

# Mode Decompositions with Sample Entropy and Optimized Extreme Learning Machine for EEG Emotion Classification

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**Abstract**— In human life, one of the crucial roles is played by emotions. Emotions are nothing but expressions of human psychology and physiology and they are related to the physical and mental states of the human being. Due to the rising advent of the brain computer interface (BCI) compiled with Pattern Recognition (PR) techniques, emotion classification from electroencephalography (EEG) has attracted a lot of attention. In this work, an interesting model is proposed for the analysis of emotion classification and recognition from EEG signals. The strategy utilizes the concept of Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), Sample Entropy, Ant Lion Optimization (ALO) with Extreme Learning Machine (ELM) known altogether as EVSAE model. The work is evaluated on two publicly available datasets, such as DREAMER and DEAP, and the best results are analyzed for both the datasets comprehensively.

**Keywords** — EMD, VMD, Reinforcement Learning, SVM, Optimization

## I. INTRODUCTION

Emotion is a behavioral response to various external and internal stimuli, and it is quite complicated [1]. Identifying human emotions from different modalities is the main intention of human emotion recognition. Emotion is just a reflection of the physiological and psychological state of a human being which in turn depends on the different mental activities that people are exposed to [2]. For automatic emotion identification, various investigations have been conducted in the past. Some of the investigations concentrate on the physiological signals of the periphery, some concentrate on the in-depth analysis of body language, speech tone and facial expressions while some investigations deal primarily with the brain signals recorded from EEG [3]. It is also proved that a lot of informative characteristics are present in brain signals and so emotional responses can be judged quickly from it. For training emotional stress in people, a lot of useful information is provided by EEG [4]. For many illnesses such as anxiety disorders, depression traumas and bipolar disorders, emotional stress is a huge contribution factor. The most widely accepted emotions belong to the positive category (such as surprise and happiness) and some belong to the negative category (fear, sad, anger, disgust) [5]. When the electrical activity of the brain is analyzed, a good temporal resolution is provided by EEG. A few related works with respect to EEG emotion classification are discussed as follows.

An accurate EEG emotion classification model using Tetromino pattern was developed by Tuncer et al where they had achieved almost 100% accuracy using DREAMER and GAMEEMO dataset [6]. An EEG emotion classification model using correlation research dependent on deep learning was developed by Li et al where the mean accuracy was increased by 1.34% in the arousal dimension and 2.28% in the valence dimension [7]. An improved cross-connected CNN was used for EEG based emotion classification by Dai where a high accuracy of 93.7% was obtained [8]. An EEG based emotion recognition using 3D convolutional neural network was employed by Shawky et al [9]. The EEG signals and facial expressions were analyzed for continuous emotion detection by Soleymani et al [10]. Deep belief network structures were utilized for human emotion recognition by Hassan et al [11]. LSTM models were used for the emotion computing analysis by Jiang and the average accuracy rate obtained was 86.48% [12]. Machine learning techniques were analyzed for emotion recognition using EEG and peripheral physiological signals by Doma and Pirouz [13]. An ensemble learning model for EEG based emotion classification was done by Dash et al reporting a high accuracy of 96.54% [14].

Deep neural networks and sparse autoencoder were used for EEG based emotion classification and a high recognition accuracy of 89.49% and 92.86% were achieved for valence and arousal respectively for DEAP dataset and 96.77% was obtained for SEED dataset [15]. A zero-time windowing based epoch estimation was used for emotion detection using EEG by Gannouni et al where the average accuracy rate exceeded 89% [16]. BiLSTM networks were employed for EEG based emotion recognition by Yang et al where an overall accuracy of 84.21% was obtained [17]. A stacking ensemble approach was proposed by Chatterjee and Byun achieving a classification accuracy of 99.55% [18]. An LSTM mechanism with Attentive mechanism was proposed by Kim and Choi and with 10-fold cross validation, an accuracy of 91.8% was obtained for valence and 91.6% was obtained for arousal respectively [19]. Self-supervised EEG emotion recognition models dependent on CNN was developed by Wang et al [20]. A group sparse canonical correlation analysis with linear SVM was used by Zheng reporting a classification accuracy of 85.23% for SEED dataset [21]. The concept of IMF with EMD along with ANN was analyzed for DEAP dataset by Mert and Akan reporting a classification accuracy of 75% [22]. A multiband feature matrix with capsule network was analyzed for DEAP dataset by Chao et al reporting a classification accuracy of 68.28% [23]. An attention based Convolutional recurrent neural network was analyzed for DREAMER and DEAP dataset

reporting an arousal of 97.98%, valence of 97.93%, dominance of 98.23% for the former and arousal of 93.14% and valence of 92.74% for the latter by Tao et al [24]. A regional asymmetric CNN was used for DREAMER and DEEP datasets reporting an arousal of 97.01% and valence of 95.55% for former and arousal of 97.11% and valence of 96.65% for the latter by Cui et al [25]. The concept of granger causality with transfer entropy and SVM was analyzed for DEAP and SEED dataset reporting a classification accuracy of 95.21% by Gao et al [26]. The concept of DWT and ELM was used for collected data by Seal et al reporting a classification accuracy of 94.72% [27]. A 3D convolutional attention neural network with SoftMax classifier was used for SEED dataset by Liu et al reporting a classification accuracy of 97.35% [28].

A rhythm specific multichannel CNN was used by Maheswari et al for DREAMER and DEAP datasets reporting an average of 98.82%, for the former and an average of 98.91% for the latter respectively [29]. The prime pattern network was implemented by Dogan et al for DREAMER and DEAP datasets where arousal, valence and dominance values were obtained as 100% for the former and an arousal value of 99.56%, valence value of 99.67% and dominance value of 99.55% for the latter respectively [30]. A lot of statistical parameters were classified with RF classifier for both DREAMER and DEAP dataset, and an arousal of 93.795 and valence of 93.65% was obtained for the former and an arousal of 89.94% and valence of 89.83% was obtained for the latter [31]. Multilevel capsule networks were analyzed for DREAMER and DEAP datasets by Liu et al, where an arousal value of 95.26%, valence of 94.59% and dominance of 95.13% are obtained for the former and an arousal value of 98.31%, valence of 97.97% and dominance of 98.32% are obtained for the latter [32]. Power Spectral density (PSD) with deep learning and ELM were used for DREAMER and DEAP datasets by Siddharth et al, where an arousal value of 79.23%, valence value of 78.99% for the former and an arousal value of 72.58% and valence value of 71.09% was obtained for the latter [33]. A positive definite matrix with domain adaptation symmetric was done by Wang et al for DREAMER and DEAP datasets, and arousal value of 76.57%, valence value of 67.99% and dominance value of 81.77% obtained for the former and arousal value of 69.79%, valence value of 66.47% and dominance value of 71.12% obtained for the latter [34]. The holographic feature maps with CNN and SVM were implemented by Topic and Russo for DREAMER and DEAP datasets and an arousal value of 90.43% along with a valence value of 88.2% was obtained for the former and an arousal value of 77.72% and valence value of 76.61% is obtained for the latter [35]. The main contributions of this work are as follows: Once the pre-processing of EEG signals using Independent Component Analysis (ICA) is done, the method is proceeded with EMD-VMD-SE-ALO: ELM methodology known as EVSAE model.

## II. PROPOSED TECHNIQUE : EMD-VMD-SE-ALO:ELM (EVSAE):

The basic pre-processing of the EEG signals is carried out using Independent Component Analysis (ICA) initially. The pre-processed EEG signals are then decomposed into

various subcomponents with the help of EMD and VMD is the initial step in this research. With the help of sample entropy techniques, the components are combined based on their similar characteristics. To predict every component, various algorithms can be used and by means of hybridizing every output of the subcomponent, the integration of the final results can be done. In our work, two decomposition techniques such as EMD and VMD are utilized. The EEG signals can be decomposed into characteristic modes with the help of EMD [36]. The basis function need not be chosen here as this is the biggest advantage. Based on the EEG signal analysis, the natural model function can be generated in an adaptive mode. To analyze nonlinear and non-stationary signal sequence, it is highly recommended as it has a high Signal to Noise Ratio (SNR). From the original time series of EEG data, the intrinsic patterns can be extracted by EMD. Every intrinsic pattern is expressed as an intrinsic mode function (IMF) and the subsequent two circumstances should be satisfied.

- The total number of zero crossings and the extreme function value must be equal to 1 or vary by not more than 1.
- The IMF's local maximum and minimum, which is formed by the average value of the upper and lower envelope equals 0.

The decomposition of the original EEG data into  $n$  IMFs and a residual are done by EMD decomposition and is written as follows:

$$P_t = \sum_{j=1}^N c_{j,t} + r_{N,t} \quad (1)$$

where the number of IMFs is represented by  $N$ . The residual is represented by  $r_{N,t}$ . The  $j^{th}$  IMF at time  $t$  is represented by  $c_{j,t}$  ( $j = 1, 2, \dots, n$ ).

Another popular technique to dispense with nonlinear and non-stationary signals is VMD [37]. The decomposition of the EEG data is done into bidimensional IMF (BIMF) when the VMF method is implemented. The IMF of the EMD technique is defined as the narrow band BIMF by VMD and is represented as:

$$P(t) = A_k(t) \cos[\phi_k(t)] \quad (2)$$

where  $\phi_k(t)$  is non decreasing in nature.  $A_k(t) \geq 0$  and the enveloping of the transformation of  $A_k(t) \geq 0$  is done simultaneously. With reference to  $k(t)$ , the instantaneous frequency  $w_k(t) = \phi'_k(t)$  is a phase moderate variation. To assess the center frequency and to trace the optimal solution, the signal is put into the constrained variational technique by VMD. The expression of objective function is done as follows:

$$\min_{\{p_k\}, \{w_k\}} \left\{ \sum_k \left\| \partial_t \left[ \left[ (\delta(t)) + \frac{j}{\pi t} \right] * P_k(t) \right] e^{-jw'_k} \right\|_2^2 \right\} \quad (3)$$

$$\text{s.t } \sum_{k=1}^K p_k(t) = p(t) \quad (4)$$

where the  $k^{th}$  modal constituent of the EEG signal is represented as  $p_k(t)$  and its corresponding center frequency is represented as  $w_k$ .  $\{p_k\} = \{p_1, p_2, \dots, p_k\}$  indicates all the modes and  $\{w_k\} = \{w_1, w_2, \dots, w_k\}$  indicates its respective related center frequency. Figure 1 shows the illustration of the EVSAE model.

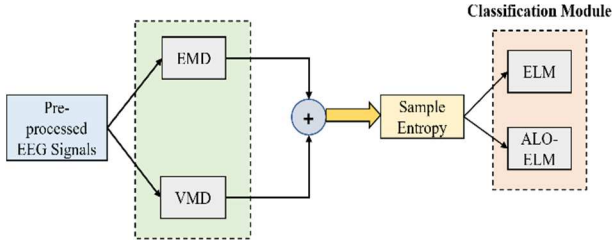


Figure 1 Illustration of the EMD-VMD-SE-ALO: ELM model

## 2.1 Implementation of sample entropy:

The Dirac function is expressed as  $\delta(t)$  and the convolutional operator is denoted as  $\sigma$ . The stability of the VMD is higher than EMD as it can trade in with both the mode mixing and the modal processing of the boundary points so that the accomplishment of manipulating the nonlinear and non-stationary process is improved. The various components of the original EEG series data are obtained after the decomposition of EMD and VMD. The prediction accuracy is enhanced by improving the prediction of each component. Sometimes, a large aggregate error is formed due to the accumulation of the prediction error of every component. Therefore, the number of components can be reduced and there is a need for the reconstruction of IMF. For the hybridizing of the decomposed components, sample entropy method is chosen here in our work [38]. The intricacies of the time series data can be analyzed well with sample entropy. The value of the sample entropy is small if the sequence autocorrelation is high. If the sequence is complex, then the entropy value is large. For the primary time series of EEG  $\{p(n)\} = \{p(1), p(2), \dots, p(N)\}$ , the sample entropy algorithm is as follows:

- a) The sequential decomposition of the sequence  $\{P_i\}$  is done into m-dimensional vector, that is,

$$P(i) = [p(i), p(i+1), \dots, p(i+m-1)] \quad (5)$$

where  $i = 1, 2, \dots, N - M + 1$ .

- b) The distance between  $p(i)$  and  $p(j)$  are as follows:

$$d_m(p(i), p(j)) = \max_{0 \leq k \leq m-1} |p(i+k) - p(j+k)| \quad (6)$$

- c) For each  $i$  value, the number of  $d_m(p(i), p(j))$  is counted which is less than  $r$ , given the tolerance  $r (r > 0)$ . The indication of it is expressed as  $A_i$

- d) The ratio of  $A_i$  to  $N - m$  is computed and represented as  $A_r^m(r)$

$$A_i^m(r) = \frac{1}{N - m - 1} A_i \quad (7)$$

- e) The mean value of  $A_r^m(r)$  is expressed as  $A^m(r)$  and is indicated as:

$$A^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} A_i^m(r) \quad (8)$$

- f) The dimension is increased to  $m+1$  and finally the mean of  $A_i^{m+1}(r)$  is expressed as:

$$A^{m+1}(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} A_i^{m+1}(r) \quad (9)$$

- g) The sample entropy (S.E) of this time series is represented as follows:

$$S.E(m, r) = \lim_{N \rightarrow \infty} \left\{ \ln \left( \frac{A^{m+1}(r)}{A^m(r)} \right) \right\} \quad (10)$$

The roughly calculated merit of sample entropy where 'n' is a finite value is as follows:

$$S.E(N, m, r) = -\ln \frac{A^{m+1}(r)}{A^m(r)} \quad (11)$$

The values of  $m$  and  $r$  are highly related to the computed results of the sample entropy. In our work,  $m=1$  and  $r=0.5$  S.D (S.D indicates the standard deviation of the original time series). The sample entropy value of components is judged and the one with nearest entropy is combined and represented as a new time series indicating the specific type of decomposed constituents. Once the sample entropy is computed, it is then fed to the ELM and the proposed ALO: ELM.

## 2.2 ELM:

An efficient and relatively new data driven technique which adopts a single hidden layer feedforward neural network is ELM [39]. As the hidden layer thresholds and input layer weights are random in nature, the output has a distinct least-squares answer and therefore classification can be performed by ELM. It also relies on the Moore-Penrose generalized inverse and it can easily solve the problems which the traditional backpropagation algorithm cannot solve. There are three layers in an ELM such as input layer, hidden layer, and output layer. To assess the connections between the two adjacent layers, input layer weights and hidden layer thresholds are utilized. There is a random generation of the weights of the input layer and the thresholds of the hidden layer. The total number of neurons must be set in the hidden layer and the activation function should also be manually set. Supposing that there are  $D$  different training samples  $(P_i, Q_i) \in \mathcal{R}^n \times \mathcal{R}^m$  and  $G$  is the number of neurons in the hidden layer, then the standard feedforward neural network is expressed as follows:

$$\sum_{i=1}^G \beta_i h(w_i \cdot p_i + b_i) = D_j, j = 1, 2, \dots, N \quad (12)$$

where the weight managing the input layer node and the  $i^{th}$  hidden layer neuron is expressed as

$w_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$ . The weight managing the  $i^{th}$  hidden layer neuron and the output layer node is expressed as  $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{in}]^T$ . The threshold of the  $i^{th}$  hidden layer neuron is expressed as  $b_j$ . The output of the network is expressed as  $D_j = [D_{j1}, D_{j2}, \dots, D_{jn}]^T$ . The activation function is specified by  $h(x)$  and the activation function used in this paper is sigmoid. The training result of the model and the expected output result  $Q_j$  is close to zero error if the output matrix of ELM is set to  $J$  after a certain training time and is represented as:

$$\sum_{i=1}^G \beta_{ij} (w_i \cdot p + b_i) = Q_j, j = 1, \dots, N \quad (13)$$

It can also be written in the following form as:

$$J\beta = Q \quad (14)$$

The output matrix is represented by  $J$  and is expressed as obtained from the hidden layer as:

$$J = \begin{bmatrix} j(p_1) \\ \vdots \\ j(p_N) \end{bmatrix} = \begin{bmatrix} j(w_1 \cdot p_1 + b_1) & \dots & j(w_L \cdot p_1 + b_G) \\ \vdots & \dots & \vdots \\ j(w_1 \cdot p_N + b_1) & \dots & j(w_L \cdot p_N + b_G) \end{bmatrix}_{N \times G} \quad (15)$$

The expected output weight matrix  $Q$  is expressed as:

$$Q = \begin{bmatrix} q_1^T \\ \vdots \\ q_N^T \end{bmatrix} = \begin{bmatrix} q_{11} & \dots & q_{1m} \\ \vdots & \dots & \vdots \\ y_{N1} & \dots & y_{Nm} \end{bmatrix} \quad (16)$$

The minimum value of the error of  $J\beta - Q'$  is calculated and it is the main purpose of ELM. The assessment of the smallest  $\hat{\beta}$  is done based on the least-squares technique where the activation function is infinitely differentiable and is represented as:

$$\min_{\beta} \|J\beta - Q'\| \quad (17)$$

The final result is as follows:

$$\hat{\beta} = J^+ Q \quad (18)$$

where the generalized inverse of  $J$  is  $J^+$  and the weight matrix of the output region is represented as  $\hat{\beta}$ .

### 2.3 Antlion algorithm (ALO) algorithm:

A famous natural heuristic algorithm is the Antlion algorithm [40]. The hunting action of antlions are modelled and it includes steps such as walking of ants in a random manner, trap construction, ants' entrapment, capturing of ants followed by the trap's reconstruction.

#### A. Walking of ants in a random manner:

In the search space the movement of ants are influenced by antlion traps by means of random walks. Based on the following equation, the positions can be changed easily as follows:

$$A(t) = [0, s(2r(t_1)-1), s(2r(t_2)-1), \dots, s(2r(t_n)-1)] \quad (19)$$

The cumulative sum is represented as  $s$ , the current iteration number is specified as  $t$ , maximum number of iterations are indicated as  $T$ , and the random function is represented as  $r(t)$  and is expressed as follows:

$$r(t) = \begin{cases} 1 & \text{if } rand > 0.5 \\ 0 & \text{if } rand < 0.5 \end{cases} \quad (20)$$

where  $rand$  denotes a uniformly distributed random number in the range of  $[0,1]$ . Within the boundary of search space, the random walks of all ants fall so that the normalization process could be carried out easily as:

$$A_i^t = \frac{(A_i^t - m_i) \times (p_i^t - o_i^t)}{(n_i - m_i)} \times o_i^t \quad (21)$$

where  $m_i$  is the least value of the random walk for the  $i^{th}$  variable and  $n_i$  is the highest value of the random walk for the  $i^{th}$  variable.  $o_i$  and  $p_i$  represent the lowest and highest values for the  $t^{th}$  iteration of the  $i^{th}$  variable.

#### B. Trap construction:

The hunting ability of the antlion is simulated with the help of the roulette wheel. With the help of roulette wheel, the most suitable antlion is selected by the ALO algorithm so that there is a higher probability of catching the ants.

#### C. Antlion trapping:

The antlion trap location is used to influence the random walk of the ants and is indicated using the following mathematical equation:

$$o_i^t = Antlion_j^t + o^t \quad (22)$$

$$p_i^t = Antlion_j^t + p^t \quad (23)$$

Among them,  $o^t$  and  $p^t$  are the lowest and highest values of all variables. The position of the  $j^{th}$  antlion in the  $t^{th}$  iteration is represented as  $Antlion_j^t$ . The roaming behaviour of the ants is defined by the variables  $o$  and  $p$  within a trap which is developed by the chosen antlion.

#### D. Progression of ant sliding towards the antlion:

The ant must slide towards antlion, where an ant progresses into the antlion's trap. Unless the trapped ant slips down, the antlion shoots sand outward. For the ant random walk, the hypersphere radius is adaptively mitigated and is represented as:

$$o^t = \frac{o^t}{I} \quad (24)$$

$$p^t = \frac{p^t}{I} \quad (25)$$

$I$  can be represented as  $I = 10^w t/T$ .

The highest number of iterations are denoted as  $T$  and the present total number of iterations are denoted as  $t$ . Based on the current number of iterations, the constant defined is expressed as  $w$ .

### E. Ants capturing and Trap Rebuilding:

The ants that slither to the extremity of the pit are captured by this final stage of antlion hunting. The probability of catching other ants is increased when the antlion updates its position to the current position of the hunted ants.

$$Antlion_j^t = Ant_i^t \quad \text{if} \quad f(Ant_i^t) > f(Antlion_j^t) \quad (26)$$

The fitness function is  $f(\cdot)$  and the position of the  $i^{th}$  ant in the  $t^{th}$  iteration is  $Ant_i^t$ .

### 2.4 Elitism principle:

In each iteration, the favorable solution obtained is the elite antlion which influences the motion of the remaining ants in the iteration. Around the antlion, the random walking of every ant happens and the elite antlion is chosen based on the roulette wheel technique such as:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (27)$$

where in the  $t^{th}$  iteration, the random walk of the antlion chosen by the roulette principle is chosen as  $R_A^t$  and at the  $t^{th}$  iteration, the random walk of the ants around the elite antlion is chosen as  $R_E^t$ .

### 2.5 Implementation of the ALO-ELM:

In the ELM, the input layer weights and the hidden layer thresholds are generated randomly so that the accuracy of the model is enhanced. For the input layer weights  $w_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$ , ALO is used and is optimized with the hidden layer threshold  $b_i$ . For evaluating the prediction results, the statistical index MSE is utilized as the individual fitness so that the accuracy is quantitatively analyzed and is expressed as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (Z - \hat{Z}_i)^2 \quad (28)$$

The sample data is represented as  $n$ ,  $Z$  is the actual EEG signal,  $\hat{Z}$  is the predicted signal and the predicted results with less MSE will be considered better.

## III. RESULTS AND DISCUSSION

We have utilized two datasets in this work, such as DREAMER [41] and DEAP [42] datasets. DREAMER dataset comprises of 3 cases such as arousal, dominance, and valence. With the help of 14 channels, the acquisition of this data was done. The DEAP dataset was collected from 32 participants and the three cases of this dataset are arousal, valence and dominance which is like the DREAMER dataset and with the help of 32 channels, the acquisition of the data was done. A 10-fold cross validation was used in our work for performance analysis.

Table 1 shows the performance analysis of EMD and VMD with sample entropy for ELM and ALO-ELM classification for DREAMER dataset. The proposed EMD-VMD-Sample entropy- ALO: ELM produced an arousal of 96.87%, valence of 95.45% and dominance of 96.09% for DREAMER dataset. Table 2 shows the performance analysis of EMD and VMD with sample entropy for ELM and ALO-ELM classification for DEAP dataset. The proposed EMD-VMD-Sample entropy- ALO: ELM produced an arousal of 97.02%, valence of 95.78% and dominance of 96.66% for DEAP dataset.

Table 1. Performance analysis of EMD and VMD with sample entropy for ELM and ALO-ELM classification for DREAMER dataset

| Methodology                | ELM         |             |               | ALO-ELM     |             |               |
|----------------------------|-------------|-------------|---------------|-------------|-------------|---------------|
|                            | Arousal (%) | Valence (%) | Dominance (%) | Arousal (%) | Valence (%) | Dominance (%) |
| EMD + Sample Entropy       | 86.45       | 85.34       | 82.12         | 92.23       | 91.23       | 93.23         |
| VMD + Sample Entropy       | 85.32       | 84.43       | 85.45         | 93.23       | 92.02       | 92.45         |
| EMD + VMD + Sample Entropy | 89.23       | 88.12       | 86.78         | 96.87       | 95.45       | 96.09         |

Table 2. Performance analysis of EMD and VMD with sample entropy for ELM and ALO-ELM classification for DEAP dataset

| Methodology                | ELM         |             |               | ALO-ELM     |             |               |
|----------------------------|-------------|-------------|---------------|-------------|-------------|---------------|
|                            | Arousal (%) | Valence (%) | Dominance (%) | Arousal (%) | Valence (%) | Dominance (%) |
| EMD + Sample Entropy       | 87.34       | 86.34       | 85.34         | 88.90       | 90.02       | 89.02         |
| VMD + Sample Entropy       | 88.34       | 87.03       | 85.03         | 92.02       | 91.03       | 93.45         |
| EMD + VMD + Sample Entropy | 90.03       | 90.02       | 89.32         | 97.02       | 95.78       | 96.66         |

## IV. CONCLUSION

Emotion is nothing but a reflection of the psychophysiological state of the human being occurring due to various mental activities. The mental state of the person can be affected by emotion. To detect human emotions, Human Computer Interface (HCI) systems are used often. To describe emotion, HCI systems utilize various parameters such as posture, facial expressions, speech etc. Therefore, to evaluate the various types of emotion in humans, EEG signals are used. In the past decade, wavelet transforms, Shapelet transforms, Fourier transforms and other efficient signal processing techniques are coupled with machine learning and deep learning for the efficient classification of emotion from EEG signals. In this work, an efficient model EVSAE is proposed and a best result with an arousal of 96.87%, Valence

of 95.45% and Dominance of 96.09% is obtained for EMD+VMD+ Sample Entropy with ALO-ELM classifier for DREAMER dataset. Also, for the DEAP dataset, the same strategy produces a good result with an arousal of 97.02%, Valence of 95.78% and Dominance of 96.66% Future works aim to incorporate a lot of other efficient statistical signal processing techniques, machine learning, transfer learning and deep learning techniques for the efficient classification of emotion from EEG signals. Future works also aim to build a telemedicine and cloud-based implementation for remote health care monitoring systems dealing with the emotions from EEG signals.

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