A Novel Two-tier Classifier based on K-Nearest Neighbour and Neural Network Classifier for Emotion Recognition using EEG Signals

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***Abstract*- Emotion has a significant part in cooperation and correspondence between individuals. Emotion can be communicated either verbally through emotional vocabulary, or by communicating non-verbal prompts, for example, sound of voice, outward appearances and motions. As of late, estimation of human emotions from Electroencephalogram (EEG) signals assumes a crucial part in evolving academic Brain Computer Interface (BCI) devices. In this article we present a novel approach to classify human emotions using a two-tier classifier which is a combination of both K-Nearest Neighbour (K-NN) and Neural Network (NN) classifier. The useful informations for classification is extracted from the input EEG signals after noise removal which is done by the process of pre-processing. The proposed work is implemented on MATLAB and the simulation results are presented.**

***Keywords*- EEG, Emotion Recognition System, Feature Extraction, K-NN, NN, Two-tier Classifier.**

I. INTRODUCTION

Language and nonverbal interactions are used to switch over information with each other [1]. Communication between humans and machines or computer agents has become supplementary frequent as well as to human-to-human communication [2]. Interaction between the human and the machine computers are never again seen as just computational trappings [3]. To interact with the users and the detecting capacities to conjecture user's characteristics the imperative and conventional high-tech systems promptly succeed in several socio emotional life perspectives [4]. A choice of life aspects are e-health, training, telemonitoring of elderly people and learning [5].

Necessitate and consequence of habitual emotion recognition in the day by day existence of individuals emotions play an essential responsibility of human computer interface applications [6]. Enchanting emotions into account in the computer software could compose such applications further comfortable for users [7]. Exceptionally emotion recognition from the text, speech, facial expression or gesture is useful for medical applications, especially for aged people [8].

Spontaneous emotion recognition from EEG signals is getting more consideration with the advancement of new types of human-driven collaboration with computerized media [9]. EEG data's are transmitted through the Bluetooth, and such device could be setup inside minutes [10]. EEG innovation has helped to promote advancement of EEG-based applications, for example, brain computer interfaces (BCIs) brain function training and execution training systems [11].

The most prominent methods employs EEG signals by geometric and wavelet-based analysis for feature extraction [12]. Those analyses are combined with classification methods such as, fuzzy k-means and fuzzy c-means [13]. Even though the classification prospective of EEG signals to expand recognition rates and realise mysterious features of emotion mechanisms accomplished in the human brain [14]. Arithmetic gratitude of EEG signals linear description may not exemplify nonlinearity of brain activities [15]. Nonlinear analysis of EEG signals could pay for further information from diverse characteristics [16].

In this article we suggest a unique two-tier classifier based on K-NN and NN classifier for effective emotion recognition. The residue of this article is organised as follows:

Some of the recent works related to the proposed work is offered in section 2. The proposed work is briefed in section 3. The simulation results of the proposed work with its performance evaluation is presented in section 4 followed by the conclusion in section 5.

II. RELATED WORKS

Some of the very recent works related to emotion recognition using EEG signals is listed below:-

Panagiotis *et al.* [17] presented an emotion inspiration and EEG-based component extraction system. The mirror neuron framework idea was used to proficiently cultivate emotion enlistment by the procedure of impersonation. What's more, higher order crossing (HOC) was utilized for the element extraction plot and a hearty arrangement technique, specifically HOC-emotion classifier

(HOC-EC), was executed trying four unique classifiers with a specific end goal to achieve productive emotion recognition. EEG information have been gathered by solid subjects utilizing just 3 EEG channels, to be specific Fp1, Fp2, and a bipolar channel of F3 and F4 positions.

Qiang Wang and Olga Sourina [18] proposed a strategy for multifractal investigation of EEG signals named comprehensive Higuchi fractal dimension spectrum (HFDS) and connected in mental number juggling undertaking recognition from EEG signals. Different components, for example, power spectral density (PSD), autoregressive model (AR), and measurable elements were dissected too. The utilization of the fractal measurement range of EEG signal in blend with different components enhanced the mental number-crunching assignment recognition exactness in both multi-channel and one-channel subject-dependent algorithms.

Wei-Long Zheng and Bao-Liang Lu [19] introduced deep belief networks (DBNs) to develop EEG-based emotion recognition models for three emotions: positive, unbiased and negative. EEG dataset procured from 15 subjects. Each subject plays out the investigations twice at the interim of a couple days. DBNs are prepared with differential entropy highlights removed from multichannel EEG information.

Toshimitsu Musha *et al.* [20] displayed the support by the brain movement, and the elements of the perspective appear in the scalp possibilities, as observed on an electroencephalogram (EEG). The EEG highlights have been separated into an arrangement of 135 state factors of cross-connection coefficients of EEGs gathered with ten scalps. The most extreme time determination of the emotion examination was 0.64s and it was done progressively.

Robert Jenke *et al.* [21] exhibited emotion recognition from EEG signals permits the immediate appraisal of the "internal" condition of a client, which is viewed as a critical factor in human-machine-collaboration. Numerous techniques for feature extraction and the determination of both proper elements and terminal areas are normally in view of neuro-logical discoveries. The appropriateness for emotion recognition, in any case, has been tried utilizing a little measure of particular capabilities and on various, typically small data sets.

III. EMOTION RECOGNITION BY PROPOSED HIERARCHICAL CLASSIFIER

In this research work, a novel two-tier classification approach that combines K-NN and NN classifiers for emotion recognition is recommended. The proposed work starts with the input EEG signal retrieved from the database which incorporates number of features and hidden informations used to the emotional states of human. The main contribution of this research work is as follows:

i. To model a two-tier classifier based on K-NN and NN to recognise human emotions from EEG signals with high accuracy.
ii. To extract the optimal features from the pre-processed signal so as to diminish the computational complexity without compromising the detection accuracy.

The overall methodology of our proposed emotion recognition system comprises the following stages such as, pre-processing, feature extraction, and classification which is shown in figure 1.

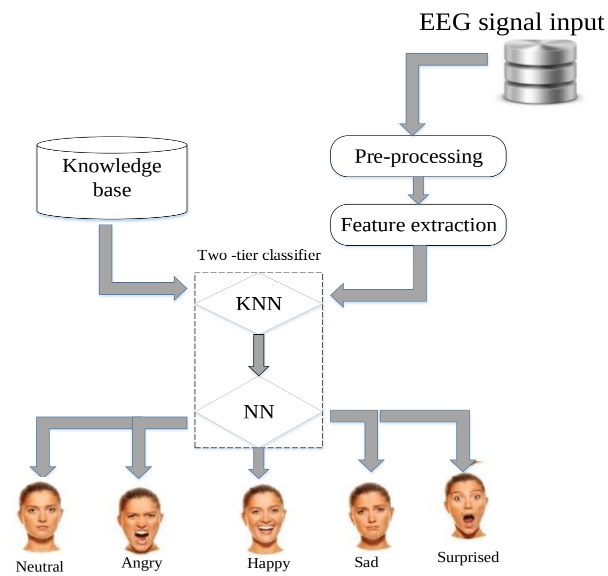

Fig. 1. Proposed Emotion Recognition Methodology

A. *Preliminaries*

Let us consider a set of EEG signals taken from different patients by placing number of electrodes on the scalp is taken as an input dataset which is stored in an array form of $X = \{x_1, x_2, ...x_n\}$. Where n is the total number of EEG signals. The EEG signals are recorded at a range of 256 Hz for sampling. The power spectral densities of EEG signals in diverse bands are associated with emotions. The recorded EEG signals also comprise noise and artifacts that can be sensed on the scalp but are not originated from the brain.

B. *EEG Signal Pre-processing*

To improve the diagnostic accuracy, the removal of noise and artifacts from the dataset $X = \{x_1, x_2, ...x_n\}$ is the core step which can be done by signal pre-processing. The process of proposed signal pre-processing comprises the following steps.

1) *Resolution Reduction [22]:*

It enhances the memory by dropping a signal resolution. Meanwhile beneficial data for emotions recognition is originated under 40 Hz, so that the resolution can be reduced to 128 Hz, conserving the original signal's information. The resolution reduced input EEG signal can be given by:

$$R_{res}(X) = X^{'} = r\left\{\prod_{i=1}^{n} x_i\right\} \tag{1}$$

Where $X^{'} = R_{res}(X)$ is the reduced resolution of dataset X, r is the resolution reduction factor, x_i is the i^{th} EEG signal.

2) Removal of Electrooculography (EOG) [23]:

With the intention of eliminating the noise produced by eyes movement, Independent Component Analysis (ICA) is applied in the EEG signals. ICA is a statistical procedure used to segregate a mixture signals into its sources. The resulting EEG signal taken by ICA is expressed as:

$$x_i(t) = f\left(s_i(t) + n(t)\right) \tag{2}$$

Where f is the unknown mixer function, $s_i(t)$ is the source of signal, $x_i(t)$ is the output vector, $n(t)$ is an additive random noise vector.

The measurement of output vector $x_i(t)$ is equivalent to the amount of restrained data channels. The complete ICA problem involves in calculating the un-mixing function by reversing f and attaining an approximation of $s_i(t)$ by mapping $x_i(t)$ to the source space. ICA is separated into two dissimilar models based on f. These prototypes may be a linear or nonlinear function. The nonlinear problem is typically too complex and intractable due to its high number of indeterminations. It is conceivable to rewrite equation (2) using a matrix multiplication as:

$$x_i(t) = A.s_i(t) + n(t) \tag{3}$$

Where A is the mixing matrix. Noise can be detached from overhead equation by assuming that the experimental data is noiseless or that the noise is too pathetic for deliberation. Finally, $s_i(t)$ and $x_i(t)$ are obtained using Infomax algorithm.

3) Band Pass Filter [24]:

The useful EEG signal information for emotion recognition is filtered at a range of 4 Hz - 45 Hz by creating bands using the band pass filter. The resulting BPF signal contains the original EEG signal which is given by:

$$\begin{aligned} X^{''} &= BPF\{x_i(t)\} \\ &= A.s_i(t) \end{aligned} \tag{4}$$

Where $X^{''}$ is the resulting BPF signal.

C. Feature Extraction

We propose to use Discrete Wavelet Transform (DWT) to decompose the filtered EEG signal into diverse frequency bands and then to perform feature extraction from the decomposed frequency band signals. Table 1 shows the different frequency bands decomposed by DWT.

Table 1: EEG signal Decomposition into several frequency bands

Frequency band	Frequency range (Hz)	Bandwidth (Hz)
θ	4-7	4
α	8-13	8
β	14-29	29
γ	30-45	45
Noise	45-110	110

Each frequency band obtained from the signal, is decomposed at 5 ranges with every type of wavelet; for analysing this signal a matrix was created for every type of wavelet, with 5 coefficients and the detail of 5th coefficient approximation of the decomposed signal. From each of the frequency band we calculate the mean, variance, energy and entropy to appropriately designate the unique signal connecting to an emotional state.

1) Mean (μ):

Mean resembles to the midpoint of a set of value. The Mean is intended for each and every frequency band signals. Which can be mathematically expressed as:

$$\mu = \frac{1}{M}\sum_{t=1}^{M} X_i(t) \tag{5}$$

2) Variance (σ^2):

Mostly variance is a geometric parameter which provides information about data dissemination from its mean or expected value. Which can be mathematically expressed as:

$$\sigma^2 = \frac{1}{M}\sum_{t=1}^{M}\left(X_i(t) - \mu_x\right)^2 \tag{6}$$

3) Energy(E):

The energy of each frequency band is premeditated by squaring the wavelet coefficients of each frequency band. Which can be mathematically communicated as:

$$E = \sum_{t=1}^{M}\left(X_i^{''}(t)^2\right) \tag{7}$$

4) Entropy(H):

The randomness of a signal is measured by a metric called entropy. To analyse psychological time series data entropy can be used as an important feature. The entropy of individual frequency bands can be computed as:

$$H = -\sum_{t=1}^{M}\left(X_i^{''}(t)^2\right)\log\left(X_i^{''}(t)^2\right) \tag{8}$$

5) Skewness (S):

Skewness is a measure of symmetry, or more precisely, the lack of symmetry which can be conveyed as:

$$S = \frac{1}{M^3}\left(X^{''}{}_i(t) - X^{''}(t)\right)^3 \tag{9}$$

Where M is the number of wavelet coefficients. The set of features fetched from each of the frequency bands are stored as a feature vector in an array form. The feature vector for each frequency band can be represented as:

$$F = \sum_{j=1}^{N}\{f_j\} \tag{10}$$

Where $f_j = \{\mu_j, \sigma_j^2, E_j, H_j, S_j\}$. These extracted set of feature vectors are used further to provide testing and training to the proposed classifier for emotion recognition.

D. Emotion Classification

Generally the classification algorithm functions admirably when the basic information disseminations have substantial between patterns of various classes and small intra-cluster distances between the patterns of similar classes. The proposed work includes training and testing the classifiers with a cross validation by presenting an efficient two-tier classifier. In the proposed two-tier classification method the K-NN classifier primarily trains the extracted features and consequently, the NN classifier trains the features. In the proposed classification phase the whole dataset signals are divided into 10 sets and the 9/10 sets of them is used for training and 1/10 is used for testing. The most significant advantage of the proposed two-tier classification is enhanced final distortion and yields deterministic reproducible results.

1) Initial training by K-NN:

K-NN is a traditional classification algorithm which dispatches the mark of a test with the common label of its k-nearest neighbour from the training set to classify an unknown information. One preferred standpoint of the K-NN algorithm over numerous other supervised learning algorithm effortlessly deal with problems in which the number of classes is greater than two. Besides, the K-NN technique permits adding examples to the training dataset deprived of retraining the classifier.

K-NN measures the similarity between the trained dataset and the knowledge base by measuring the cosine distance. Which is expressed as:

$$Sim(\vec{f}_1, \vec{f}_2) = \frac{\vec{f}_1 \bullet \vec{f}_2}{\|\vec{f}_1\|^2 \|\vec{f}_2\|^2} \tag{11}$$

Where $\vec{f}_1, \vec{f}_2$ are the sub space feature vectors. The classes of the neighbours are weighted using the similarity of each neighbour to F as follows:

$$score(\vec{F}, C_i) = \sum_{\vec{f}_j \in KNN(\vec{F})} Sim(\vec{F}, \vec{f}_j)\varphi\left(\vec{f}_j, C_i\right) \tag{12}$$

Where $KNN(\vec{F})$ denotes the set of k-nearest neighbours of input feature vector $\vec{F}$, $\varphi\left(\vec{f}_j, C_i\right)$ is the classification of $\vec{f}_j$ with respect to class C_i which is given by:

$$\varphi\left(\vec{f}_j, C_i\right) = \begin{cases} 1, & \vec{f}_j \in C_i \\ 0, & otherwise \end{cases} \tag{13}$$

2) Testing of EEG signal by NN:

To recognize and classify the different type of emotions using EEG signals we use a three layer NN classifier with one input, hidden and an output layer. The structure of the proposed NN is shown in figure 2.

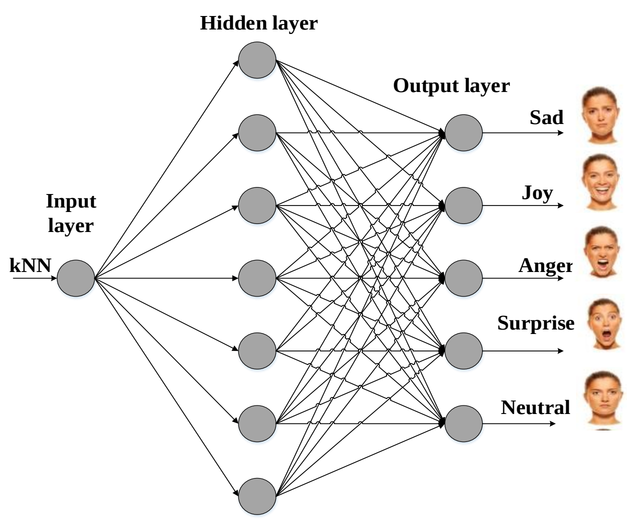

Fig. 2. Structure of the Proposed NN

The proposed NN has a single neuron in the input layer which represent the activity on the K-NN classifier or the learning behaviour of the current NN. The input signal to NN is derived from the output of K-NN classifier. When the network runs the input layer perform its function and transfers the result to the next layer (hidden layer). The activation function of the hidden layer is given by:

$$H(Y) = h_{hidden}(wx + b) \tag{14}$$

Where $h_{hidden}(x) = \frac{1}{1+e^{-x}}$, b is the bias, w is the weight of the signal, x is the input signal. The output of the NN is modelled as:

$$O(Y) = a\psi(wx - \delta) \tag{15}$$

Where a is a constant, ψ is a nonlinear function which takes value [0-1] and δ is the threshold. The input signal is segregated and coded into binary vectors and the network output layer outputs a binary representation of its class number for each input signal. An iterative training produce is performed by the network to learn the weights of each signal. When the training procedure has converged, the data are fed into the network for the classification and the network outputs the class of each signal.

IV. SIMULATION RESULTS

In this section we present a comprehensive report of the proposed simulation results and the dataset used to estimate the performance of the proposed emotion recognition system. In addition to that we presented a brief comparison of the proposed work with some existing works.

A. Dataset Description

To calculate the performance of the proposed emotion recognition system in this research work, we use a set of EEG signals obtained from the following link as our dataset.

https://bsi-ni.brain.riken.jp/modules/xoonips/detail.php?item_id=37

B. Results and Comparison

Initially we sample and pre-process the EEG signals from five discrete emotions. In our investigation, the time period of video clips diverge from one another. The subsequent step is to train the KNN classifier with a best value of K while NN classifier works for categorising the emotions with the knowledge of trained KNN. The classification capacity of a statistical feature set can be restrained over classification accuracy by averaging five times over a 5 fold cross-validation. With the purpose of advancing the reliability and efficiency of emotion recognition system with reduced number of electrodes, we have matched the classification accuracy of the various classifiers.

Table 2, 3 and 4 shows the emotion classification rate of diverse classifiers for EEG signal over power, standard deviation and variance respectively.

Table 2: Emotions classification rate (%) for EEG over Power

	Disgust	Happy	Neutral	Surprise	Fear
KNN-NN(Proposed)	38.6569	67.3016	41.8788	80.43	89.23
KNN[25]	58.33	60	39.58	70	39.58
LDA[25]	80	40	75	73.33	52.08

Table 3: Emotions classification rate (%) for EEG over Standard deviation

	Disgust	Happy	Neutral	Surprise	Fear
KNN-NN(Proposed)	82.7968	94.7026	65.2065	79.57	87.12
KNN[25]	56.67	66.67	47.92	66.67	52.08
LDA[25]	86.67	70	79.17	78.33	54.16

Table 4: Emotions classification rate (%) for EEG over Variance

	Disgust	Happy	Neutral	Surprise	Fear
KNN-NN(Proposed)	81.824	76.702	83.206	88.12	90.18
KNN[25]	63.33	78.33	37.5	65	39.58
LDA[25]	78.33	50	62.5	80	41.67

From Table 2-4, we inferred that, the proposed KNN-NN classifier gives higher average classification accuracy than KNN and LDA. The maximum classification accuracy of 67.301%, 80.43% and 89.23% is obtained using power feature, 82.796%, 87.12% and 94.702% is obtained using standard deviation feature and 90.18%, 88.12% and 83.20% is obtained using variance feature.

The supreme separations of emotions classification rate of 86.67% for disgust, 94.702% for happy, 88.12% for surprise, 83.20% for neutral and 90.18% for fear is accomplished. Hence, the proposed classifier achieves superiority over other classifiers for classification of human emotion through EEG.

The Average classification accuracy of the KNN-NN classifier is compared with some conventional classifiers like KNN, ANN, SVM and Bayes Network is shown in figure 3.

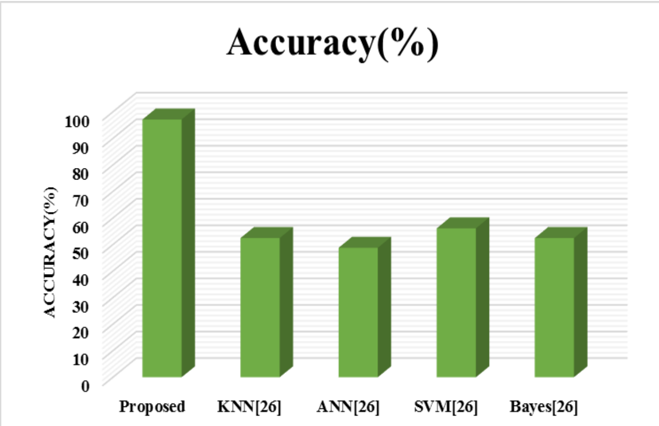

Fig. 3. Average Classification Accuracy

From figure 3 the proposed KNN-NN classifier produces maximum classification accuracy of 97.10% which is significantly higher than the other classifiers KNN, ANN, SVM and Bayes Network. The proposed KNN-NN classifier enhances the classification accuracy by nearly 38% greater than the SVM classifier which produces the second maximum classification accuracy.

V. CONCLUSION

In this paper we have presented a novel approach for emotion recognition using EEG signals. By introducing a two-tier classifier based on K-NN and NN we have classified human emotions efficiently. The process of pre-processing and optimal feature extraction becomes an additional boost up for the proposed classification. The simulation results and performance analysis presented in this paper shows the significance of the proposed work and the comparison presented in this paper shows the superiority of the proposed work than the existing works. As of its method of simplicity the proposed emotion recognition approach can be used as a better of choice in the current trend.

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