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Efficient EEG Based Emotion Recognition Using Adaptive NFIS Classifier

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Abstract Emotion recognition is a main task for computer to comprehend the human status in brain computer interface (BCI) frameworks. EEG signal gives us a non-obtrusive approach to recognize the emotion humans through EEG headset electrodes set on their scalp. This paper proposes an efficient EEG based emotion recognition utilizing adaptive NFIS classifier. 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 spectral centroid and spectral flux are extracted pre-processed EEG signals and the extricated features are given as the input to the Adaptive Neuro fuzzy inference system (NFIS) classifier. Lastly, Adaptive NFIS classifier results the 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

Emotion acts as an imperative part in human-human communication. Thinking about the expansion of equipment in our ordinariness, emotion interactions amongst people and technology has been standout amongst the most significant issue in highly developed human-machine interaction (HMI) and brain-computer interface (BCI) nowadays [1-3]. An emotion adds to correspondence between people, as well as assumes a basic part in rational and intelligent behaviour. Its functions can be seen in numerous parts of our everyday lives. This manner, the investigation of emotion recognition is vital [4, 5].

Emotion recognition should be possible from the content, discourse, facial appearance or motion. As of late, more explores were done on recognition of emotion in EEG [6, 7]. Customarily, EEG-based innovation has been utilized in healing applications. As of now, new remote headsets that meet customer criteria for wearability, value, movability and usability are going to the market [8]. It makes conceivable to spread the innovation to the zones, for example, diversion, e-learning, virtual universes, cyberworlds, and so forth. Programmed emotion recognition from EEG signals is accepting more consideration with the advancement of new types of human-driven and human-driven association with computerized media [9].

All the more as of late, new procedures for the investigation of non-stationary and non-straight signals have been proposed which are mostly in light of empirical mode decomposition [10].The logical IMFs for seizure categorization in EEG signals [11]. They have utilized the weighted frequencies in the IMFs to recognize seizures in the EEG signals. The amplitude adjustment data transmission and frequency regulation transfer speed of IMFs for the order amongst seizure and non-seizure EEG signals [12]. The higher order statistics of the IMFs are satisfactory for the order of EEG signals [13]. Other than the qualities of feature extraction techniques identified with IFs, take note of that the extraction of IF is more significant when IMFs are extricated from the EEG signals are mono-part [14].

Various types of emotion recognition algorithms in view of EEG have been presented as of late. The stage space direction of the signal utilizing the non-straight algorithm, specifically Recurrence Plot examination is utilized as an element [15], where KNN is utilized as a classifier. Generative models as Hidden Markov Models (HMM) rather than highlight extraction is accounted in [16]. Notwithstanding, emotion recognition (ER) of various measurements is still remains a confront [17].

II. RELATED WORK

Ahmet Mert and Aydin Akan [18] have examined the possibility of utilizing time–frequency (TF) portrayal of EEG signals for emotional state recognition. An ongoing and progressed TF dissecting technique, multivariate synchro squeezing transform (MSST) was embraced as an element extraction strategy due to multi-channel signal processing and minimized part localization capacities.

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Yong Zhang *et al.* [19] EEG signal has been broadly utilized in emotion classification. Be that as it may, an excessive number of channels and separated highlights are utilized in the present EEG-based emotion recognition strategies, which prompt the unpredictability of these techniques. This investigates on EEG-based emotion classification model to conquer the burdens, and investigated an emotion recognition strategy in light of EMD and entropy using feature extraction.

John Atkinson and Daniel Campos [20] have exhibited a novel feature-based emotion recognition show for EEG based BCIs. Not at all like different methodologies, has their strategy investigated a more extensive arrangement of feeling composes and fuses extra features that were important for signal pre-preparing and recognition classifications, in light of a dimensional model of emotions: Valence and Arousal. That expects to enhance the exactness of the emotion classification task by joining common data based feature determination techniques and kernel classifiers.

Debashis Das Chakladar and Sanjay Chakraborty [21] have exhibited a "Correlation-based subset selection" system presented for length lessening in EEG signal based emotion detection. At that point they continue with arrangement process utilizing "Higher Order Statistics" highlights of the diminished arrangement of channels. Be that as it may, they have grouped four classes of feelings such as positive, negative, angry and harmony in their paper.

Raja Majid Mehmood and Hyo Jong Lee [22] have displayed a feature extraction technique for feeling acknowledgment in EEG-based human mind signals. In the displayed investigate; basic cerebrum signals were pre-prepared utilizing independent component analysis (ICA) to expel ancient rarities. They presented an element extraction technique utilizing LPP, and actualized a benchmark in light of measurable and recurrence area features. The LPP-based outcomes demonstrate that the most astounding exactness when utilizing SVM in the all-chose feature set.

III. PROPOSED METHODOLOGY

This research represents an efficient EEG signals 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 normalized using Gabor filtering in the pre-processing step. After the pre-processing of EEG signals, effective features such as spectral centroid and spectral flux are extracted for the effective classification. Finally, ANFIS classifier classifies the EEG signal emotions effectively based on the extracted features. The Proposed work flow is shown in figure 1.

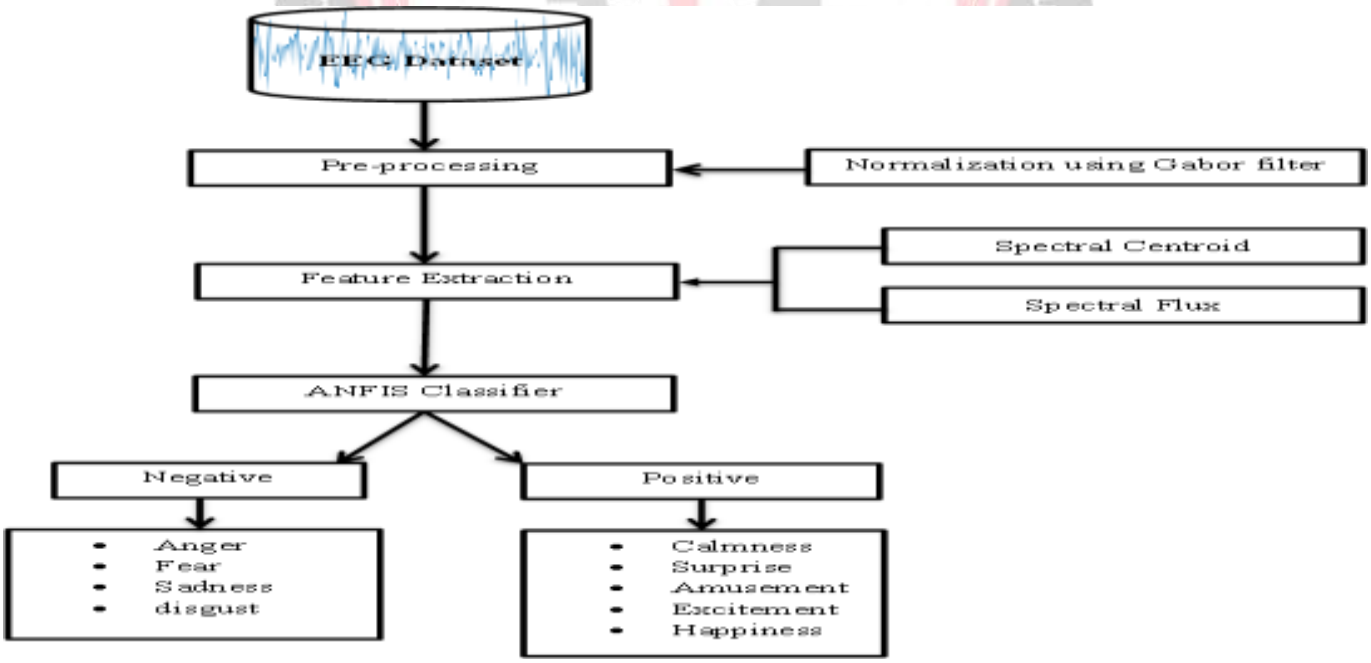

Figure 1: Block diagram of the proposed methodology

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.

$$S_n = \frac{\tilde{X}}{\sqrt{\sum_{i=1}^{N} \left| A_i^{\,2} \right| / N}} \qquad (1)$$

Where, $\tilde{X}$ the set of EEG signals in the dataset S_n is the normalization factor and N is the number of records.

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To make the feature extraction effective the pre-preparing is performed previous to the feature extraction step. Pre-processing mainly consists of two steps they are windowing and framing. Windowing3 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.

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

(2)

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 an 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.

Spectral Centroid

It is the point of convergence of the decomposition co-efficient and it has a shine impression along with robust connection, correspondingly to the Fourier spectrum. The term of spectral centroid is expressed as

$$S_c = \frac{\sum_{m=1}^{M} p(G(f)).r}{\sum_{m=1}^{M} p(G(f))} \quad (3)$$

Where, $p(G(f))$ is characterized as the Fourier transform's magnitude and r is the frequency bin.

Spectral Flux

The distinction between the normalized magnitudes square of progressive otherworldly circulations are defined by

$$S_f = \sum_{m=1}^{M}[M_k(m) - M_{k-1}(m)]^2 \quad (4)$$

Where, $M_k(m)$ and $M_{k-1}(m)$ are defined as the Fourier transform's normalized magnitude of the previous frame $k-1$ and the current frame k .

C. EMOTION CLASSIFICATION USING ADAPTIVE NFIS

NFIS is a feed-forward neural network. In the proposed work, NFIS is adapted with krill herd optimization algorithm and it is named as adaptive NFIS. In order to present the NFIS architecture based on a first order Sugeno model, two fuzzy rules are considered:

Rule 1: IF x' is A_1 AND y' is B_1, at that point

$$f_1 = p_1 x' + q_1 y' + r_1$$

(5)

Rule 2: IF x' is A_2 AND y' is B_2, at that point

$$f_2 = p_2 x' + q_2 y' + r_2$$

(6)

Where, A_1, A_2 and B_1, B_2 are the member functions for x' and y' respectively. p_1, q_1, r_1 and p_2, q_2, r_2 are the associated parameters of the output functions that are defined in the training phase. The adaptive NFIS model comprises of five layers as represented in figure 2.

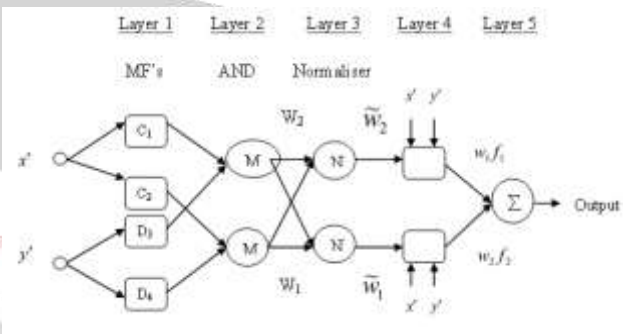

Figure 2: Structure of ANFIS Classification

Layer 1:

In the primary layer, the yield of every node is ascertained by:

$$O_{1,j} = \mu_{Cj}(x') \qquad j = 1,2 \quad (7)$$

$$O_{1,j} = \mu_{Dj-2}(y') \qquad j = 3,4 \quad (8)$$

Where, x', y' are the first contribution to node j, and C_j, D_j are the membership values of the membership functions μC and μD individually.. $\mu_{Cj}(x')$ and $\mu_{Dj-2}(y')$ are the generalized Gaussian membership function that characterized by,

$$\mu(x) = e^{-\left(x - p_k/\sigma_k\right)^2} \quad (9)$$

Where, σ_k and p_k are the premise parameters set, which represent the standard deviation and mean of data.

Layer 2: In the second layer, each node processes the terminating quality of a rule as by (10). Here the nodes are non-versatile and it can be named as M to demonstrate that they expect the part of a basic multiplier. The below expression exhibits the yields of these nodes which represents the terminating quality.

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$$O_{2,j} = w_j = \mu_{Cj}(x') * \mu_{Dj}(y') \qquad j = 1,2$$

(10)

Layer 3: Nodes in this layer are likewise fixed nodes. These are marked as N' to show that these perform a standardization of the terminating quality from going before layer. The yield of every node in this layer is evaluated as:

$$O_{3,j} = \tilde{w}_j = {w_j}/{w_1 + w_2} \qquad j = 1,2$$

(11)

Layer 4: Here each node is versatile node. The outcome of each node is basically the consequence of the standardized terminating quality and a first request polynomial:

$$O_{4,j} = \tilde{w}_j * f_j = \tilde{w}_j (p_j x' + q_j y' + r_j)$$

(12)

Where, p_j, q_j and r_j are design parameters (consequent parameter since they manage with the then-part of the fuzzy rule). Here, the subsequent parameters are updated by utilizing krill herd optimization algorithm.

Layer 5: It consists of single node which is marked as S' to perform basic adder and the corresponding result is expressed as follows:

$$O_{5,j} = \sum \tilde{w}_j f_j = {\sum_j w_j f_j}/{\sum_j w_j} \qquad (13)$$

The output of adaptive NFIS results the positive and negative emotions.

IV. Results And Discussion

The proposed efficient EEG signal based emotion recognition using adaptive NFIS is implemented in the working platform of MATLAB. In this section, the experimental results accomplished for the proposed method are given. The publicly available EEG database is utilized to assess the classification of emotional signals into positive or negative. The performance of the proposed entropy based graph classification is compared with the prevailing K-nearest neighbour (KNN), 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	0.946	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 accuracy, sensitivity and specificity are expressed by TP, FP, FN and TN esteems. The performance of our proposed work is studied by utilizing the statistical measures mentioned in this section,

Accuracy

It quantifies the degree of accurateness of a data classification. Accuracy is ascertained by utilizing the condition (14).

$$\text{Accuracy} = \frac{(\text{TN} + \text{TP})}{\text{TN} + \text{TP} + \text{FN} + \text{FP})} \qquad (14)$$

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 entropy based graph classification with existing KNN, and SVM classification regarding accuracy is depicted in figure 3.

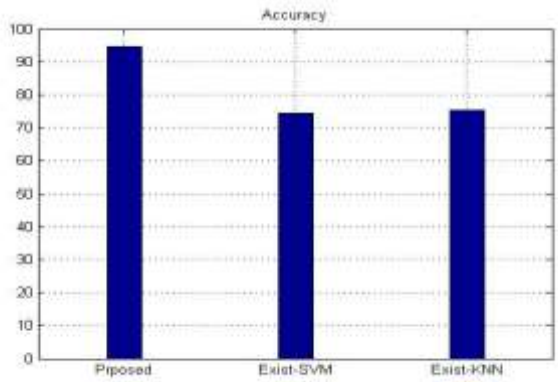

Figure 3: Comparison graph in terms of accuracy

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

Sensitivity

It indicates how great the analysis is at classifying the data and it is computed by utilizing the condition (15).

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

(15)

The comparison graph of proposed entropy based graph classification with existing KNN; and SVM classification as far as sensitivity is appeared in figure 4.

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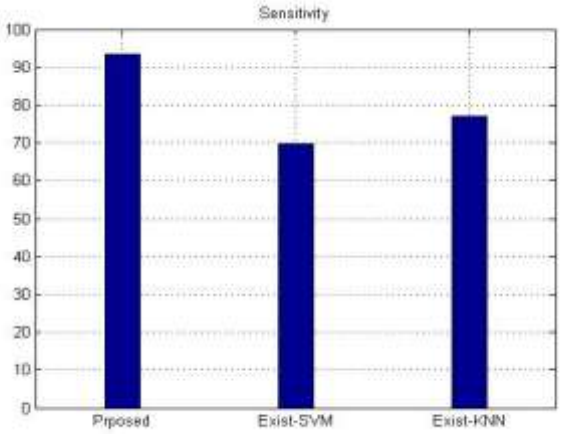

Figure 4: Comparison graph in terms of sensitivity

The above graph illustrates the proposed entropy based graph classification gives good classification results than the prevailing KNN, and SVM classifications.

Specificity

It recommends how great the analysis is at distinguishing normal data and it is computed by utilizing the condition (16).

$$Specificity = TN/(TN + FP) \quad (16)$$

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

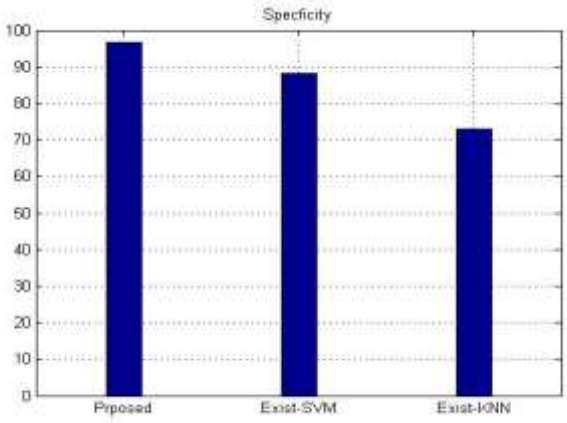

Figure 5: Comparison graph in terms of specificity

The figure 5 represents the proposed entropy based graph classification provides good classification results than the prevailing 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 (17).

$$FDR = \frac{FP}{FP + TP} \quad (17)$$

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

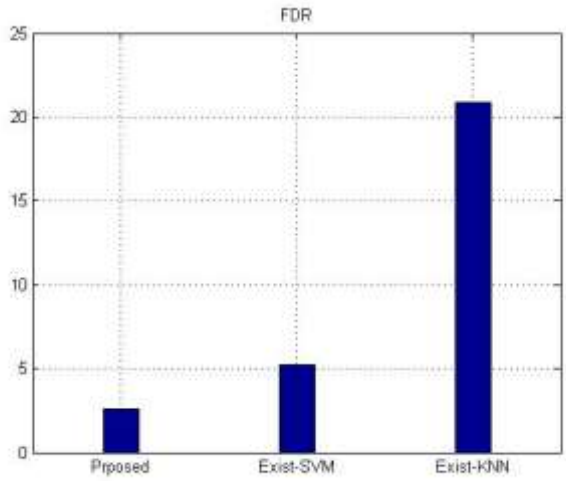

Figure 6: Comparison graph in terms of False discover rate (FDR)

The figure 6 outlines the proposed entropy based graph classification results good classification than the existing 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 (18).

$$FPR = \frac{FP}{FP + TN} \quad (18)$$

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

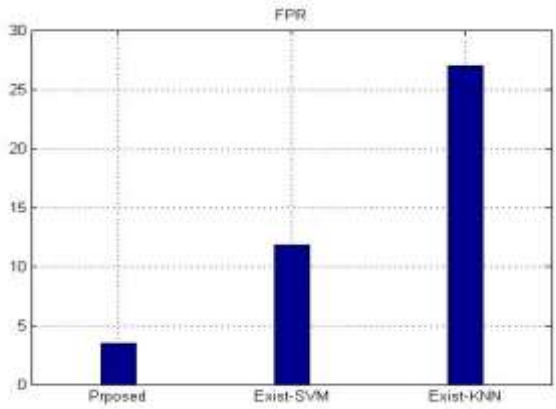

Figure 7: Comparison graph in terms of False positive rate (FPR)

The above graph illustrates the proposed entropy based graph classification provides good classification results than the existing 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 (19).

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$$FNR = \frac{FN}{FN + TP} \quad (19)$$

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

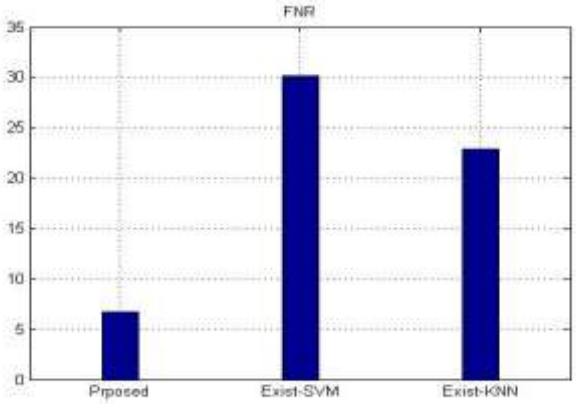

Figure 8: Comparison graph in terms of false negative rate (FNR)

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

Positive predictive value (PPV)

It is the probability that data classification with a correct test result truly has specific information. Positive predictive value is typically expressed in the condition (20).

$$PPV = \frac{TP}{TP + FP} \quad (20)$$

The comparison graph of proposed entropy based graph classification with existing KNN, and SVM classification in positive predictive value is appeared in figure 9.

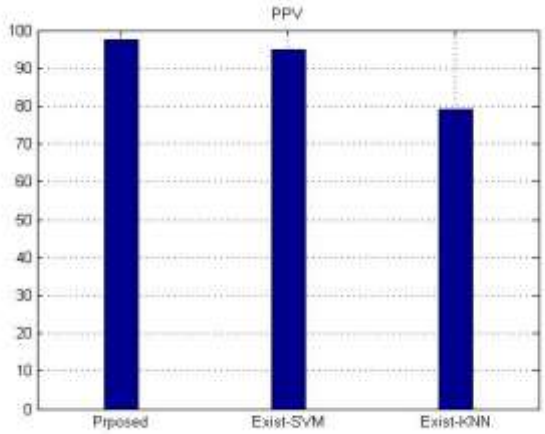

Figure 9: Comparison graph in terms of positive predictive value (PPV)

The above graph shows the proposed entropy based graph classification provides good classification results than the prevailing KNN, and SVM classifications.

Negative predictive value (NPV)

It 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 (21).

$$NPV = \frac{TN}{TN + FN} \quad (21)$$

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

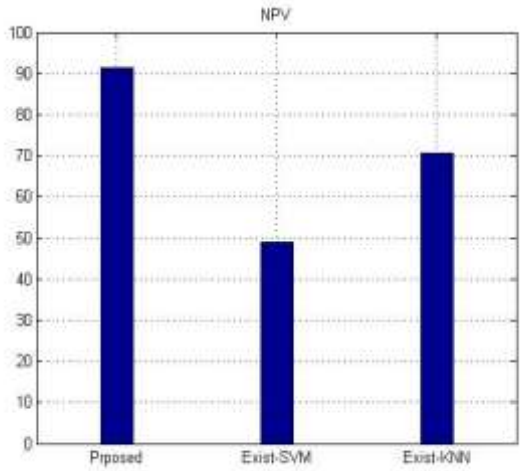

Figure 10: Comparison graph in terms of negative predictive value (NPV)

The above graph illustrates the proposed entropy based graph classification gives good classification results than the existing KNN, and SVM classifications.

F-measure

It picks up its best value at 1 accompanied by most unpleasant at 0. It is calculated by the equation (22).

$$F = \frac{2TP}{2TP + FP + FN} \quad (22)$$

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

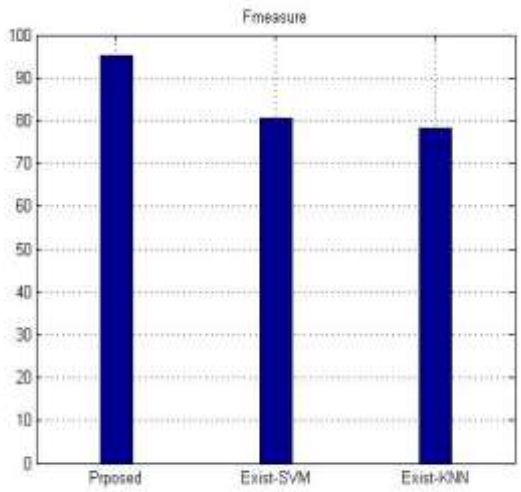

Figure 11: Comparison graph in terms of F-measure value

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The above diagram outlines the proposed entropy based graph classification provides good classification results in terms of F-measure than the existing 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 (23).

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (23)$$

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

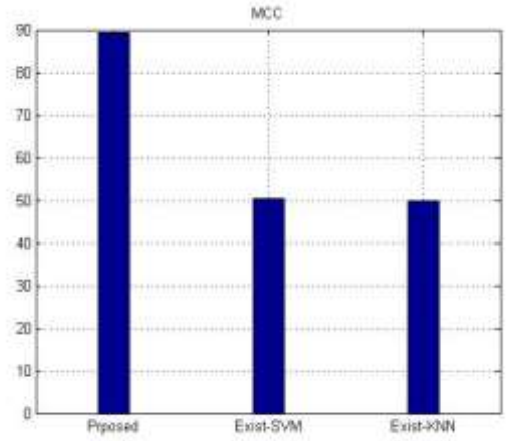

Figure 12: Comparison graph in terms of Mathew's correlation coefficient

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

V. Conclusion

In this research we have projected a proficient EEG based emotion recognition using adaptive NFIS classifier for the effective classification EEG signals into positive or negative emotions. In the proposed method, the input EEG signals are pre-processed using gabor filtering and results the normalized signal. Then from the normalized signal spectral flux and spectral centroid features are extracted and based on the extracted features adaptive NFIS classifier effectively recognize the positive and negative emotions. The experimental outcomes exhibits that our proposed classification outperforms the prevailing 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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