \log_2 \{P(v_j)\} \tag{3}$$

Where, $P(v_j)$ is the probability of getting j^{th} value is random selection of one from the signal.

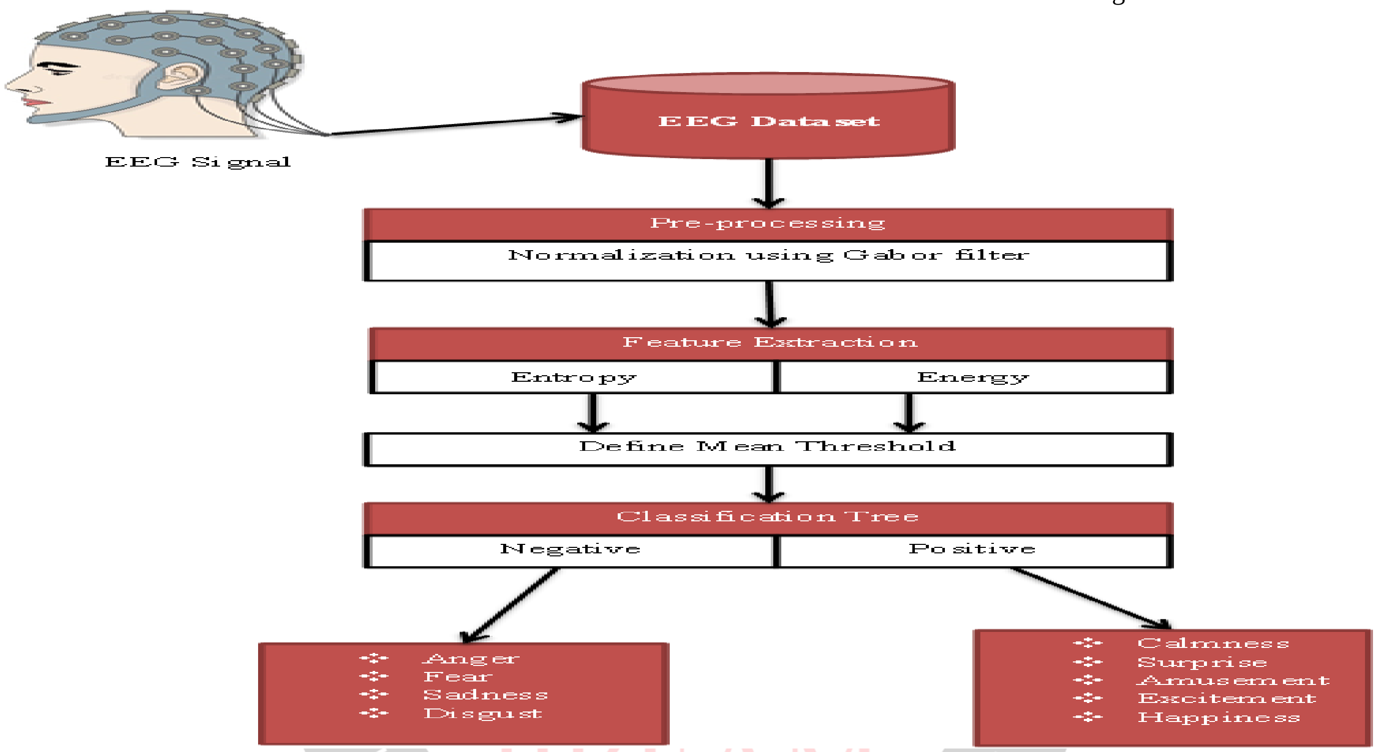

Figure 1: Block diagram of the proposed methodology

Energy:

Energy efficiency is the energy consumed per bit of data processed. Performing calculations in terms of energy per bit also allows the results to be easily scaled to any usage level. The idle power consumption can be determined by using the following equation (4) and it returns the sum of squared elements in the grey level co-occurrence matrix.

$$E = \sum_{x',y'} P(x', y')^2 \tag{4}$$

The energy of a signal can be used as a measure of the strength of a signal.

Correlation:

Correlation is a statistical measures of how well predicted values are matches the actual values. This feature measures how correlated a pixel is to its neighborhood. Here the correlation is estimated between the energy and entropy feature. It is the measure of gray tone linear dependencies in the signal. Correlation can be calculated as.

$$C_n = \frac{\sum_{y=o}^{N-1}\sum_{z=0}^{N-1}(u,v)\, P(u,v) - \mu_a \mu_b}{\sigma_a \sigma_b} \tag{5}$$

Where, μ_a and μ_b are the means σ_a and σ_b are the standard deviations for energy and entropy features respectively.

Mean Estimation

The correlation value is obtained for all the features extracted. For all those correlation values the mean value is calculated. The mean value is obtained by using the formula,

$$M = \frac{\sum_{i=1}^{n} S_{Cn}}{n} \tag{6}$$

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Where, S_{Cn} is the sum of correlation value. After the mean calculation the threshold is calculated for the derived mean value. The threshold is obtained using the formula,

$$Th = m(S_{Cn}) \tag{7}$$

Where, Th is the threshold, m is the mean value. Threshold value is used for generating the hash tag tree.

C. EMOTION CLASSIFICATION USING MEAN THRESHOLD BASED GRAPH

Generate mean threshold based graph for identifying the emotions for any given EEG signal is possible using mean threshold based graph classification. For the mean threshold based graph $D_b = \{s_1, s_2, s_3, ...s_n\}$ is the collection of EEG signal from the database D_b. For all the $s_n \in D_b$ compute the corresponding correlation and the threshold value by referring the equation. After computing the correlation of the energy and entropy features then mean of the correlation value is evaluated and also the estimated mean value is considered as Th. Then compute the threshold value named as Th.The maximum correlation value is determined as the header node which is defined as (H_{node}). If the mean value of the test signal is lesser than the threshold value is classified as positive emotions such as calmness, surprise, amusement, excitement, happiness and if the mean value of the test signal is lesser than the threshold value is classified as negative emotions such as anger, fear, sadness, disgust. The pseudo code for emotion recognition using mean threshold based graph is shown in algorithm 1.

Input: $D_b = \{s_1, s_2, s_3, ...s_n\}$
Output: Recognized emotions

Begin
For each $s_n \in D_b$ do
    Estimate correlation S_{Cn} of s_n
    Estimate threshold Th of S_{Cn}
    $\max node \leftarrow Th$
End for
For $x = 1$ to n do
    If $(\max node == node\ Th)$ then
        Return Header node (H_{node})
    Else
    If $(nodeTh > \max node)$ Then
        $R \leftarrow P(correlation\ mean)$
        Positive class
    Else
        $R \leftarrow N(correlation\ mean)$
        Negative class
        End
    End
End for
Return R
End

Algorithm 1: Pseudo code for mean threshold based graph.

The estimated threshold value of the given test signal is lesser than the header node, and then the emotion of the signal is kept in the left hand side. The left hand side node is defined as the positive class node. The positive node comprises of five emotions such as calmness, surprise, amusement, excitement, happiness. If the threshold value is greater than the header node then the emotion for the corresponding signal is kept inside the right hand side. The right hand side node is termed as the negative class node. The angry, disgust, fear and sadness emotion signals are kept inside the negative node. The mean threshold based graph classification model diagram is given in figure 2.

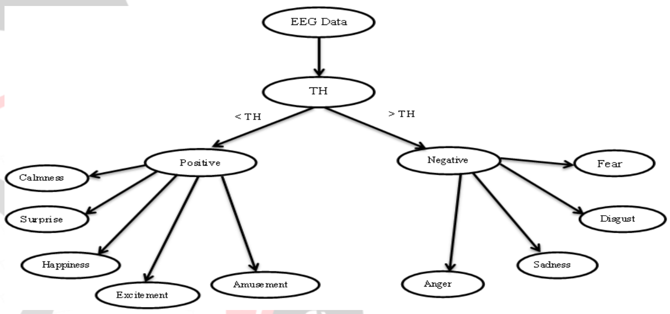

Figure 2: Model representation mean threshold based graph

The figure 2 shows the Model representation mean threshold based graph classification. The emotions are classified based on the estimated threshold. If the test signal mean value is greater than the threshold value means it classified as negative emotions such as angry, disgust, fear and sadness and if the test signal mean value is lesser than the threshold value means it classified as positive emotions such as calmness, surprise, amusement, excitement, happiness.

IV. RESULTS AND DISCUSSION

The proposed efficient EEG signal based emotion recognition using mean threshold based graph is implemented in the working platform of MATLAB. In this section, the experimental results accomplished for the proposed method are given. The publicly available DREAMER-EEG database is utilized to assess the classification of emotional signals into positive or negative. A DREAMER database consisting of recordings of EEG signals captured while audio-visual stimuli was presented to the participants in order to elicit specific emotions. The performance of the proposed mean threshold based graph classification is compared with the prevailing Adaptive NFIS, K-nearest neighbour (KNN),

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and Support vector machine (SVM) classifications regarding accuracy, sensitivity, specificity, PPV, NPV, FPR, FNR, FDR, F-measure and MCC. The comparison results regarding of various performance measures are depicted in table 1.

Table: 1 Comparison analysis of proposed method in terms of different performance measures

Methods	Accuracy	Sensitivity	Specificity	PPV	NPV	FPR	FNR	FDR	FM	MCC
Proposed	0.975	0.982	0.967	0.973	0.978	0.032	0.017	0.026	0.978	0.951
Adaptive NFIS	0.946	0.933	0.965	0.973	0.913	0.034	0.066	0.026	0.953	0.892
SVM	0.743	0.698	0.882	0.947	0.489	0.117	0.301	0.052	0.804	0.503
KNN	0.753	0.771	0.730	0.791	0.706	0.269	0.228	0.208	0.781	0.499

A. PERFORMANCE ANALYSIS

The statistical metrics of sensitivity, specificity and accuracy can be expressed in the terms of TP, FP, FN and TN esteems. The performance of our proposed work is studied by utilizing the statistical measures mentioned in this section,

Accuracy

Accuracy is the amount of true outcome, either true positive or true negative, in a populace. It quantifies the degree of accurateness of a data classification. Accuracy is ascertained by utilizing the condition (8).

$$\text{Accuracy} = \frac{(\text{TN}+\text{TP})}{\text{TN}+\text{TP}+\text{FN}+\text{FP})} \qquad (8)$$

Where, TN is true negative, TP is the true positive, FP is the false positive, and FN is the false negative. The comparison graph of proposed mean threshold based graph with existing Adaptive NFIS, KNN, and SVM classification regarding accuracy is depicted in figure 3.

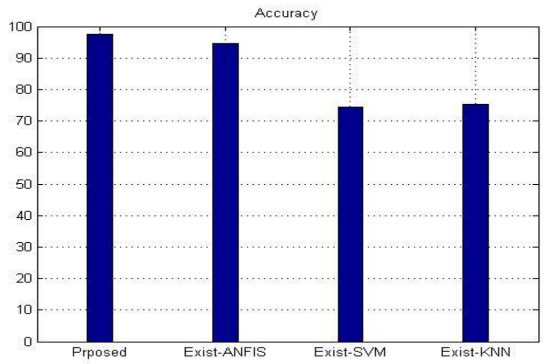

Figure 3: Comparison graph in terms of accuracy

The figure 3 illustrates the proposed mean threshold based graph classification gives good classification results than the existing Adaptive NFIS, KNN, and SVM classifications.

Sensitivity

Sensitivity is the amount of true positives that are effectively distinguished by a classification test. It indicates how great the test is at classifying the data. Sensitivity is computed by utilizing the condition (9).

$$\text{Sensitivity} = \text{TP}/(\text{TP}+\text{FN}) \qquad (9)$$

The comparison graph of proposed mean threshold based graph with existing Adaptive NFIS, KNN and SVM classification as far as sensitivity is appeared in figure 4.

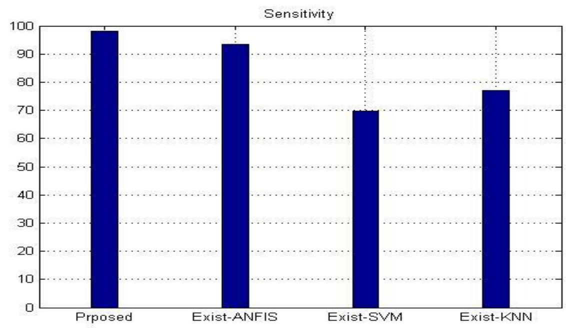

Figure 4: Comparison graph in terms of sensitivity

The above graph illustrates the proposed mean threshold based graph classification gives good classification results than the prevailing Adaptive NFIS, KNN, and SVM classifications.

Specificity

Specificity is the quantity of the true negatives correctly identified by a classification test. It recommends how great the test is at distinguishing normal data. Specificity is computed by utilizing the condition (10).

$$\textit{Specificity} = TN/(TN+FP) \qquad (10)$$

The comparison graph of proposed mean threshold based graph classification with prevailing Adaptive NFIS, KNN, and SVM classification regarding of specificity is appeared in figure 5.

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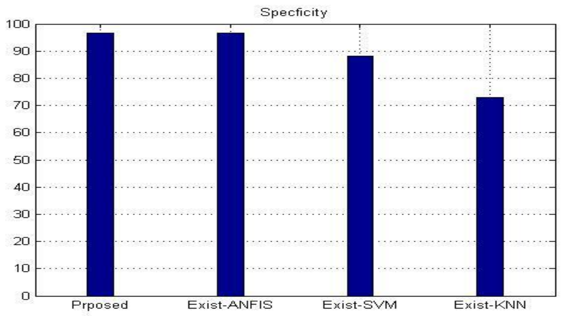

Figure 5: Comparison graph in terms of specificity

The figure 5 represents the proposed mean threshold based graph classification provides good classification results than the prevailing Adaptive NFIS, KNN, and SVM classifications.

False Discovery Rate

False Discovery Rate is characterized as the expected proportion of false negatives amongst the entire hypothesis rejected. False Discovery Rate is ascertained by utilizing the condition (11).

$$FDR = \frac{FP}{FP + TP} \tag{11}$$

The comparison graph of proposed mean threshold based graph classification with prevailing Adaptive NFIS, KNN, and SVM classification in terms of false discovery rate is shown in figure 6.

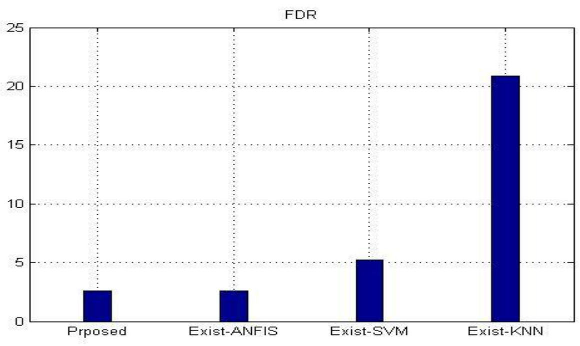

Figure 6: Comparison graph in terms of False discover rate (FDR)

The figure 6 outlines the proposed mean threshold based graph classification results good classification than the existing Adaptive NFIS, KNN, and SVM classifications.

False positive rate

False positive rate is ascertained as the proportion among the quantity of negative events incorrectly considered as positives and the aggregate quantity of actual negative events. False Positive Rate is computed by utilizing the condition (12).

$$FPR = \frac{FP}{FP + TN} \tag{12}$$

The comparison graph of proposed mean threshold based graph classification with prevailing Adaptive NFIS, KNN, and SVM classification in light of false positive rate is appeared in figure 7.

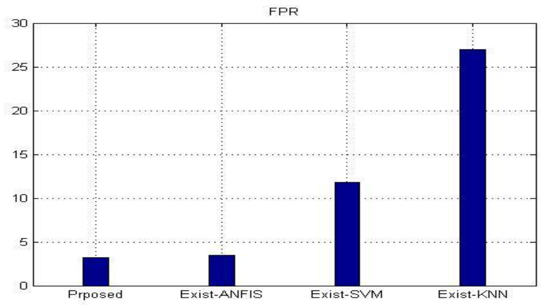

Figure 7: Comparison graph in terms of False positive rate (FPR)

The above graph illustrates the proposed mean threshold based graph classification provides good classification results than the existing Adaptive NFIS, KNN, and SVM classifications.

False negative rate

False negative rate is the extent of positives which gives the negative test outcomes, i.e., the conditional likelihood of a negative test outcome get that the condition being looked for present. False negative rate is computed by utilizing the condition (13).

$$FNR = \frac{FN}{FN + TP} \tag{13}$$

The comparison graph of proposed mean threshold based graph classification with existing Adaptive NFIS, KNN, and SVM classification regarding false negative rate is appeared in figure 8.

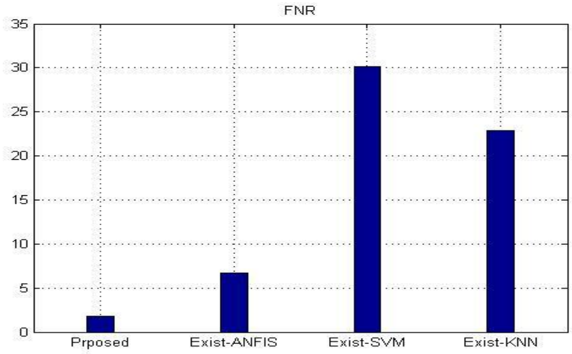

Figure 8: Comparison graph in terms of false negative rate (FNR)

The above graphical representation depicts the proposed mean threshold based graph classification provides good classification results than the existing Adaptive NFIS, KNN, and SVM classifications.

Positive predictive value

A Positive Predictive Value (PPV) is the probability that data classification with a correct test result truly has specific information. Positive predictive value is typically expressed in the condition (14).

$$PPV = \frac{TP}{TP + FP} \tag{14}$$

The comparison graph of proposed mean threshold based graph classification with existing Adaptive NFIS, KNN,

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and SVM classification in positive predictive value is appeared in figure 9.

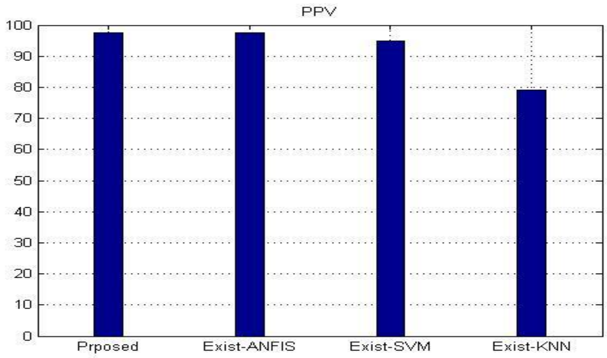

Figure 9: Comparison graph in terms of positive predictive value (PPV)

The above graph shows the proposed mean threshold based graph classification provides good classification results than the prevailing Adaptive NFIS, KNN, and SVM classifications.

Negative predictive value

A Negative Predictive Value (NPV) is the possibility that information classification with a false result truly does not have those specific information. False negative rate is ascertained by utilizing the condition (15).

$$NPV = \frac{TN}{TN + FN} \tag{15}$$

The comparison graph of proposed mean threshold based graph classification with existing Adaptive NFIS, KNN, and SVM classification in terms of negative predictive esteem is appeared in figure 10.

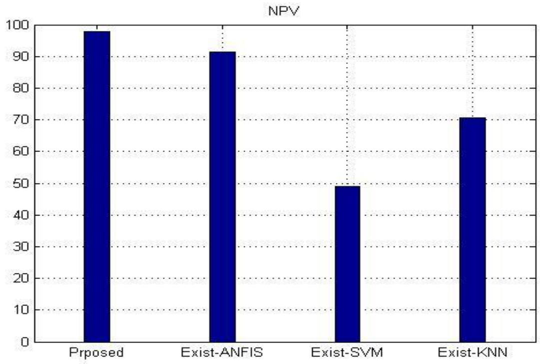

Figure 10: Comparison graph in terms of negative predictive value (NPV)

The above graph illustrates the proposed mean threshold based graph classification gives good classification results than the existing Adaptive NFIS, KNN, and SVM classifications.

F-measure

It is a measure of a test's accuracy. The F measure picks up its best value at 1 accompanied by most unpleasant at 0. It is calculated by the equation (16).

$$F = \frac{2TP}{2TP + FP + FN} \tag{16}$$

The comparison graph of proposed mean threshold based graph classification with existing Adaptive NFIS, KNN, and SVM classification as far as F-measure is appeared in figure 11.

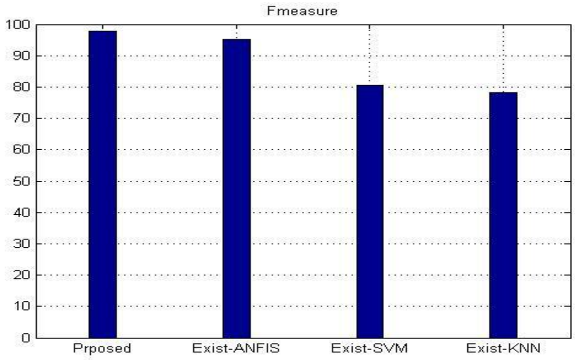

Figure 11: Comparison graph in terms of F-measure value

The above diagram outlines the proposed mean threshold based graph classification provides good classification results in terms of F-measure than the existing Adaptive NFIS, KNN, and SVM classifications.

Mathew's correlation coefficient

MCC is the measure which can be used in regardless of whether the classes are on the whole of different sizes. Mathew's correlation coefficient is computed by utilizing the condition (17).

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{17}$$

The comparison graph of proposed mean threshold based graph classification with existing Adaptive NFIS, KNN, and SVM classification as far as MCC is appeared in figure 12.

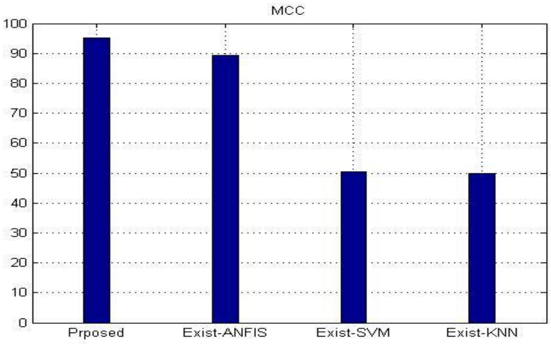

Figure 12: Comparison graph in terms of Mathew's correlation coefficient

The above graphical representation shows the proposed mean threshold based graph classification provides better classification brings about terms of Mathew's correlation coefficient than the prevailing Adaptive NFIS, KNN, and SVM classifications.

V. CONCLUSION

In this paper we have presented a proficient EEG based emotion recognition using mean threshold based graph for the effective classification EEG signals into positive or negative emotions. In the proposed method, the input EEG

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signals are pre-processed using Gabor filtering and results the normalized signal. Then from the normalized signal energy and entropy features are extracted and based on the extracted features correlation is estimated and subsequently mean is is estimated for the correlation values. The estimated mean is taken as an threshold value and finally mean threshold based graph classifier effectively recognize the positive and negative emotions. The experimental outcomes exhibits that our proposed classification outperforms the prevailing Adaptive NFIS, KNN and SVM classifications regarding performance measures such as, accuracy, sensitivity, specificity, PPV, NPV, FPR, FNR, FDR, F-measure and MCC.

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