

Leveraging EMD and VMD for Emotion Recognition in EEG-Based Brain-Computer Interfaces

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Abstract

This paper addresses the development of an innovative framework for emotion recognition through brain-computer interface (BCI) technology, which has opened new avenues for communication, particularly benefiting individuals with disabilities. Emotion recognition holds significant potential in various fields, notably in medical treatment and intelligent transportation systems (ITS), where the ability to understand emotional states can enhance user interaction and system performance. The proposed framework utilizes electroencephalograms (EEG) for emotion recognition, capitalizing on recent advances in human-computer interface technologies. By employing Variational Mode Decomposition (VMD), nonlinear and non-stationary EEG signals are decomposed into intrinsic mode functions (IMFs) at various frequencies. This decomposition serves as the foundation for subsequent emotion classification. To enhance the classification process, VMD is integrated with a range of feature extraction techniques, followed by the application of different machine learning classifiers, including K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM). The methodology was tested using data from eleven subjects, providing experimental validation of its effectiveness. The results demonstrate that the combination of VMD for feature extraction with SVM for classification yields the highest accuracy, achieving an impressive 96.77% in the experimental trials using a publicly available dataset. This suggests that the proposed SVM-based framework offers superior performance in emotion recognition, outpacing other classification methods in terms of accuracy and reliability. Overall, the study highlights the potential of combining advanced signal processing techniques like VMD with powerful machine learning algorithms such as SVM, offering a promising approach for emotion recognition in various applications. We recorded EEG data from eleven participants and demonstrated the classification of four emotional states with a mean accuracy of 90.43% using empirical mode decomposition (EMD) and 96.77% using variational mode decomposition (VMD). These results indicate that the classification performance using VMD is superior.

Key words-*k-Nearest Neighbor; Naive Bayes; Convolutional Neural Network; variational mode decomposition; Weighted cascade forest ; Empirical mode decomposition ; Support Vector Machine*

I. INTRODUCTION

The development of Brain-Computer Interfaces (BCIs) has marked a significant advancement in brain-based technologies, enabling novel methods of communication and control for devices like wheelchairs, robotic systems, and security or alarm solutions. Brain-Computer Interfaces (BCI) communication methods for controlling device. These systems leverage electroencephalography (EEG) to detect neural signals, which are then processed to execute specific tasks. EEG signals, captured non-invasively through scalp electrodes, provide a wealth of information about brain activity and have become a key component in various applications, particularly in emotion recognition. EEG-based emotional sensing has garnered significant attention due to its potential to enhance systems such as health care monitoring and adaptive human-machine interactions[1][2]. The study of human emotions is critical across fields like mental health diagnosis, decision-making, and social interaction[3]. Traditionally, humans have communicated emotions through facial expressions, body posture, and gestures, but machines lack this innate ability. Affective computing aims to bridge this gap by enabling machines to detect and interpret human emotions, improving accessibility, usability, and the overall effectiveness of human-machine interactions. Emotional experiences are intrinsically tied to physiological changes, such as variations in heart

rate, skin conductance, and pupil dilation. EEG signals offer a reliable way to analyze these physiological changes and classify emotional states. Recent advances in EEG-based emotion recognition focus on extracting meaningful features from the signals to enhance classification accuracy. Among feature extraction methods, Empirical Mode Decomposition (EMD) has been widely used due to its ability to decompose non-linear and non-stationary signals into intrinsic mode functions (IMFs). However, EMD faces significant challenges, including sensitivity to noise, mode mixing, and difficulties in separating overlapping frequencies. These limitations often result in suboptimal classification performance[4][5]. Variational Mode Decomposition (VMD) has emerged as a promising alternative, addressing these issues through superior frequency separation and adaptive decomposition. VMD offers a more robust framework for extracting features from EEG signals, potentially enhancing classification accuracy in Brain-Computer Interface (BCI) applications. This paper investigates an analytical comparison between features derived from VMD and EMD for emotional state classification in BCI applications. Specifically, the study examines the efficacy of these methods in classifying emotional states such as happiness, sadness, tension, and relaxation. In addition, advanced classification methods, including deep learning (DL) algorithms like Convolutional Neural Networks (CNNs) and traditional approaches

like Support Vector Machines (SVMs), are employed to evaluate the performance of features extracted using VMD and EMD.

The table(I) indicates to Previous studies have extensively utilized EMD in emotion recognition but have reported significant challenges with noise handling and frequency separation. On the other hand, VMD offers improved frequency separation and reduced interference, making it a promising technique for extracting EEG features. The combination of VMD with machine learning classifiers, including CNNs, SVMs, and K-Nearest Neighbors (KNNs), is evaluated to determine its effectiveness in addressing the limitations of EMD and enhancing classification performance. The primary contribution of this study is twofold:

- 1) it provides a detailed analysis of VMD and EMD for EEG-based emotion classification
- 2) it investigates the integration of these feature extraction methods with advanced classification techniques.

This research aims to establish whether VMD outperforms EMD in terms of feature quality and classification accuracy, offering a robust solution for emotion recognition in BCI systems. The paper is organized as follows: Section II describes the system model and experimental setup, Section III presents the results and analysis, and Section IV concludes the study with insights and future directions.

II. RELATED WORK

This section reviews and analyzes previous works related to emotion classification using EEG signals in Brain-Computer Interfaces (BCI). The analysis focuses on feature extraction methods, classification techniques, the number of classified emotions, the number of participants in the experiments, and the achieved classification accuracy.

A. Analysis of Previous Works

1) Using Frequency Transforms and Deep Learning Techniques:

- **Study:** Emotion Sensing[17].
- **Feature Extraction Method:** Frequency transforms such as DFT, FFT, and CUDA.
- **Classification Techniques:** Convolutional Neural Networks (CNN)
- **Number of Classes:** 22 classes representing imaginary emotional states using verbal suggestions.
- **Number of Participants:** Not specified.
- **Accuracy:** 72.03%.

2) Classification in Virtual Environments:

- **Study:** Emotional State Evoked by Virtual Environment[7].
- **Feature Extraction Method:** Principal Component Analysis (PCA).
- **Classification Techniques:** XGBoost, SVC, and Logistic Regression (L.R).
- **Number of Classes:** 15.
- **Number of Participants:** Not specified
- **Accuracy:** Best classification achieved among used models.

3) Classification Using Deep Neural Networks:

- **Study:** Emotion Detection[8].
- **Feature Extraction Method:** Statistical modeling methods and LCT
- **Classification Techniques:** CNN, RNN, KNN, DNN.
- **Number of Classes:** Four emotions (anger, calm, happy, sad).
- **Number of Participants:** 22.
- **Accuracy:** 75%.

4) Classification Using Manual Features and CNN:

- **Study:** Emotion Classification Using EEG[9].
- **Feature Extraction Method:** Manual feature extraction.
- **Classification Techniques:** AsMap+CNN.
- **Number of Classes:** Positive, negative, neutral.
- **Number of Participants:** 15.
- **Accuracy:** 97.10%.

5) Classification Using FFT and Other Methods:

- **Study:** Fear Learning in Humans[10].
- **Feature Extraction Method:** Fast Fourier Transform (FFT).
- **Classification Techniques:** Neuromeric EEG.
- **Number of Classes:** One (fear).
- **Number of Participants:** 30.
- **Accuracy:** 95.56%.

6) Using Python Tools for Emotion Recognition:

- **Study:** Emotion Recognition[11].
- **Feature Extraction Method:** Librosa tool in Python.
- **Classification Techniques:** SVM, Random Forest, Decision Tree.
- **Number of Classes:** Happiness, sadness, anger, fear.
- **Number of Participants:** Not specified.
- **Accuracy:** 90%.

7) Cross-Day Emotion Recognition:

- **Study:** Cross-Day EEG-Based Emotion Recognition[12].
- **Feature Extraction Method:** Transfer Component Analysis (TCA).
- **Classification Techniques:** SVM.
- **Number of Classes:** Positive-negative, joy-sadness, joy-anger, joy-fear.
- **Number of Participants:** 12.
- **Accuracy:** 83.03%.

8) Multi-Class Emotion Recognition Using PCD:

- **Study:** Multi-Class Emotion Recognition[14].
- **Feature Extraction Method:** PCD.
- **Classification Techniques:** Random Forest Classifier (RFC).
- **Number of Classes:** 23 (within the Valence-Arousal-Dominance model).
- **Number of Participants:** Not specified.
- **Accuracy:** 99.79%.

9) Using EMD and VMD with Deep Learning Classification:

- **Study:** Emotion Recognition Based on EEG Signal Using Deep Learning[15].
- **Feature Extraction Method:** Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD).

TABLE I: SUMMARY OF SURVEYED ON BCI BASED ON EMOTIONAL DETECTION

Activity	Feature Extraction Method	Classification Method	Number of Classes	Number of Participants	Classification Accuracy
Emotion Sensing [6]	DFT, FFT, CUDA	CNN	Imagination of emotional states using verbal suggestions	22	72.03%
Emotional State Evoked by Virtual Environment [7]	PCA	XGBoost, SVC, L.R.	EEG signals in virtual environments to identify emotional states	15	Best classification
Emotion Detection [8]	Statistica modelling method, LCT	CNN, RNN, KNN, DNN	Anger, calm, happy, and sad	22	75%
Emotion Classification Using EEG [9]	Manual feature extraction	AsMap+CNN	Positive, negative, and neutral	15	97.10%
Fear Learning in Humans [10]	FFT	Neuromeric EEG	Fear	30	95.56%
Emotion Recognition [11]	The Librosa tool in the Python package	SVM, Random Forest, Decision Tree	Happiness, sadness, anger, fear	2	90%
Cross-Day EEG-Based Emotion Recognition [12]	TCA	SVM	Positive-negative, joy-sadness, joy- anger, joy-fear	12	83.03%
The Brain Wave of Humans Lies [13]	Wave voltage powers	Statistical significant values	Pictures of various animals simulating human lies	5	Theta, Alpha, and Gamma
Multi-Class Emotion Recognition [14]	PCD	RFC	Emotions within the Valence-Arousal-Dominance model	23	99.79%
Emotion Recognition Based on EEG Signal Using Deep Learning [15]	EMD and VMD	SVM, KNN	Excited,delighted, calm, content, tired, depressed, frustrated, angry, tense, bored, relaxed	28	70.89%
Emotion Detection Using EEG [16]	DWT, HOC, STFT, MI	PCA, SVM, LDA	Databases studied for emotion detection using EEG signals		

- **Classification Techniques:**SVM and KNN.
- **Number of Classes:** 10 (e.g., happy, tired, angry).
- **Number of Participants:** 28.
- **Accuracy:**70.89%.

10) *Classification Using a Combination of Signal Techniques:*

- **Study:**Emotion Detection Using EEG[16].
- **Feature Extraction Method:**Discrete Wavelet Transform (DWT), Higher-Order Statistics (HOC), Short-Time Fourier Transform (STFT), Mutual Information (MI).
- **Classification Techniques:** PCA, SVM, LDA.
- **Number of Classes:** Multiple.
- **Number of Participants:** Not specified.

III. METODOLOGY SYSTEM MODEL

A. Experimental Setup

Twenty-one healthy participants, aged between 20 and 30 years (6 men and 15 women), took part in the experiment.

The standard deviation of the participants' ages was 4.1 years. Figure(1) illustrates the experimental setup, which included a Muse headset and a portable, rechargeable headband for electroen- cephalography (EEG) recording. The device was equipped with four EEG electrodes: two located near the ears (TP9 and TP10), one positioned just above the eyes, and two placed on the forehead (AF7 and AF8). Additionally, the headset incorporated a gyroscope and an accelerometer to monitor head orientation. The ground electrode and signal reference were placed on the right ear lobe. The EEG system sampled data at a frequency of 500 Hz. During the experiment, the Mind Monitor software generated raw EEG data at a sampling rate of 256 Hz, as depicted in Figure(2).

B. The proposed approach

To assess emotions, this study designed EEG experiments to analyses emotional responses[18]. This approach provides a sufficient number of emotional samples for deep neural

network analysis and evaluation of EEG signal characteristics. Emotional video materials were curated to offer participants both visual and auditory stimuli, creating the impression of real-life scenarios. The selected videos demonstrated four emotion types: happiness (guffaw), sadness, tension, and relaxation. The affective content spanned genres including comedy, crime, war, documentary, and horror, as illustrated in Figure(3). Additionally, a mental task requiring cognitive engagement was incorporated into the experimental session. Throughout each session, participants viewed a video on the screen that represented a specific emotional scenario. Each stimulus was presented for three minutes, after which the screen went blank for one minute before the next stimulus was introduced. This one-minute interval allowed participants to blink, stretch, or adjust, helping to maintain comfort and reduce potential interference with EEG data collection.



Fig. 1: EEG Muse device

C. Pre-processing

Pre-processing is a critical step in enhancing the characteristics of EEG signals. The input signals undergo multiple processing stages to reduce the signal-to-noise ratio and data dimensionality. This includes the elimination of data artefacts, as well as EMG, eye movement, and eye blink potentials. Several pre-processing steps were applied, as illustrated in Figure(4), including the use of a temporal filter—a 0.5 Hz to 30 Hz band-pass filter—based on a third-order Butterworth filter and a fast Fourier transform (FFT) filter for reference[15].

D. Feature Extraction

The feature extraction process involves various approaches to analyze and interpret EEG signals, including the use of Variational Mode Decomposition (VMD). Variational mode decomposition Variational Mode Decomposition (VMD) is an adaptive, quasi-orthogonal signal decomposition technique that solves a minimization problem through an iterative sub-optimization process. VMD enables the decomposition of multi-component signals into several band-limited intrinsic mode functions (IMFs) that consist of amplitude- and frequency-modulated signals with constrained bandwidths. The goal of VMD is to decompose a complex EEG signal, $x(t)$, into a specified number of modes, $(t)/\mu(t)$, referred to as sub-signals[18]. The VMD algorithm performs this adaptive decomposition[19]. VMD transforms the signal decomposition process into a variational framework, allowing the signal to be adaptively decomposed by seeking the optimal constrained variational model solution. Throughout the iterative solution process, the algorithm continuously estimates the center frequency and bandwidth of each intrinsic mode function (IMF) component. This results in adaptive frequency band division based on the signal's frequency characteristics, generating several narrow- band IMFs[20]. When the original signal is decomposed into K IMF components using VMD, the restricted variational model is expressed[19].

E. Feature selection

The study emphasized EEG classification by applying the Variational Mode Decomposition (VMD) approach. The pur-

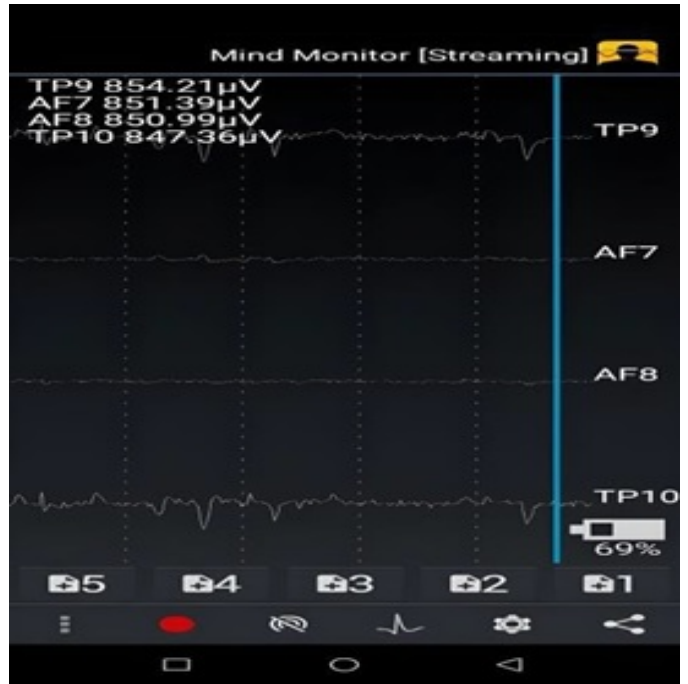


Fig. 2: Mind monitor RAW EEG

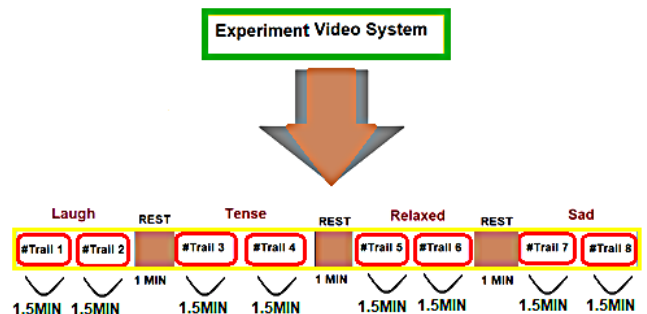


Fig. 3: Experimental session protocol

pose of using VMD was to reduce the dimensionality of EEG

data, as illustrated in Figure(6). To retain critical information while minimizing data size, the study focused on statistical features such as energy, entropy, and absolute power values. These features were chosen to provide insights into different aspects of the EEG signals. Specifically, energy represents the overall strength level of the signal, entropy quantifies the randomness or disorder within the signal, and absolute power values indicate the intensity of various frequencies present in the signal. By focusing on these features, the researchers aimed to effectively characterize EEG data for classification, improving the analysis quality if these methods are applied.

F. Classification

1) **ARTIFICIAL NEURAL NETWORKS:** The most commonly used classification method in Brain- Computer Interfaces (BCIs) is the Artificial Neural Network (ANN), which provides a robust foundation for pattern recognition tasks. Similar to human cognitive processes, ANNs can analyze, identify, and model nonlinear interactions, as illustrated in Figure(7)[21].

2) **SUPPORT VECTOR MACHINES:** Support Vector Machine (SVM) is one of the most widely recognized methods for supervised learning (S.L.), commonly applied to solve classification and regression problems. SVM works by selecting the critical data points, known as support vectors, to define the hyperplane that separates different classes within the dataset. This method is referred to as a "support vector machine" due to its reliance on these extreme data points to construct the decision boundary[22][21].

3) **K-NEAREST NEIGHBORS:** K-Nearest Neighbors (KNN) is a straightforward supervised machine learning (SML) technique commonly used for missing value imputation, as well as for classification and regression tasks. The core idea behind KNN is that the samples most similar to a given data point are those that are closest to it in the dataset. This proximity allows the classification of unknown data points based on the values of the existing nearest neighbors. The value of K determines how many of the closest neighboring observations are considered in the algorithm, and this parameter can be adjusted by the user to fine-tune the model[22][21].

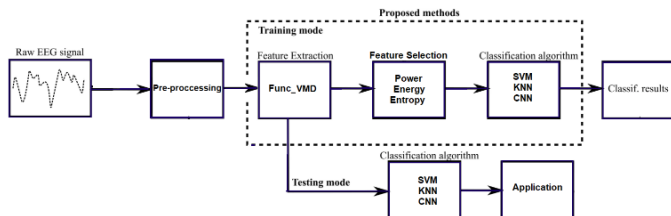


Fig. 4: Block Diagram Pre-processing

4) **EMPIRICAL MODE DECOMPOSITION:** Empirical Mode Decomposition (EMD) represents a conceptual advancement in time-frequency analysis for non-stationary and nonlinear signals. Using EMD, any EEG data can be decomposed into multiple independent intrinsic mode functions

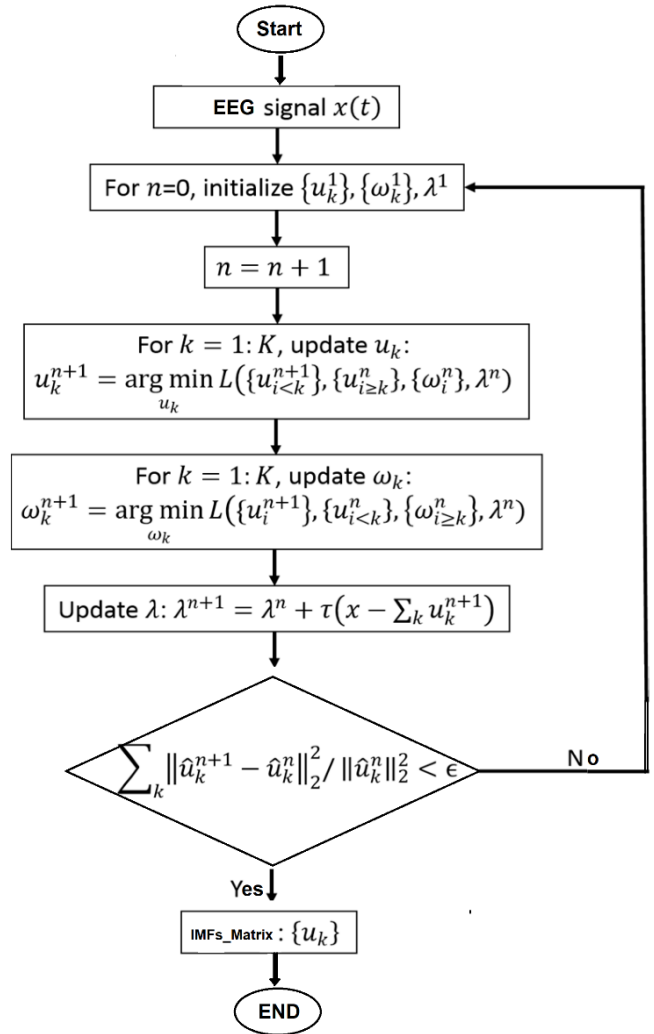


Fig. 5: Flowchart of empirical mode Variational decomposition algorithm.

(IMFs) and a residual component, based on the local characteristic scales of the signal. Specifically, the EMD algorithm adaptively decomposes a signal $x(t)$ into intrinsic mode functions $c_i(t)$, for $i=1,2,\dots,n$, along with a residual $r(t)$.

$$X(t) = \sum_{i=1}^n c_i(t) + r(t) \quad (1)$$

where n is the average number of intrinsic mode functions (IMFs). The residual $r(t)$ reflects either the average trend of the signal $x(t)$ or a constant value. The algorithm proceeds as follows:

- 1) Identify the upper envelope $x_u(t)$ based on the local maxima and the lower envelope $x_l(t)$ based on the local minima of the data
- 2) Calculate the mean $m(t)$ at each point of the envelopes.

$$m(t) = \frac{x_u(t) + x_l(t)}{2} \quad (2)$$

- 3) Obtain $h_1(t)$ by subtracting the mean $m(t)$ from the original data $x(t)$.

$$h(t) = x(t) - m(t) \quad (3)$$

- 4) Verify that $h_1(t)$ satisfies conditions for IMFs. Repeat Steps 1 to 4 with $h_1(t)$, until it is an IMF 5. Get the first IMF (after k iterations)

$$c_1(t) = h_{1(k-1)}(t) + m_{1K}(t) \quad (4)$$

- 5) Compute the first residue

$$r(t) = x(t) + c_1(t) \quad (5)$$

- 6) Repeat the entire algorithm with $r_1(t), r_2(t), \dots$ until the residual becomes a monotonic function. 8. After n iterations, the signal $x(t)$ is decomposed as per Equation (1). In this study, three types of features were extracted: energy, entropy, and absolute power. The aforementioned procedures were repeated for each class. These features serve as inputs to the artificial neural network (ANN) classifier, as illustrated in Figure(8) below[23].

IV. RESULTS AND ANALYSIS

A. Variational mode decomposition

For the presentation of results, the EEG data from a single subject is shown in Figure(9). This figure provides a graphical representation of the absolute brain waves recorded using the Mind Monitor app. The x-axis represents time in seconds, while the y-axis represents the amplitude of the brain waves in microvolts. Different colored lines on the graph correspond to different brain wave frequencies. The graph shows that the magnitude of brainwaves is relatively low at the beginning of the recording but increases over time. Additionally, brief periods of high-magnitude brainwave activity are observed, indicating moments of heightened concentration, focus, or other mental activities. Overall, the graph reflects typical brainwave activity during a state of relaxed wakefulness. Figure(10) presents the EEG signal from the TP9 channel of the Muse device, recorded while a single participant watched a video. The x-axis represents time, and the y-axis shows the magnitude of the EEG signal in microvolts. The graph includes two lines: the blue line represents the raw EEG signal, while the red line indicates the filtered EEG signal. The filtered EEG signal has been processed to remove high-frequency noise that may result from non-brain sources. The displayed EEG signal shows a mix of rhythmic low-amplitude, high-frequency activity alongside high-amplitude, low-frequency waves. The high-amplitude, low-frequency waves are indicative of delta waves, which are typically associated with deep sleep. In contrast, the low-amplitude, high-frequency oscillations are characteristic of alpha waves, which are generally observed during a wakeful state. Figure(11) displays a series of intrinsic mode functions (IMFs) obtained after performing Variational Mode Decomposition (VMD) on a single subject's EEG signal. The x-axis represents time in seconds, while the y-axis shows the magnitude of the EEG signal in microvolts. Each row in the figure corresponds to Different IMFs, with IMF1 representing the component with the highest frequency and IMF5 representing the component with the lowest frequency. These IMFs capture

various oscillatory patterns within the EEG signal, such as the alpha, beta, and theta bands. By analyzing the IMFs, it is possible to extract features related to brain activity and the subject's state of mind. These decomposed components provide valuable insights into the underlying neural processes. The features from IMF1 to IMF5 are extracted using a sliding window technique, resulting in 16,800-dimensional characteristics. To reduce the computational cost and improve efficiency, variable selection methods are applied to reduce the dimensionality of the features. The selected features, after dimensional reduction, are then fed into the Weighted Classification Function (WCF) for classification. This process enhances the classification performance by focusing on the most relevant features, thus minimizing the time required for analysis.

Algorithm :

```

1 Input: Raw EEG signal
2 Output: feature selection
   Data: Calculating [ Power, Energy, Entropy ]
3  $\sum_{i=1}^n := 0$  //  $i = 0, 1, 2, 3, \dots, N-1$ , where  $N$  = number of samples
   /* Step 1: Choose a sampling set */
   /* Step 2: Determine a EEG Feature Extraction using Func VMD */

4 for  $i = 1: N$  do
5   IMF_Matrix =  $\min_{m_n(t)} \sum_n \left\| \frac{\partial}{\partial t} \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * m_n(t) \right] e^{-j\omega_n t} \right\|_2^2$ 
                      s.t.  $\sum_n m_n(t) = f(t)$ 
6   [XN] = ImfS (N, i)
7   Power =  $\frac{1}{N} \sum_{k=1}^N (XN(k)^2)$ 
8   Energy =  $\sum_{i=1}^N |XN|^2$ 
9   Entropy =  $-\sum_{i=1}^N XN$ 
10  END

```

Fig. 6: The proposed approach for Feature Extraction Code using the VMD method and Power, Energy, and Entropy

B. Classification outcome

Table(II) shows the accuracy as measured from three classifiers. The table illustrates the classification accuracy of the subjects through the following algorithms: ANN, SVM, and KNN. Subject 1 shows an accuracy of 86.8% for ANN, 94.20% for SVM, and 87.8% for KNN. For subject S2, the accuracies are 82.5% for ANN, 96.70% for SVM, and 85.8% for KNN. Subject S3 achieved accuracies of 87.6% for ANN, 95.80% for SVM, and 87.1% for KNN. Subject S4 had accuracies of 90.1% for ANN, 98.50% for SVM, and 91.8% for KNN. Subject S5 had accuracies of 87.2% for ANN, 98.70% for SVM, and 88.5% for KNN. Subject S6 obtained accuracies of 88.3% for ANN, 94.70% for SVM and 89.2% for KNN. Subject S7 illustrated accuracies of 87.5% for ANN,

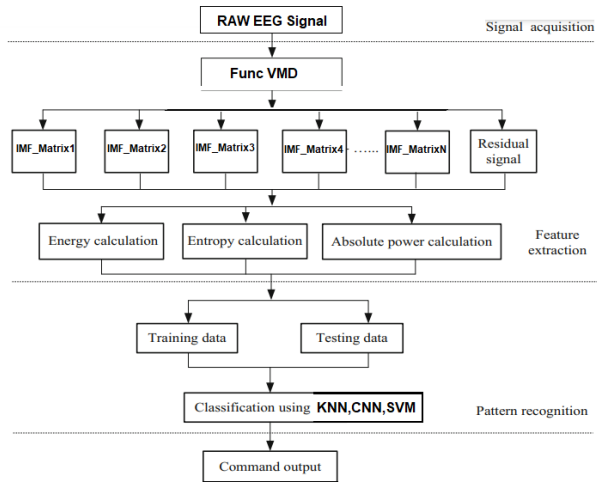


Fig. 7: Flowchart of the proposed classifier using the VMD method

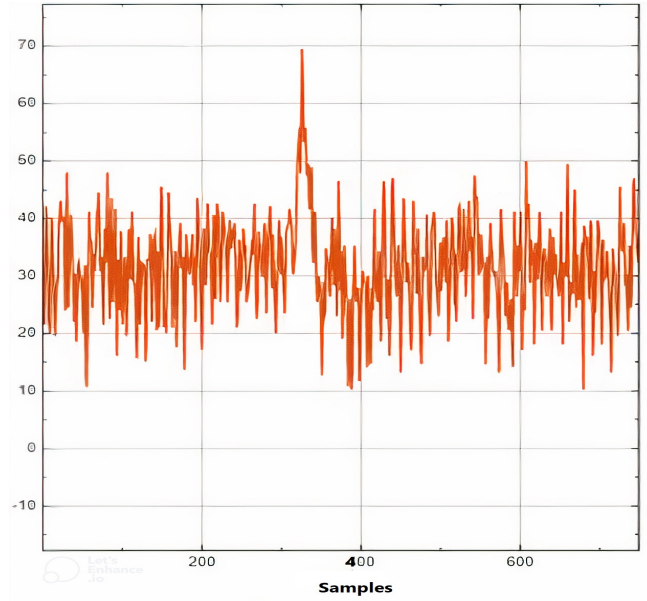


Fig. 10: A single subject in the TP9 channel EEG signal

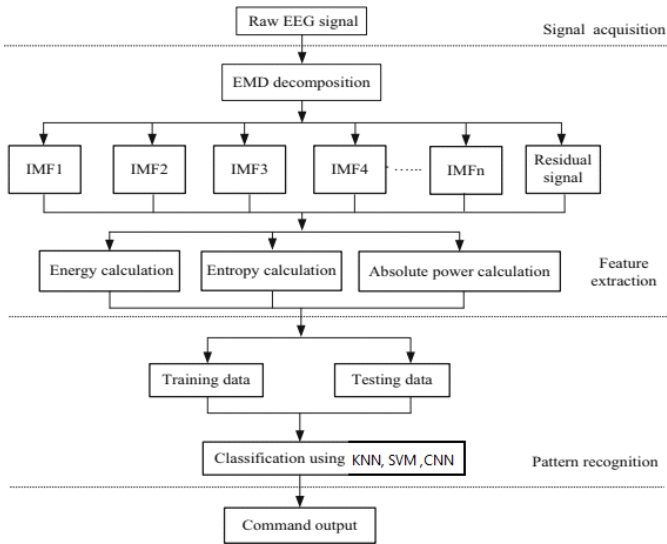


Fig. 8: Flowchart of the proposed classifier using the EMD method

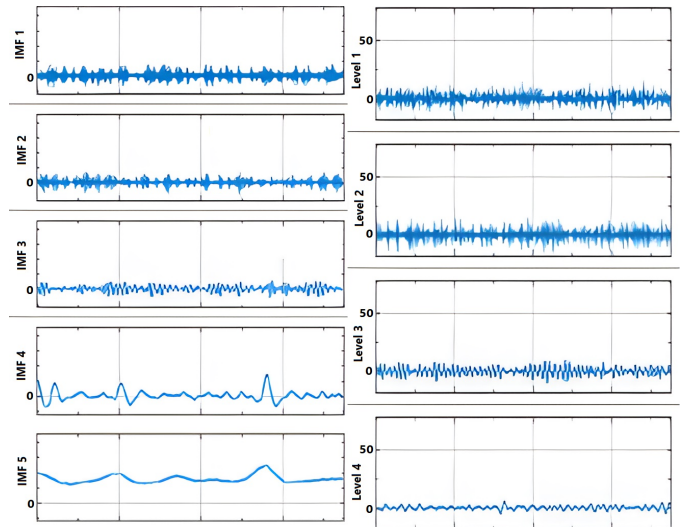


Fig. 11: IMFs after EEG signal decomposition of a single

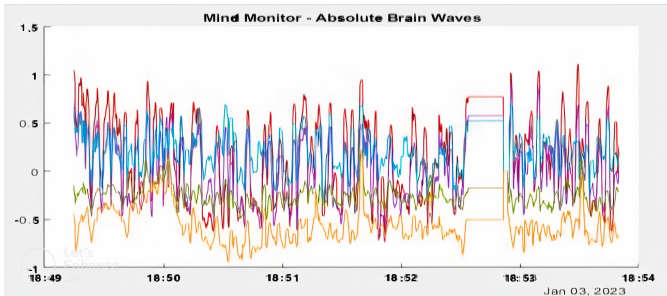


Fig. 9: Mind Monitor –Absolute Brain Waves

97.40% for SVM, and 88.3% for KNN. Subject S8 showed accuracies of 84.7% for ANN, 99.40% for SVM, and 85.3% for KNN. Subject S9 obtained accuracies of 85.1% for ANN, 94.90% for SVM and 85.8% for KNN. Subject S10 87.1% for ANN, 94.90% for SVM and 87.4% for KNN. Subject S11

88.1% for ANN, 95.50% for SVM and 89.6% for KNN. The mean accuracies are 86.97% for ANN, 96.77% for SVM, and 87.92% for KNN. Figure(12) compares the accuracy of three classification algorithms—KNN, SVM, and ANN—across four subjects: S1, S2, S3, and S4. The x-axis represents the subjects, while the y-axis represents the system's accuracy. The figure illustrates the performance of each algorithm using three lines, each corresponding to a different classification method. For subject S1, KNN achieves the highest accuracy compared to both SVM and ANN. In the case of subject S2, both KNN and SVM show the same accuracy, slightly outperforming ANN. For subject S3, SVM delivers the highest accuracy, surpassing both KNN and ANN. Finally, for subject S4, ANN achieves the best accuracy, followed by KNN and SVM. In conclusion, SVM demonstrates the highest average accuracy across all subjects, making it the top-performing model for

this classification task. KNN ranks second, while ANN ranks third. However, it is important to note that the performance of these algorithms can vary depending on the dataset and the parameters selected. The results indicate that, for this particular study, SVM provides the most accurate classification, although the efficiency of the algorithms may be influenced by the specific data and parameter choices. Figure(13) presents the Receiver Operating Characteristic (ROC) curves for the 4-Class motor imagery classification using the SVM classifier. The horizontal axis represents the false positive rate, while the vertical axis corresponds to the true positive rate. Each curve corresponds to a specific class, with the Area under the Curve (AUC) value given as 0.9333. The higher a curve is, the better the classifier performs for that particular class, with the leftmost top curve indicating a perfect classifier for the class. The dashed diagonal line represents random chance, where a classifier would perform with no distinction between the classes. In conclusion, the SVM classifier used in this study demonstrates satisfactory performance in classifying the four motor imagery classes, as evidenced by the high AUC value and the positioning of the curves relative to the diagonal line.

1) **CLASSIFICATION PERFORMANCE FOR EMD:** Table(III) shows the accuracy as measured from three classifiers. The table illustrates the classification accuracy of the subjects through the following algorithms: ANN, SVM, and KNN. Subject 1 shows an accuracy of 96.20% for ANN, 90.90% for SVM, and 95.70% for KNN. For subject S2, the accuracies are 92.30% for ANN, 96.00% for SVM, and 91.40% for KNN. Subject S3 achieved accuracies of 93.70% for ANN, 92.50% for SVM, and 95.70% for KNN. Subject S4 had accuracies of 91.1% for ANN, 100.00% for SVM, and 85.60% for KNN. Subject S5 had accuracies of 72.00% for ANN, 87.50% for SVM, and 77.50% for KNN. Subject S6

TABLE II: RESULTS OBTAINED FROM THE CLASSIFICATION OF PARTICIPANTS

Subject	ANN Accuracy (%)	SVM Accuracy (%)	KNN Accuracy (%)
S1	86.8	94.2	87.8
S2	82.5	96.7	85.8
S3	87.6	95.8	87.1
S4	90.1	98.5	91.8
S5	87.2	98.7	88.5
S6	88.3	94.7	89.2
S7	87.5	97.4	88.3
S8	84.7	99.4	85.3
S9	85.1	94.9	85.8
S10	87.1	94.9	87.4
S11	88.1	95.5	89.6
S12	86.5	96.1	87.2
S13	85.7	97.8	88.1
S14	89.3	98.4	90.3
S15	86.9	94.5	86.7
S16	88.4	97.2	89.4
S17	85.6	96.9	87.5
S18	87.7	99.1	88.9
S19	84.9	95.6	85.4
S20	87.3	96.4	88.2
S21	86.8	97.0	87.8
Mean	86.97	96.77	87.92

obtained accuracies of 66.20% for ANN, 88.10% for SVM and 55.30% for KNN. Subject S7 illustrated accuracies of

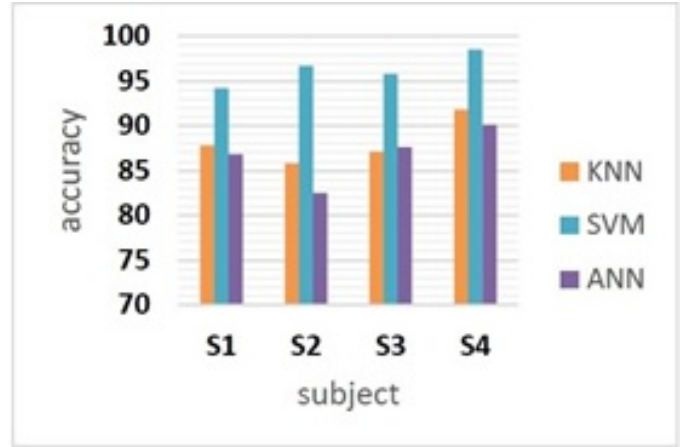


Fig. 12: the comparisons among KNN, SVM, and ANN

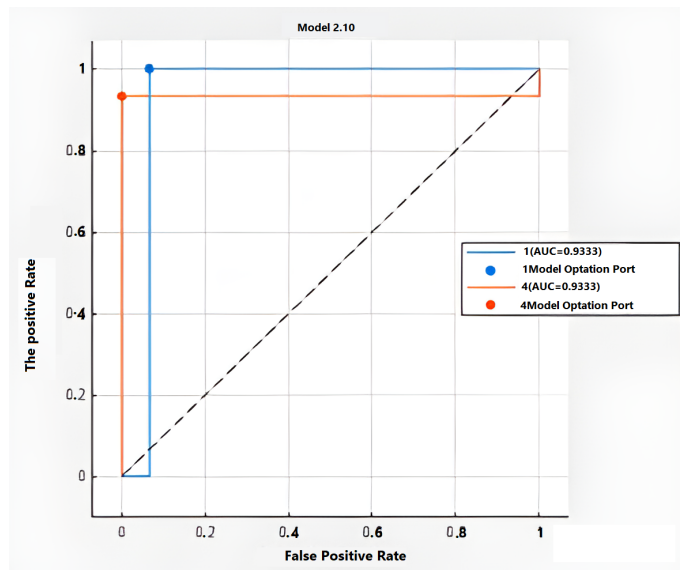


Fig. 13: the Roc curve for 4 Class motor imagery using SVM

71.00% for ANN, 91.40% for SVM, and 81.00% for KNN. Subject S8 showed accuracies of 80.90% for ANN, 85.30% for SVM, and 80.50% for KNN. Subject S9 obtained accuracies of 64.30% for ANN, 79.70% for SVM and 66.90% for KNN. Subject S10 78.10% for ANN, 89.40% for SVM and 75.40% for KNN. Subject S11 69.00% for ANN, 91.80% for SVM and 70.10% for KNN. The mean accuracies are 81.90% for ANN, 90.43% for SVM, and 84.80% for KNN.

2) **THREE CLASSIFICATION RESULTS:** We evaluated the proposed methods using raw EEG signals from all eleven participants. The objective of this study was to explore the potential to distinguish between four emotional states (guffaw, sad, tense, and relaxed) using EEG signals. Additionally, we investigated whether features derived from VMD were more effective than those from EMD in tasks related to emotion classification. Figure(14) compared EMD and VMD features, we evaluated three classifiers ANN, SVM, and KNN individually and calculated the accuracy associated with both EMD and VMD features. Statistical measures of sensitivity and specificity were applied to assess the performance of the

proposed methods. Table(II) presents the performance of all participants using VMD features, while Table(III) presents the performance with EMD features. The overall mean accuracy was 96.77% for VMD features and 90.43% for EMD features, indicating that VMD features outperformed EMD features.

TABLE III: COMPARISON OF CLASSIFICATION ACCURACY BETWEEN EMD AND VMD FEATURES

Subject	ANN Accuracy (%)	SVM Accuracy (%)	KNN Accuracy (%)
S1	96.20	90.90	95.70
S2	92.30	96.00	91.40
S3	93.70	92.50	95.70
S4	91.00	100.00	85.60
S5	72.00	87.50	77.50
S6	66.20	88.10	55.30
S7	71.00	91.40	81.00
S8	80.90	85.30	80.50
S9	64.30	79.70	66.90
S10	78.10	89.40	75.40
S11	69.00	91.80	70.10
S12	85.00	90.50	83.00
S13	87.00	92.00	88.00
S14	82.50	91.00	81.50
S15	90.00	93.50	89.00
S16	76.50	88.00	77.00
S17	80.00	90.00	82.00
S18	88.00	94.00	85.00
S19	85.50	92.50	84.50
S20	91.00	96.00	90.00
S21	89.50	93.00	88.50
Mean	81.90	90.43	84.80

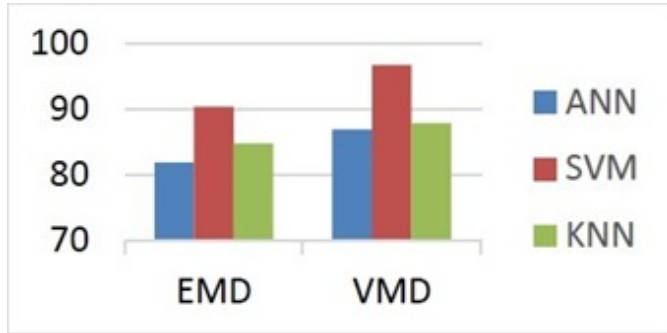


Fig. 14: Comparison the mean for EMD and VMD

V. CONCLUSION

A system based on Muse EEG and VMD feature extraction was successfully developed. The system achieved an impressive average accuracy of 96.77% using the SVM classifier. However, higher performance could be attained by exploring additional key factors involved in the experiments. These factors include experimenting with various EEG acquisition tools, enhancing the system's adaptability, selecting optimal electrode placements near brain regions associated with visual processing, and conducting further testing. The performance of the framework is also evaluated under different conditions and variations to optimize its effectiveness.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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