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Emotion detection using EEG: hybrid classification approach

Deepthi D. Kulkarni[1], Vaibhav Vitthalrao Dixit[2], Shweta Shirish Deshmukh[3]
[1]G. H. Raisoni College of Engineering and Management, Pune, India
[2]RMD Sinhgad Technical Institute Campus, Pune, India
[3]Smt. Kashibai Navale Medical College and General Hospital Pune, Pune, India

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ABSTRACT

The field of emotion research facilitates the development of several applications, all of which aim to precisely and swiftly identify emotions. Speech and facial expressions are the main focus of typical emotion analysis, although they are not accurate indicators of true feelings. Signal analysis, namely the electroencephalograph (EEG) of the brain signals, is the other area in which emotions are analyzed. When compared to other modalities, EEG offers precise and comprehensive data that facilitates the estimation of emotional states. In order to categories the emotions using an EEG signal, this work suggests a hybrid classifier (HC). The input EEG data is preprocessed using the wiener filtering approach to extract the original information from the noisy signal. The preprocessed signal is used to extract features, such as entropy and a new hybrid model that includes models such as Bi-directional long short-term memory (Bi-LSTM) and improved recurrent neural networks (IRNN), which trains using the retrieved features, is included as part of the classification process. Happy, sad, calm, and angry are the categorization findings; the suggested work demonstrates more accurate classification results than the traditional approaches. All these are done on DEAP dataset with 60%, 70%, 80%, and 90% training sets and also a new DOSE dataset is been created similar to DEAP dataset.

Corresponding Author:

Deepthi D. Kulkarni
G. H. Raisoni College of Engineering and Management
Wagholi, Pune, Maharashtra, India
Email: deepthi.me2009@gmail.com

1. INTRODUCTION

In order to enhance potential of machines for use in human-computer interaction, automatic emotion identification has gained more and more attention [1]. Numerous modalities-including speech, facial expression, electroencephalography (EEG), electrocardiogram (ECG), pupillary diameter (PD), and more [2] contain information on emotions [3]. Both positive and negative experiences are possible [4]. Given this, physiological markers such blood pressure, heart rate, respiration signals, and EEG signals may be helpful in accurately identifying emotions [5]. With the advent of the brain-computer interface (BCI) and EEG data, more precise techniques for identifying human emotions were made possible [6], [7], even stress and anxiety detection are possible using EEG signals [8]. The most widely used techniques for EEG emotion recognition were support vector machines (SVM), linear discriminant analysis (LDA), k-nearest neighbours (K-NN), and empirical mode decomposition (EMD) employing Hilbert Huang shift. Numerous studies looked for reliable patterns that withstood fuzzy boundaries [9]. Recent years have also seen the introduction of deep learning-based models for automated emotion detection using multichannel EEG signal in addition to the 3-D representation of multichannel EEG using deep convolutional neural network (CNN) [10]–[12]. They have been successfully employed by several researchers in the field of emotion identification because they can generate robust and expressive feature visualisations on their own, beating conventional methods [13]. The DBN architecture reduces the quantity of data and the need for multimodal sleep measurements [14], [15]. The methodology presented in depends on frequency band searching to determine the optimal range for emotion detection [16], after which the SVM algorithm for emotion classification is applied. It has been noted that the gamma band works well for emotion categorization based on EEG data [17]. There are techniques which has been verified using EEG signal datasets that are freely accessible, including the dataset for emotion analysis using physiological signals (DEAP), SEED, and CHB-MIT set of data for emotion detection. The DEAP set of data for valence and arousal categorization showed average subject-independent accuracy rates of 65.9% and 69.5%, respectively, using the suggested technique [18]. In light of the problems, this study proposes a unique hybrid model with an desired feature set for emotion detection.

2. METHOD AND MATERIALS

The main agenda of this paper is to find emotions which are calm, happy, sad, and angry, to depict these emotions through EEG signal we can go through Figure 1 which is systematic block diagram of proposed work. The underlying mechanisms include EEG signal as input to the machine which is nothing but database acquisition, then after band selection, feature extraction is done in preprocessing technique and there after four emotions which we shall target are being categorized [19]. Theta, alpha, beta, and gamma bands are separated using a wiener filter. By extracting the most useful characteristics from the signal, the stage of feature extraction seeks to increase the classifier's results to get high rate of results. During the categorization stage, we employed three machine algorithms to identify tension and anxiety: Bi-directional long short-term memory (Bi-LSTM), recurrent neural networks (RNN), Naïve Bayes (NB), bidirectional gated recurrent unit (BI-GRU), CNN, deep neural network (DNN), and deep-CNN (DCNN) in comparison with our new hybrid classifier (HC) which is Bi-LSTM with improved RNN.

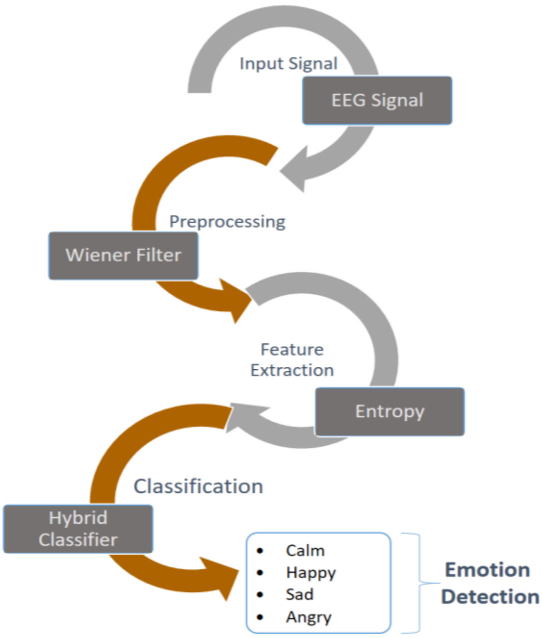

Figure 1. Systematic block diagram of proposed work

2.1. Data acquisition system

2.1.1. Dataset for emotion analysis using physiological signals

A dataset witch is multimodal for the investigation of emotional levels 32 individuals had their peripheral physiological data and EEG recorded while they watched 40 one-minute music video clips. Based on the videos' arousal, valence, like/dislike, dominance, and familiarity levels, members rated each one. For 22 of the 32 people, front face videos were also noted. The set of data discusses the methods and results of classifying arousal, valence, and like/dislike ratings on a single trial using EEG, auxiliary physiological data, and analysis of multimodal content. The dataset is publicly available so that other scholars may use it to test

themselves emotional state estimate logics [20]. The study included 32 healthy participants, 50% of whom were female, with ages ranging from 19 to 37 (mean age, 26.9). Prior to the trial, every participant had to fill out a questionnaire and sign a consent form. After reading a set of instructions outlining the experiment's technique and the significance of the many scales used for self-test, the participants finished a practice trial to get a feel for the system. The findings were given to the participants following the installation of the sensors and confirmation of their signals. Once the scientist had completed capturing the physiological data and exited the room, by hitting a key on the keyboard, the participant began the experiment. Following steps were followed by 40 videos were shown in 40 repetitions, this included the following steps for each:
- A two-second screen updating participants on their performance by showing the current trial number.
- A baseline recording of five seconds.
- The song video lasts for one minute.
- Arousal, valence, liking, and dominant self-evaluations.

After 20 trials, the participants rested for a little while.

2.1.2. New database created-database of sentiments and emotions (DOSE)

DOSE is created utilising a 24-channel EEG equipment and a mix of audio-video recordings and creating various visual issues. Positive and negative feelings to minimise the effects of residual emotions in the subject's head, the EEG recording was done on different days. Three to four appropriate-feeling video clips and music which are listed in Table 1 are selected for each emotion and real EEG recording was taken for every twenty minutes.

Table 1. Information on session and stimuli

Session No.	Emotions	Stimuli
1	Relax	Video clip: (1) Gajal (2) Instrumental
2	Happy	Movie clip: (1) Hera Pheri (2) Khichadi: The movie
3	Sad	Songs: (1) Taare Zameen Par: Maa (2) Damlelya Babachi hi Kahani tula
4	Angry	Movie clips: (1) Terrorist attack on CST station

A. Test setup

The required assistance has been provided by Smt. Kashibai Navale Medical College and General Hospital, Pune, India, in order to conduct EEG testing on the volunteers [21]. The ethical committee has given its approval for the testing for the study project. Medicare systems (RMS) and 32 electrode recorders were used to collect EEG data at a sample rate of 256 Hz as per the international electrode placement standard 10-20. 24 of the 32 electrodes were utilised for recording EEG, with the remaining electrodes being used for recording EMG and other remaining were affixed to the scalp. Under the supervision of knowledgeable clinical authorised technicians, the recording was completed. A very skilled neurologist checked the accuracy of the data. The afflicted segment of the recording was manually deleted from the data, along with the eye-blink and muscular artefacts. The usage of a high resolution, high quality mobile screen for watching videos is demonstrated in Figure 2.

a) Subjects
   - No. of subjects= 20 subjects (12 male and 8 female).
   - Average age = Around 37 years.
   - Care has been made to ensure that subjects had normal or corrected-normal vision while choosing them.
   - The subjects have been duly informed of the purpose, extent, and urgency of the experiment beforehand.

b) Stimuli

   Database
   - Positive emotions=relax and happy.
   - Negative emotions=sad and angry.
   - Stimuli-Hindi and Marathi mp3 and mp4 clips.
   - Positive and negative feelings were recorded on separate days to guarantee proper emotion induction.

Figure 2. Watching videos for various emotions

2.2. Preprocessing

Let the input signal, first pre-processed to extract the original data by filtering out the noise. This is crucial because the signal's noise taints the data's originality [22]. Diverse methodologies have been implemented to retrieve the uniqueness and eliminate noise over the whole signal spectrum. In order to remove noise, this work employs the wiener filter approach.

2.2.1. Wiener filter

The wiener filter is a filter designed to restore the original signal *O(n)* when it is hampered by external noise *E(n),* here both are considered as wide-sense stationary (WSS) random process, and wiener desires to design a filter which would produce the minimum mean-square error (MSE) [23]. The MSE denoted as € is given as (1) and (2).

$$\varepsilon = E\{|d(n)^2|\} \tag{1}$$

$$\textit{Where}\ d(n) = O(n) - p^{|}(n) \tag{2}$$

O(n) is desired signal.
$p^{|}(n)$ is predicted signal.
Now (1) can be written as (3):

$$\varepsilon = E\{|d(n)^2| = E\{|O(n) - p|(n)^2|\} \tag{3}$$

we tried to get minimum €, hence we considered a linear shift-invariant [LTI] filter. It is considered that the minimum MSE signal and the noise signal received are jointly WSS with known autocorrelations, cross-correlations, and assuming a(m-1) order filter, the system function is given as (4):

$$W(z) = \sum_{n=0}^{m-1} w(n) Z^{-n} \tag{4}$$

with the help of projection theorem or orthogonality condition above desired signal of (4) is received which is further fetched to weight vector as the system functionality we will receive the approximation of the required signal. It has been noted that statistically dependent signals are produced by the wiener output when base-band signals are used as input.

2.3. Feature extraction

Entropy is a set of characteristics derived from *O(n)* may serve as a measure for the degree of disorder used to calculate the original data's uncertainty [24]. Entropy measures are statistically utilised to evaluate any ambiguity or inconsistency of a biological signal, such the EEG [25]. Here p_i signify probability in (5).

$$Fs^{En} = -\sum p_i \log g_i \tag{5}$$

2.4. Classification

In order to expedite the classification process, this study uses a hybrid model that combines two classifiers. Here, the hybrid model uses the IRNN and Bi-LSTM classifiers, each of which provides a separate feed to the models for emotion classification [26]. To ascertain whether the input signal is calm, happy, sad or angry, the intermediate result (final classification outcome) is calculated by averaging the scores from both models. The overview of both the models clubed as hybrid classifier is shown in Figure 3.

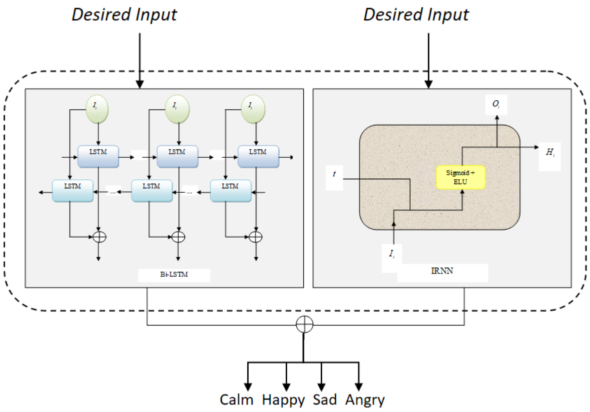

Figure 3. Framework of Hybrid classification model of emotions

2.4.1. Improved RNN

The input layer, hidden layer, and output layer are the three layers that make up an RNN [27]. The RNN technique, which is used with the following equations, is improved in this study. The input desired signal is subjected to the RNN model. The hidden layer H_t and output term O_t encoded in (6):

$$O_t = f(w_{ho} H_t + b_{iasf}) \tag{6}$$

here, $w_{ho} H_t$ denotes weight relating features set and b_{iasf} denotes bias function.

In the RNN layer, the sigmoid activation function is used. The sigmoid-weighted linear unit is a sigmoid function weighted by its input g that can be found and even the ELU activation function deploys in the RNN layer that can be defined as in (7):

$$ELU(g) = \begin{cases} g; g > 0 \\ \alpha.(exp(g) - 1); Otherwise \end{cases} \tag{7}$$

the aforementioned activation function is changed in the enhanced IRNN and can be substituted with a determined mixture of the sigmoid weighted linear unit and ELU as (8).

$$ELU(g) = \begin{cases} \frac{g\left(1+Sig^2(g)\right)}{1+Sig(g)}; g > 0 \\ \frac{\alpha.(exp(g)-1)+g.Sig(g)}{2}; Otherwise \end{cases} \tag{8}$$

2.4.2. Bi-LSTM network

In order to properly fit and analyses the dataset while addressing challenging issues, many models have been developed. Neural network topologies such as RNNs have evolved to meet this need. In an RNN, a neuron’s output can directly affect itself at the next timestamp. Because of its limited memory, RNNs can only remember information from previous phases. Gradient explosion and disappearance become frequent events as the session goes on. To resolve this problem LSTM is shown [28]. For handling time sequences, LSTM is utilized. Its unique benefit is that gradient disappearance and gradient explosion are no longer a concern since memory cells are used in place of hidden layer nodes. The model picks up on the temporal information in the EEG signal after receiving continuous time sequences. Three control gates make up an LSTM network: input (I_t), output (O_t), forget gate (F_t), and memory cell (C_t). correspondingly [29]. Effectively combining bidirectional characteristics with agating architecture, Bi-LSTM effectively combines two LSTM units to recall and process more data. The input sequence layer is used to send the characteristics that were extracted from the EEG data into the network, as seen in Figure 4. The EEG data’s long-term bidirectional dependencies are detected by the Bi-LSTM layer. This data is received by the fully linked layer. During training, the weighted matrices are used to learn and store the relationship between locations. The classes and the completely linked layer have the same size. The SoftMax layer uses the SoftMax function to categories the labelled output. The long-term associations between the time steps in the sequential data are retained by the LSTM cell [30].

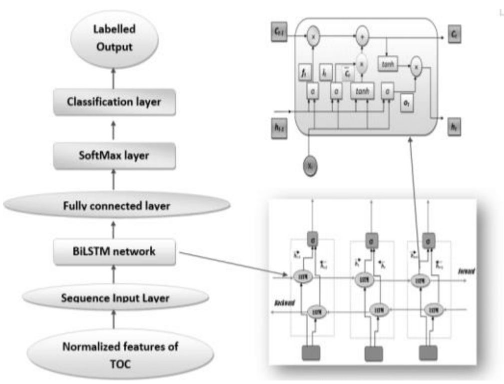

Figure 4. The Bi-LSTM architecture

3. EXPERIMENTS AND RESULT

3.1. Experiment setup

In this study, we employed the BI-LSTM, RNN, NB, BI-GRU, CNN, DNN, DCNN network to recognize four emotions. A number of indicators, such as accuracy, sensitivity, and specificity and precision which are considered as positive metrics, have been used to validate the results of the suggested technique. These measurements are represented as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) using confusion matrix parameters.

In this paper we have concentrated only on DEAP dataset with training dataset among that considered in a varied manner as of 60%, 70%, 80%, and 90% remaining were treated as testing dataset of DEAP respectively. The results are depicted below from Figure 5. Where we can see that the grey scale of hybrid classifier which we proposed had given higher scale of all the metrics. For example, if we consider 60% training dataset and remaining 40% in it would be testing dataset of DEAP, then the other classifiers which we considered gave us less accuracy than the HC. In all the metrics like accuracy, sensitivity, and specificity and precision which are positive metrics gave improved and excellence in hybrid classifier as compared to other classifiers.

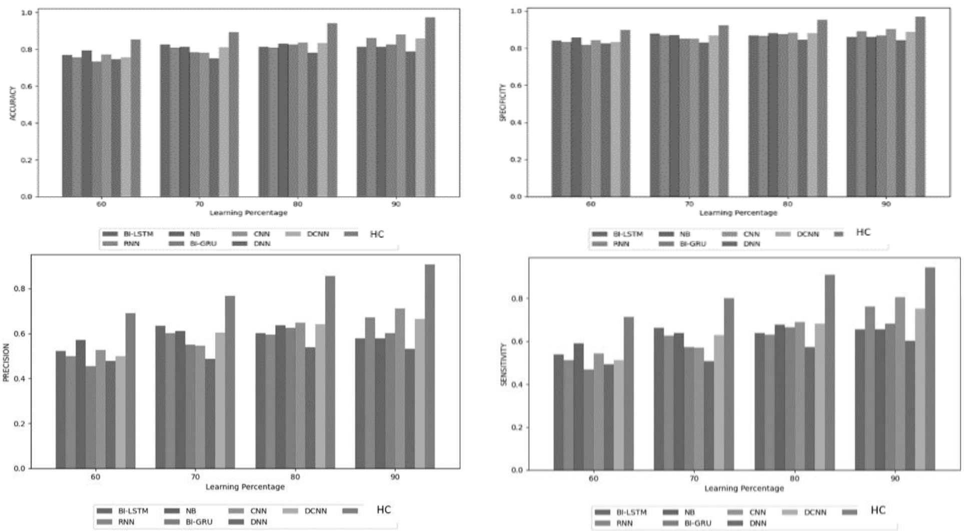

Figure 5. Emotion classification on hybrid classifier using positive metrics

3.2. Statistical evaluation

To prove our hybrid classifier excellent work, we and correctness of the hybrid classification we had even done a new evaluateion using five different kinds of statistical measurements. Table 2 summarises the statistical analysis on HC for emotion classification using EEG data and compares it with the RNN, NB, Bi-GRU, CNN, DNN, and DCNN. These state-of-art classifiers which we considered had the lowest accuracy scores as compared with our new hybrid classifier. We added the pertinent results shown below in order to compare performance with the established approach. As seen in Table 2, the suggested method HC performs better in terms of classification accuracy than the other existing approaches.

Table 2. Statistical analysis on HC for emotion classification using EEG

Metrics	Bi-LSTM	RNN	NB	Bi-GRU	CNN	DNN	DCNN	Proposed HC
Mean	0.804669	0.808279	0.812318	0.791204	0.817033	0.766309	0.813548	0.914549
Median	0.812782	0.80870	0.813408	0.803479	0.808768	0.765897	0.82125	0.91718
Std	0.022195	0.037697	0.013693	0.037845	0.044939	0.018868	0.037926	0.045845
Min	0.767339	0.75455	0.791933	0.732907	0.769306	0.744712	0.75455	0.851943
Max	0.825773	0.861167	0.830525	0.82495	0.881288	0.788732	0.857143	0.971891

4. CONCLUSION

This study presented the hybrid classification model, which uses emotion detection. The input signal was preprocessed using the wiener filter approach to eliminate noise from the signal band. The hybrid model was used to the generated features during the recognition or classification stage. Using an EEG input to train the features and classify the emotions, the hybrid model combined the capabilities of Bi-LSTM and IRNN. Furthermore, the HC at 90% training rate of DEAP dataset yields an accuracy that is far greater than that of the Bi-LSTM, RNN, NB, Bi-GRU, CNN, DNN, and DCNN using only DEAP dataset. Future work would be working with the new dataset collected DOSE acting as testing dataset percentage with same HC algorithm. The new dataset was collected but wasn't used in the analysis on primary basis in this paper presented.

5. ACKNOWLEDGEMENT

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BIOGRAPHIES OF AUTHORS

Ms. Deepthi D. Kulkarni awarded ME degree from MAE, Alandi under SPPU in 2012. Currently pursuing Ph.D. from G.H. Raisoni college Pune. She is working as assistant professor in Trinity Academy of Engineering Pune and have completed 15 years of teaching Experience. Her research areas include biomedical image processing and signal processing. She can be contacted at email: deepthi.me2009@gmail.com.

Dr. Vaibhav Vitthalrao Dixit received his Ph.D. degree in Electronics and Telecommunications Engineering g in 2015 from SPPU, Pune, (India). Presently he is working as Principal, RMD Sinhgad School of Engineering and Director of RMD Sinhgad Technical Institutes Campus, Warje, Pune, (India). His research areas include pattern recognition, neural networks and biomedical applications. He has 21 years of teaching and 5 years industrial experience. He can be contacted at email: vvdixit73@gmail.com.

Dr. Shweta Shirish Deshmukh , MBBS DNB MEDICINE, IDCCM, working as Assistant Professor Department of Medicine, SKNMC GH Pune. Her research areas include all kind of biomedical applications. She can be contacted at email: shwetas602@gmail.com.