A Cognitive Signal Analysis Using Hybrid Machine Learning Methods for Human Sentiment Classification

Dr. A. Inna Reddy

Asst. Prof. of Computer Applications, Govt. Degree College, Chanchalguda, Hyderabad, TS

Abstract: Emotions play an important role in human psych science and Cognitive. It develops from everyday experiences from the people you communicate with and the environment in which they communicate. In this paper, we propose an efficient Cognitive signal analysis using the Conglomerate machine learning technique for human emotions classification. The main contributions of the proposed technique are, A scheduled optimal wavelet packet transform (SOWPT) used to obtain characteristic features (i.e., feature extraction), which provides both time scale and time-invariant property features. It is also used to decompose the ECG signals into the sample of sub-signals. The fish swarm-based feature selection (FSFS) algorithm is utilized to select optimal features among multiples, which reduces the number of features in the ECG signal. Taguchi-based discernibility matrix used to calculate an optimal best feature in EEG signal, which enhances classification correctness by selective manner. The extracted features from both ECG/EEG signals are classified in the final stage i.e., classification, we use numerical shape induced artificial neural network (NS-ANN) for signal categorization. Moreover, we develop a Grain Size Optimal Deep Neural Network (GS-DNN) for emotions classification with the help of classified Cognitive signals. To evaluate the performance of the proposed technique through different real-time data-sets using our proposed method. The results can compare with the existing state-of-art techniques in terms of classification accuracy, precession, F-measure, and Recall.

Keywords: Human emotion classification, Feature extraction, Feature selection, FSFS, ECG signals, EEG signal, SOWPT, NS-ANN, GS-DNN.

I. INTRODUCTION:

Migraines, strokes, and Alzheimer's disease are all illnesses of the human brain. more people die of heart disease each year than another illness. About 18 million people have died from heart disease in recent years that represents 31% of all diseases worldwide. Eighty-five percent of 31% have had a heart attack or stroke. The signals of ECG are not stable and extremely tough to investigate. The signal is not constant as medical care takes time.

Therefore, Computer technology is utilized for ECG examination Basic electrical activity of the ECG signal. It spreads throughout the body and is absorbed through the casing. Therefore, an automated system capable of reliably processing ECG data in the pocket would be very useful ECG classification for arrhythmia is considered a common problem in machine learning, which classifies time-related signals into unbalanced classes, whereas typical pulses (my pulses) are usually super ventricular ectopic strokes (SVEP or S strokes, ventricular ectopic (beating).

Brain-computer interface (BCI) technology, which allows users to control computers and other functional devices in the brain, is the best way to use brain information. Such technology does not believe in the traditional separation of peripheral nerves and muscles in the brain. Motorized images are models of the function of the reproductive muscles in many ways. Additionally, linking multiple images associated with the image will replace traditional screen authentication methods and provide a new way of tagging images based on BCI.

ML-ELM is a neural network based on the Extreme Learning Machine (ELM). At the same time, ML-ELM is a kind of in-depth neural network that not only approximates complex operations but also requires no repetition during preparation. It has excellent generalization efficiency and speed. Harmless adaptation can be used in the procedure of an ambiguous type of the Discernibility matrix, the performance of which can be compared with that of the principal components analysis (PCA) and traditional discernibility matrix (DM).

Contribution The main contribution of PSA-HML technology is the delivery of an analytical signal for the classification of human emotions. Performance, selection, and performance classification are important factors in the development of an EEG / ECG-based emotional discrimination system. The features that are a part of this handset are quite sophisticated. For this purpose, optimal conductor switching features are used to obtain features from EEG signals. Finally, NS-ANN and DS-DNN use useful classifiers to identify signals and emotions.

Section 2 provides a detailed report on the literary study of this paper. Section 3 describes the methodology used in this paper. Section 4 shows the accuracy of the classification compared to existing techniques. Section 5 concludes this paper.

Problem methodology and system model

3.1 Problem methodology

Huang et al. have proposed a canny ECG classifier utilizing the fast compression residual convolution neural networks (FCResNet). SOWPT is used to provide a wide range of floor layouts and lengths to convert basic ECG signals into smaller resolution models. Samples of the five types of arrhythmias used with FCRNet, i.e., the ECGs found, were compared with the arrhythmia types. In-depth research reduces the problems of low statistical analysis, data collection, and sample reduction. In the novel random forest classification (NRFC), PCA is designed as a standard or standard for automated search and configuration. NRFC methods are used to separate different samples from the sample before processing. The following sections and gray-level co-occurrence matrix (GLCM) sections have been taken from the paper to improve accuracy.

3.2 Research Gap

Emotions and emotional well-being related to a person's personality are important to a person's life. Improving a person's health and functioning is good and negative emotions can improve health. Several interior models are currently included. However, the lack of time for the emotional activity is highly regarded. The cost of new documents, computer work, and general statistics show that parts of the human body, such as the ECG and EEG, are more accurate. The challenge for research is to go beyond areas such as time constraints and the lack of the right to evaluate clinical evidence using effective methods. ECG / EEG signal processing technology reduces the information needed to propagate fractions of medical signals and to maintain risky clinical trials.

To overcome existing issues, we propose an efficient physiological signal analysis using the Conglomerate machine learning technique for human emotions classification. The main objectives of proposed PSA-HML technique are given as follows:

- To study and analyze on classification of ECG/EEG signals for emotional prediction
- To illustrates enhanced techniques for the physiological signal pre-processing
- To introduce an optimal feature extraction technique to collect multiple features from both physiological signals.
- To propose a machine learning technique-based classifier for multi-class classification of ECG/EEG signals.
- To develop a Conglomerate machine learning technique for human emotions classification.

3.3 System model

This section describes the reception of physiological signals from the EEG / ECG under certain emotional stimuli. This section describes the physiological signals EEG / ECG under certain emotional stimuli. The basic stages of the human sensory process (deletion of attributes do not produce emotional information) are physical processing, initial processing of the acoustic signal, natural division over time, property selection, and its characteristics that change over time. Different ways of expressing emotions in human emotions are used to create a database of brain waves of different emotions. A block diagram or classification of human emotions using EEG / ECG signals is shown in Figure 1.

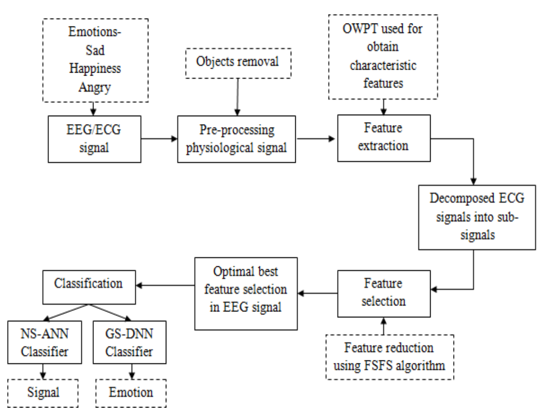

Fig.1 Proposed Conglomerate machine learningtechnique for human emotion classification

4.1 Feature extraction using SOWPT

Scheduled Optimal Wavelet Packet Transform (SOWPT)It is characterized by multiple resolutions analyses, the basic principle of which is to deliver a signal to a subfield with significant orthogonal frequency functions. By changing the speed, the signal can be transmitted at different levels so that the signal characteristics can be achieved at different frequency ranges, and then the domain characteristics of the domain are retained at each level. However, bandwidth change can only describe certain types of low-frequency signals and does not distort signals with detailed information (high frequency). Changing the bandwidth pocket can lead to distortion of low-frequency and high-frequency bands, the setting of self-adjusting resolution across different frequency ranges, and detailed analysis of optimal areas.
The relationship between scale function and driver function can be expressed

$$\begin{cases} v_0(t) = \sqrt{2}\sum_{u=z} h_u v_0(2t-u) \\ v_1(t) = \sqrt{2}\sum_{u=z} g_u v_0(2t-u) \end{cases}$$

Where $v_0 = \phi(t), v_1 = \varphi(t)$ are input signal taken from dataset

Then,

$$\begin{cases} v_{2n}(t) = \sum_{u=z} h_u v_n(2t-u) \\ v_{2n+1}(t) = \sum_{u=z} g_u v_n(2t-u) \end{cases}$$

Concerning the wavelet heap of balanced scale work portraying $v_0 = \varphi(t),$ wavelet bundle work Vn(t) = (n=0,1,2,3,). The impulse response of filter is $h_u v_n(2t-u)$ and $g_u v_n(2t-u)$ For any nonnegative number, its equal structure is conveyed:

$$n = \sum_{i=1}^{\infty} \varepsilon_i 2^j, \varepsilon_i = 0 \ or \ 1 \tag{3}$$

$$\hat{v}_n(\omega) = \prod_{i=j}^{\infty} p_{\varepsilon_i}\left(\frac{\omega}{2^i}\right) \tag{4}$$

Where, $\hat{v}_n(\omega)$ are the wavelet coefficients and $p_{\varepsilon_i}\left(\frac{\omega}{2^i}\right)$ scaling coefficients

$$p_0(\omega) = \frac{1}{\sqrt{2}}\sum_u h_u e^{-ju\omega}$$
$$p_1(\omega) = \frac{1}{\sqrt{2}}\sum_u g_u e^{-ju\omega} \tag{5}$$

In eq. (5), $p_0(\omega)$ and $p_1(\omega)$ are packet data collection from signal changing the gear pocket appears to be a cleaning process, passing through a continuous signal band similar to the original. Therefore, by selecting the correct frequency pocket and scattering layer, the vibration characteristics of the original signal can be obtained in different frequency ranges.

Portraying the projection coefficients is f(t) on subspaces vi(2n) and vi(2n+1) as di(2n) and di(2n+1), according to figuring, the brisk rot of wavelet bundle is:

$$c_i^{2n}(u) = \sum_{l \in z} h_{l-2u} d_{i+1}^n [l] \tag{6}$$

$$c_i^{2n+1}(u) = \sum_{l \in z} g_{l-2u} d_{i+1}^n [l] \tag{7}$$

Furthermore, the reconfiguration of the wavelet parcel is:

$$c_{i+1}^n [u] = \sum_{l \in z} h_{u-2l}\, c_i^{2n}[l] + \sum_{l \in z} g_{u-2l} c_i^{2n+1}[l] \tag{8}$$

The Eq. (8) shows that the bandwidth pocket configuration function shows that the bandwidth function is not related to specific formats, but uses low performance and performance coefficients {hl-2u} - {gl-2u} -. Filter to participate in the calculation. The advantage of the carpet system is that you can change the signal by selecting the frequency completely or partially and moving it to another frequency range if required. As long as the effective and inefficient components of the signal are distorted by different frequency bands, the effective component of the original signal that filters the noise interference can be easily connected.

4.2 Feature selection using fish swarm based feature selection (FSFS)

In this part, we segment incorporate assurance for game plan into three families according to the segment structure - procedures for level features, systems for coordinated features and methodologies for streaming features as displayed in Figure 3. In the going with sections, we will review these three social occasions with delegate counts in detail. Anticipate $F = \{f_1, f_2, ... f_m\}$ that and $C = \{C_1, C_2, ... C_k\}$ demonstrate e the rundown of capacities and the class name set where m and K are the amounts of features and stamps, independently. is the place where n is the amount of events and the imprint information of the I-th event xi is connoted as yi .

- **Filter Methods**

Behavioral sampling methods use statistical scales to evaluate each attribute. Properties for database installation were evaluated and selected. Because the methods are often homogeneous, the behavioral or dependent variable is considered independent. Fisher Point: High quality attributes should give the same values for events in the same class and different values from different classes. With this awareness, the fifth vision of the Si is to consider the score as the Fisher score; $S_i = \frac{\sum_{k=1}^{k} n_j(\mu_{ij} - \mu_i)^2}{\sum_{k=1}^{k} n_j P_{ij}^2}$ (9)

Classij and Pij are the averages and variables of the i-class characteristic in class 1, nj is the number of events in the class in the j-class, and ii is the array of the special label for the i-class characteristic features:

$$G(i, j) = \begin{cases} \sqrt{\frac{n}{n_j}} - \sqrt{\frac{n_j}{n}} & if \ X_i \in C_j \\ -\sqrt{\frac{n_j}{n}} & otherwise \end{cases} \qquad (10)$$

- **Select optimal features**

Packaging methods are considered a search problem, and different combinations are produced, evaluated, and compared. We evaluated the prediction model to evaluate the combination of characteristics and the accuracy of the sample. The search process can be as formal as a good first search, it can be as random as a random climbing algorithm, or you can use situations like adding and removing features. In the case of pre-classification, a typical packaging model will perform the following steps:

Pseudo code for fish swarm based feature selection algorithm

```
Input: ECG signal
Output:Best solution from feature extraction
Initialize
Do
For k = 1 to iteration number k
For i = 1 to Population Size N
Update the best position using Eq. (9)
Update the global best position using Eq. (10)
For d = 1 to Dimension D
Velocity updating using Eq. (9)
Position updating using Eq. (10)
Next d
Next i
```

Next k
Until termination criterion is met

- **Feature reduction**

Gaining practical information using regular methods, also known as penalty methods, introduce additional additions for optimization of the prediction algorithm (e.g. regression algorithm) depending on the less complex (for lower coefficients) model.

1. Quadratic cost:

$$d(u,Y) = \sum_{j=1}^{n}(x_j - u^T y_j)^2 \quad (11)$$

2. Hinge cost:

$$d(u,Y) = \sum_{j=1}^{n}\max(0, 1 - x_i u^T y_j) \quad (12)$$

3. Logistic cost:

$$d(u,Y) = \sum_{j=1}^{n}\log(1 + \exp(-x_i(u^T y_i + a))) \quad (13)$$

To handle features with high correlations, FSFS regularization is proposed as

$$p(u) = \sum_{j=1}^{n}\left|u\right|^{\gamma} + (\sum_{j=1}^{n}u_j^2)^{\lambda} \quad (14)$$

4.3 Optimal feature selection in EEG signal

The Takuchi method was developed based on the concept of orthogonal sequence (OA), which can effectively reduce the number of experiments required in the design process. The Takuchi method provides an excellent method for determining the optimal parameters of the optimization process. The Takuchi method provides an excellent method for determining the optimal parameters of the optimization process. The OA code is used to denote the OA (s, N, t, K) and T forces of the K columns (for k parameters) of the N columns. The territory of the OA has basic characteristics such as causal features, attractive and reasonable features, and orthogonality. The main advantage of using OA to solve a problem is that only N tests are needed to find the best combination of parameter values. However, it is necessary to study the Scheduled Castes and Scheduled Tribes if a comprehensive component strategy is used to solve a similar problem. Since this is much larger than Sk n, the number of experiments is significantly reduced. The start of the talkie method involves the origin of the problem, including the location of the solution, the exercise activity, and the selection of the correct OA. If the U systems are optimal, the selected OA should be larger than or equal to the U. Generally, two levels of OA are taken at two levels to determine the linear effects of the problem. If K> u, the OA columns are independent of each other, so the remaining columns without orthogonal influence in OA will be ignored.

After determining the corresponding values for the positions of each input parameter, n tests are performed and their exercise values are calculated. The optimal signal-to-noise ratio (SNR) for each exercise value can be obtained using the following eq. 15:

$$\eta = -20 \log (fitness)(db) \qquad (15)$$

Therefore, the cost of a little exercise increases. The response table data can be defined by the following eq. 16

$$\widehat{\eta}(l, p) = \frac{q}{N} \sum_{j, OA(j,n)=l} \eta_j \qquad (16)$$

L is the level of l and the parameter p pth, so the average value of the 3rd parameter is the level of l. The optimal level values for each parameter can be set to the maximum level. Tests for the value of the optimal level of each parameter, and its exercise value are used to specify the purpose of the design. If the results of the current iteration do not reach the design goal, the optimal level values are used as the core values of the following values.

$$LD_{j+1}(n) = RR.LD_1(n) \qquad (17)$$

The subscription refers to the fifth iteration. RR = 0.85i is used in this study. The higher the RR value, the slower the fusion rate. The processing optimization process is repeated until the design goal is achieved or the exercise value is integrated.

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4.3.1 Discernibility Matrix

The Visibility Matrix was first introduced by Professor Scoron. It is a matrix based method that many researchers can focus on, which is intuitive and easy to understand. The solution table is S = (R, f, U, V), where U = y1, y2, 2, yna is the sum of the properties of the domain, the set of attribute conditions, and the value of the yi form in the yi attribute. If transparency is a component of the i-row and j-columns of the matrix, the resolution matrix can be defined as follows:

$$C_d(i,j) = \begin{cases} (b_l \mid b_l \in P \wedge b_l(y_j) \neq b_l(y_i)), & d(y_j) \neq d(y_i); \\ 0, & d(y_j) = d(y_i) \end{cases} \tag{18}$$

The perceptual matrix can be identified according to the basic diagonal symmetry, and the upper triangle or lower triangle can store memory space. When the two models contradict each other, the corresponding components of the cognitive matrix are empty. An attribute with a strong ability to distinguish between different objects often appears in the perception matrix. The smaller the number of attributes in a matrix element, the stronger the ability to distinguish different objects associated with the element, and the more important the attributes.

The calculation method is relatively simple and intuitive. In the perception matrix, if an element has only one attribute, then the attribute is the main attribute. The basic computational process can be divided into two parts: the calculation of the cognitive matrix and the search for matrix components. The time complex of the algorithm is O (n2). Although the data in the final list is small, the knowledge panel is very simple to use; As the features listed in the results list develop, the complexity of group time and space issues increases rapidly. Therefore, the basic attribute algorithms based on the cognitive matrix have drawbacks.

4.4 Signal classification using NS-ANN

The failure of the numerically stimulated synthetic neural network (NS-ANN) for signal classification leads to the enslavement of the initial centers of the slaves and significantly affects the final groups of nodes. When clustering data objects, the most accurate cluster group results can be achieved by selecting a data model for accurate data distribution, selecting cluster centers correctly, and updating the clustering center. The idea of selecting cluster centers for the optimal ANN classifier: first, k rejects isolated points (k data objects and other objects that are rapidly added to the Euclidean distance of the cluster data); Calculate all the centers of the remaining objects, select the point closest to the center of the first point, and repeat to find the point farthest from the starting point (the selected focus will no longer participate in the selection of the next center). The hierarchical system moves on to the next step until a point is found

Like many clustering algorithms, ANN uses a functional process. For each iteration it tries to reduce the number of cassettes in the cluster, i.e. to increase the similarity between the objects in each cluster. At this time, RjRm CJ and ‖ And refers to clusters. ‖ 2 is the double Euclidean law. Like many clustering algorithms, the Q-algorithm uses an operational process. At each iteration, it tries to reduce the cluster size of the squares, i.e. increase the similarity between the objects in each cluster. Here, RjRm CJ and ‖ And carving. ‖ 2 is the double Euclidean law. The standard ANN can be described in three steps as given below.

(a) Initialization step:

In the introduction step, the k-implies calculation instates μj of group cj¬, i.e,

$$\mu_j^{(1)} = \{y_p : y_p \in \times, \mu_i^{(1)} \neq y_p, 1 \leq j \leq k, j \neq i\} \tag{19}$$

Different types of ANN can use different methods. However, the most common method is to use random data points other than x to extract each centroid. After the introduction of Android, the Q-algorithm speeds up the process and updates the status.

(b)Assignment step:

Presently, every data point is named to a bundle whose centroid gives minimal squares in the gatherings.

$$c_i^{(t)} = \left\{ y_n : \| y_n - \mu_i^{(t)} \|^2 \le \| y_n - \mu_i^{(t)} \|^2, \forall j, 1 \le i \le k \right\} (20)$$

Over time, XP is only assigned to one cluster with j one i. Over time XP can be assigned to another cluster, which reduces the cluster size of the squares. The data point here does not belong to multiple clusters.

(c) Update step:

During the update phase, Centroids K- or algorithm calculates the following iterations based on data from each cluster period.

$$\mu_j^{(k+1)} = \frac{1}{\left| c_j^{(k)} \right|} \sum_{x_i c_i^{(k)}} x_i \tag{21}$$

For a given threshold $\xi \ge 0$, if $\mu_j^{(k+1)} - \mu_j^{(k)} | \le \xi, \forall j,\ 1 \le j \le t,$ this stops the iteration process because the algorithm has already reduced it. Otherwise, it returns to the work position and drops sets k= k+1.

Pseudo code for numerically stimulated synthetic neural network classifier

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Input: Received signal to be processed

Output: Classified signal

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Begin
Generate the initial solution randomly
Evaluate each individual in the population f(x) based on error rate
Find the best solution from the population
While (stop when criteria satisfied)
For i=1 to n do
For j=1 to n do
if (f(xj)<f(xi))
Calculate signal by eq.
Calculate the distance between each signal i and j by eq.
Move all signal (xi) to the best solution (xj) by eq
End if
End for j
End for i
Moves best solution randomly by eq
Find the best solution from the new population
End while
Return best (TP), (TN), (FP) and (FN)
End of the algorithm

4.5 Human emotion classification using GS-DNN

The grain size optimal deep neural network (GS-DNN) with a single unidirectional affirmed layer. In the specific utilitarian sort of how dormant segments and discernments interface was truly searing. This is certainly not a significant issue, when versatility to show different sorts of affiliations. With a singular layer, by some coincidence, this can be incredibly trying. By reasonableness of the announcement we fixed this issue by including more layers. Inside DRNNs this is reliably harmed, since we first need to pick how and where to join extra nonlinearity. Our trade underneath stores up in a general sense as for Long Short Term Memory (LSTM) yet this mayapply to some other models, also. We could stack different layers of LSTMs more than one another. This outcomes in a structure that is gainfully versatile, because of the blend of several immediate layers. Specifically, information may be epic at various degrees of the stack. For example, we should keep assembled level information about money related budgetary conditions (bear or truly slanting business division) open at an epic level, while at a lower level we basically record shorter-term transient parts.

4.5.1Mathematical Dependencies

At duration point t, the terms mi ni pack $Y_t \in R^{nxd}$ (no. of models: n, no. of information sources: d). When layer l (l = 1,….T) is $G_t^{(l)} \in R^{n\times h}$ have secured condition (no. of units hidden: h), the yield variable layer $Out_t \in R^{n\times q}$ a confirmed layer affirming work h1 for level l. We figure the checked condition of level l as already, utilizing Yt as information. For each following layer the confirmed condition of the past level is utilized in its domicile.

$$G_t^1 = h_1(Y_t, G_{t-1}^1) \tag{22}$$

At long last, the yield of the yield layer is essentially picked the confirmed condition of camouflaged layer L. We utilize the yield work g to point out as,

$$Out_t = k_1(G_t^{(L)}) \tag{23}$$

Specifically, we can pick a standard GS-DNN, the LSTM to fathom the model. A GS-DNN is a class of fake neural system that builds up the standard feed forward neural structure with coasts in affiliations. As opposed to a feed forward neural structure, a GS-DNN can process the consecutive obligations by having a convulsive camouflaged express whose start at each improvement constant store of the past progress. Right now, structure can show dynamic passing lead. Given improvement information, where yi denotes the information at jth duration point, a GS-DNN fortifies its sporadic confirmed gtinput state by

$$g_t = \begin{cases} 0, & if\ t=0 \\ \phi(g_{t-1}, y_t), & otherwise \end{cases} \tag{24}$$

where ϕ denotes limitation of nonlinear, for instance, a determined sigmoid limit or hyperbolic deviation work. Then again, the GS-DNN required a yield y. For specific tasks, for instance, hyper powerful picture course of action, this required only one yield, i.e., yT. In the standard GS-DNN type, which upload standard of the dull covered state is ordinarily executed as seeks after:

$$g_t = \phi(Uy_t + Vg_{t-1}) \tag{25}$$

Where U and V are the terms in grids dedicating present movement and for the foundation of unpredictable secured units at the past advancement, solely. Definitely, a GS-DNN can display a likelihood allotment all through the going with fragment of the social occasion information, given its current input state ht, by getting a stream over game-plan information of length variable. Let y1, y2 and yn be the social occasion likelihood, which can be deteriorated into A broken layer with standard repetitive concealed units is appeared in (26), which just registers a weighted direct total of wellsprings of information and in this manner applies a nonlinear utmost. Abnormally, based on LSTM dreary layer makes a memory part bt at duration t. The beginning units of LSTM can be figured by

$$g_t = out_t \tanh(b_t) \tag{26}$$

Where tanh(•) denotes digression hyperbolic capacity and out_t is the yield door that decides the piece of the content memory that will be uncovered.

The conditions that figure these two entryways are according to the accompanying:

$$j_t = \sigma(U_j jy_t + U_{jh}h_{t-1} + U_{jc}b_{t-1}) \qquad (27)$$

$$p_t = \sigma(U_p jx_t + U_{ph}h_{t-1} + U_{pc}b_{t-1}) \qquad (28)$$

5. Performance metrics and comparative analysis

To analyze the performance of each class in the model identification field, we used the accuracy, recall, F1 score, accuracy, and loss as performance evaluation criteria. Each class is calculated using accuracy (A), F-measure, recall (R) and precision (P).

$$A\ (\%) = \frac{TP+TN}{TP+TN+FP+FN} * 100 \qquad (29)$$

$$F1Score = 2 * \frac{P*R}{P+R} \qquad (30)$$

$$R\ (\%) = \frac{TP}{TP+FN} * 100 \qquad (31)$$

$$P\ (\%) = \frac{TP}{TP+FP} * 100 \qquad (32)$$

where TP means true positive, which means that the correct classification is arrhythmia; TN refers to the actual negative, i.e. the correct classification is normal; FP stands for false positives, i.e. misclassification as arrhythmia; FN means false negative, i.e. false classification is common. In relation to the loss metric, it is defined as the difference between the estimated value of the sample and the actual value of a particular sample.

Table 2 performance comparison of proposed and existing techniques

Techniques	%			
	R	P	A	F
PSA-HML	96.54	99.50	98.8	98.49
MOWPT + FCResNet [31]	95.16	99.39	98.79	97.23
DWPT + FCResNet [31]	91.31	98.35	97.66	94.70

6. Conclusion

In this paper, we will explore the reliable aspect of EEG / ECG-based emotion recognition from three aspects of time domain characteristics (average, constant variance, and number of peaks). Observed features derived from distorted EEG / ECG signals in the alpha, beta, and alpha + beta frequency bands. Based on the test results, we believe that the average features of the beta and alpha + beta bands are reliable enough to distinguish between happy and sad emotions. This indicates a high accuracy of 99.18. Numerical shape induced artificial neural network (NS-ANN) and grain size optimal deep neural network (GS-DNN). At the same time, the number of characteristic features is not associated with an increase in taxonomic accuracy. It has been shown to reduce the tendency for the three features to be used together in all frequency ranges. Furthermore, as a result, on average, we find evidence that happy feelings are higher than basics and that most participants are generally higher than sad feelings, so happy feelings are more valuable than sad feelings.

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