

PERFORMANCE ANALYSIS OF SUPERVISED LEARNING ALGORITHMS FOR IDENTIFICATION OF AUTISM SPECTRUM DISORDER USING EEG SIGNALS

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Abstract-Autism Spectrum Disorder (ASD) is a sort of developmental issue of the nervous system, with center impedances in social connections, creative mind, communications, adaptability of thought, intrigue and restricted range of activities. Examination of electroencephalographic (EEG) signals based on autism is explored in this work. Even so, it is critical to identify autism by the analysis of the EEG signal. Hence feature extraction based on the EEG signals takes part a prominent role in autism recognition. A practical feature extraction technique variational mode decomposition (VMD) to diagnose autism is narrated in this paper. Further, the features extracted are fed to classifiers ANN, KNN and SVM to stratify autism. SVM classifier shows a finer classification performance when compared to extant techniques.

Keywords: Variational Mode Decomposition, Electroencephalogram, K-Nearest Neighbor, Artificial Neural Network Support Vector Machine.

I. INTRODUCTION

Autism spectrum disorder (ASD) is a complex formative condition which incorporates autism, Asperger's syndrome, and pervasive developmental disorder [1]. The electrical impulses of brain behaviors are reflected by electroencephalogram (EEG) signals. A significant clinical tool is formed for diagnosing and monitoring neural disorders like autism from EEG signals using signal processing methods. Most encephalopathy diagnoses are currently conducted manually by skilled clinicians or neurologists through physical examination of EEG signals.

In human body, brain is the extremely complicated area and provides a good sort of information associated with the limbic system and nervous system disorders. In the past few years, researchers in collaborative discipline of neurophysiology, engineering, bioengineering and neuroscience etc, attempted to attain advantageous knowledge from EEG signals in various application domains, like medical diagnosis, controls and communications. To enhance and improve an effective diagnosing system currently, in this field numerous studies

are being conducted. A computer-aided diagnosis (CAD) is a computer set up to assist a doctor or a clinician in diagnosing a specific disease or disorder. A CAD system isn't purposive to detect by itself even so as an aiding tool for the clinician to diagnose, saving them time, increasing accuracy, and providing a second opinion. In recent times, researchers attempting to establish a computer-aided ASD diagnosis supported electroencephalographic signals [2].

The frequency range of encephalon's electrical signals in the range of 4 Hz to 80 Hz and around 100 μ V of smaller amplitude. Usually every EEG signal split into different sub-bands: Delta in the range of 0.5 Hz -4 Hz, Theta in the range of 4 Hz -8 Hz, Alpha in the range of 8 Hz - 12 Hz, Beta in the range of 13 Hz -30 Hz, and Gamma in the range of 30 Hz -60 Hz.

The frequency-based frequency and energies in distinct sub-band features employed to ANN for categorizing autism besides typical EEG [6]. The time dependent standard deviation and spectral based entropy features employed to KNN for categorizing autism besides typical EEG [3]. Spectral features of EEG are used with SVM, KNN, decision tree, Bayes network, and naive Bayes classifier to classify autism [4].

The time dependent approximation entropy and Hurst exponent features employed with SVM to categorize autism besides normal electroencephalogram [5].

The nature of encephalographic signals could portray best by feature extraction and are eminent for the classification of autism. EEG signals unseen special attributes are encapsulated with the extraction of features, and significant feature optimizations influence absolute classification accuracy. This work, motivated by the evaluation of encephalographic data. An approach presented that incipiently performs VMD on different autistic and typical controls to extract spectral and statistical features.

The EEG dataset of autism adopted from Kaggle database [8]. The channels order in the data matrices is C3, Cz, C4, CPz, P3, Pz, P4, POz. The EEG dataset of typical controls is acquired from the Bonn University Hospital of Freiburg [9]. It contains five separate subsets (A-E) named Z, O, N, F, and S. Typical controls were recorded from Set A & B. By using the frequency decimation technique, the frequencies of both datasets are equalized.

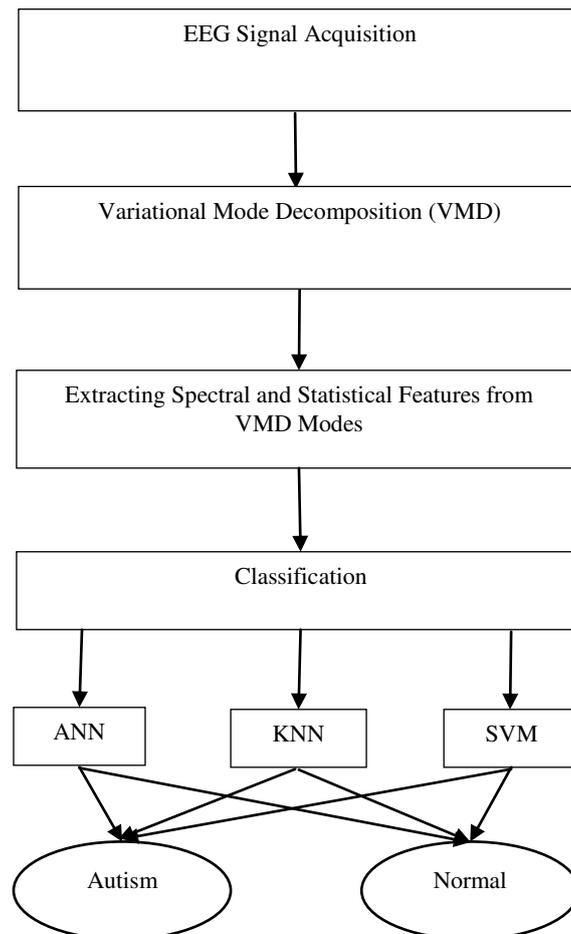


Figure 1: Flow diagram of EEG signals classification using VMD method.

The residue of the paper as follows: Methodology of VMD, extraction features in domain of VMD, and introduced three classification techniques in Section II. Section III discussed, every individual classifier's extracted features performances concerning their confusion matrix to locate performance parameters. The experimental results and comparison between various researches is explained in same section. Section IV finally concludes.

II. METHODOLOGY

A VARIATIONAL MODE DECOMPOSITION

Variational mode decomposition (VMD) a novel adaptive signal fragmentation, it fragments each real-time signal to variational modes (u_k) or a band limited functions. For the reconstructing an input signal, each method transpired concurrently and exhibited sparsity property. VMD fragments real-time signals into k modes (u_k) surrounding its centerfrequency (ω). Frequency shifting property and Hilbert transform are beneficial variables in formulation and optimization of a problem. The constrained variational problem formulation is [10],

$$\min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}$$

$$\sum_k u_k = f \quad (1)$$

The quadratic penalty factor and Lagrangian multiplier (λ) converts to (2) from (1), The unimpeded optimization issue is denoted as (2)

$$\ell(\{u_k\}, \{\omega_k\}, \lambda) := \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \quad (2)$$

To resolve (2) Lagrangian function ℓ , the optimization method is Alternate Direction Method of a Multiplier. To upgrade every mode $u_k(\omega)$ perfectly in spectral domain Wiener filter imposed in VMD.

Algorithm: EEG signals decomposition using VMD described in the following steps.

1: K is predetermined, no. of modes.

2: Initializing of $\{\hat{u}_k^1\}$, $\{\omega_k^1\}$, $\hat{\lambda}^1$, and $n = 0$;

3: For $n = n+1$: K for $\omega \geq 0$, Repeat the loop till $k=1$. $\hat{u}_k(t)$ keeps on changing in spectral domain [10],

$$\hat{u}_k^{n+1}(\omega) \leftarrow \frac{\hat{f}(\omega) - \sum_{i < k} \hat{u}_i^{n+1}(\omega) - \sum_{i > k} \hat{u}_i^n(\omega) + \frac{\hat{\lambda}^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \quad (3)$$

$$\hat{u}_k^{n+1}(t) = \text{Real}\{\text{ifft}(\hat{u}_k^{n+1}(\omega))\}$$

$$\text{Update } \omega_k \text{ with} \quad (4)$$

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega} \quad (5)$$

4: Repeat till k equals K and n iteration of the loop, Assign $k=k+1$.

5: λ , upgraded for all $\omega \geq 0$ from dual-ascent

$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau \left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega) \right) \quad (6)$$

6: Repeat steps 2 to 5 till the obtained modes meet the convergence condition.

$$\sum_{k=1}^K \frac{\left\| \hat{u}_k^{n+1} - \hat{u}_k^n \right\|_2^2}{\left\| \hat{u}_k^n \right\|_2^2} < \varepsilon \quad (7)$$

Here ε , τ and τ represent dual ascent convergence time steps and Tolerance Fourier transform respectively. Real (), Ifft () represents real part of the analytic signal and Inverse Fourier transform. In VMD choosing parameter is an initial function.

Figure 2 a, b represents the decomposition of mode of typical control and autistic EEG signals respectively.

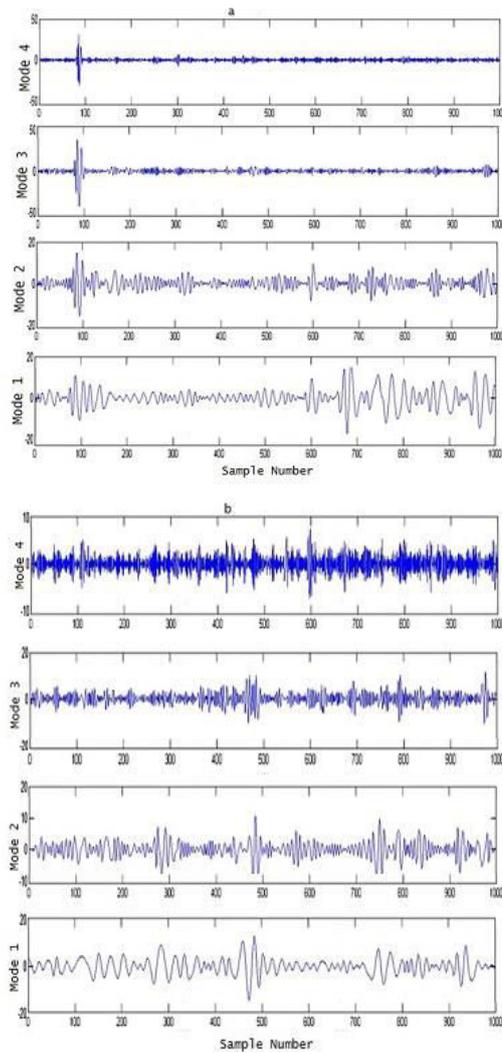


Figure 2: (a) Autistic Signal (b) Typical Control EEG signal

Feature extraction:

Statistical features:

Mean: It is expressed as [13],

$$\mu = \frac{1}{N} \sum_{i=1}^N Y_i \quad (8)$$

Standard deviation: Is expressed as

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (Y_i - \mu)^2} \quad (9)$$

Coefficient of variation (COV): Is given as [11].

$$COV = \frac{\sigma}{\mu} \quad (10)$$

Entropy (H): It is expressed as [11],

$$H(Y) = -\sum_{i=1}^N p(y_i) \log(p(y_i)) \quad p(y_i) = [p(y_1), p(y_2), \dots] \quad (11)$$

Inter quartile range (IQR): Is expressed as

$$IQR = Q3 - Q1 \quad (12)$$

Here, Q1 first quartile and Q3 third quartile respectively.

Skewness: It can be given as

$$\text{Skewness} = \frac{1}{N} \sum_{i=1}^N \left(\frac{y_i - \mu}{\sigma} \right)^3 \quad (13)$$

NegEntropy: It can be derived as

$$J(Y) = H(Y_{\text{gauss}}) - H(Y) \quad H(Y_{\text{gauss}}) = \frac{1}{2} \log(2\pi e \sigma^2) \quad (14)$$

Kurtosis: It is expressed as

$$k = \frac{1}{N} \sum_{i=1}^N \left(\frac{y_i - \mu}{\sigma} \right)^4 \quad (15)$$

Spectral features :

Spectral flatness (SF): It is given as [10],

$$SF = \frac{\prod_{m=0}^{N-1} |Y[m]|^{\frac{1}{N}}}{\frac{1}{N} \sum_{m=0}^{N-1} |Y[m]|} \quad (16)$$

Spectral spread (SS): It can be expressed as

$$SS = \frac{\sum_{m=0}^{N-1} (m - SC)^2 |Y[m]|}{\sum_{m=0}^{N-1} |Y[m]|} \quad (17)$$

Spectral centroid (SC):

$$SC = \frac{\sum_{m=0}^{N-1} m |Y[m]|}{\sum_{m=0}^{N-1} |Y[m]|} \quad (18)$$

Spectral decrease (SDec): It is given by [10],

$$SDec = \frac{\sum_{m=1}^{N-1} \frac{1}{m} (|Y[m]| - |Y[0]|)}{\sum_{m=1}^{N-1} |Y[m]|} \quad (19)$$

B K-NEAREST NEIGHBOR CLASSIFIER (KNN): Among the non-parametric approaches used for classification of electrophysiological signals, KNN is one. The input comprises K closest training samples (data points), and the output is a class member in the classification problem. A sample will be classified with the majority vote of the neighbours and assigned to a class which is most common among K-nearest neighbours. Class membership is the output in KNN for classification. To achieve the classification results testing and training datasets of autistic EEG are applied to K-nearest neighbours. The processing function used is Spearman distance [14].

Spearman Distance

The distance between the data vectors x_s and y_t are defined as

$$d_{st} = \left(1 - \frac{(r_s - \bar{r}_s)(r_t - \bar{r}_t)}{\sqrt{(r_s - \bar{r}_s)(r_s - \bar{r}_s)^T} \sqrt{(r_t - \bar{r}_t)(r_t - \bar{r}_t)^T}} \right) \quad (20)$$

CARTIFICIAL NEURAL NETWORK (ANN): ANNs are motivated with biological neural networks, i.e., animal central nervous systems especially brain. These are used to approximate or estimate functions that can depend on a high number of unknown inputs. Different connections have different numeric weights, which can be turned based on experience, makes the ANNs capable of learning and are more adaptive to inputs. The set input neurons get activated by the input data. The output neuron determines the target class to which the data belongs to. For testing the performance, using ANN for categorization of autism EEG dataset is used [15]. The processing function used is sigmoid function.

Sigmoid Function

Sigmoid function corresponds to the shape of "S" (sigmoid curve) and it is a mathematical function which belongs to a special incident of the logistic function. It can be expressed as

$$S(t) = \frac{1}{1 + e^{-t}} \quad (21)$$

A sigmoid function has a positive derivative for all real input values that is defined, it is a bounded differentiable real function.

D SUPPORT VECTOR MACHINES (SVM): The classifier is given to above features for categorization of typical EEG signal. Decision function in two class problem is expressed as

$$g(x) = \text{sign}[w^T f(x) + b] \quad (22)$$

Optimization problem is given as

$$\text{Minimize } J(w, b, e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^N e_i^2 \quad (23)$$

$$\text{Subject to } y_i [w^T f(x_i) + b] = 1 - e_i, \quad i=1, 2, \dots, N \quad (24)$$

Here x_i is N input with i^{th} feature vectors, and y_i is the class label of 1 or -1 for x_i . γ is the parameter of regularization, α_i is a Lagrangian multiplier and b is the bias term. its SVM classifier output derived as

$$g(x) = \text{sign} \left[\sum_{i=1}^N \alpha_i y_i K(x, x_i) + b \right] \quad (25)$$

SVM classifier needs kernel for training. The Gaussian RBF kernel is the efficient one. RBF kernel is expressed as

$$K(x, x_i) = f^T(x) f(x_i) = e^{-\frac{\|x-x_i\|^2}{2\sigma^2}} \quad (26)$$

Parameter σ is an optimization kernel width [12].

III. RESULTS WITH DISCUSSION

In this work, a systematic procedure for categorization of the autistic and typical EEG along with the assistance of features based on VMD is propounded, devised, developed and imposed. The propounded classification algorithms of autistic signals are enacted and simulation done in MATLAB, and this section presents the simulated results.

Table 1 illustrates the simulation results of the classification algorithm of autism along with ANN. In accordance with the attained confusion matrix, classification algorithm based on ANN classifier accomplishes an overall sensitivity 90.83%, overall accuracy 88.80%, overall specificity 86.66%, overall F_measure 88.97%, overall precision 87.20% and overall G_mean 88.72%.

Table1. Autism Classification using ANN Confusion Matrix

Signal	Autism(%)	Typical Control (%)
Autism	90.8	13.3
Typical Control	9.2	86.7

Table 2 illustrates the simulation results of the classification algorithm of autism along with KNN. In accordance with the attained confusion matrix, classification algorithm based on KNN classifier accomplishes an overall sensitivity 94.16%, overall accuracy 89.60%, overall specificity 85.00%, overall F_measure 90.03%, overall precision 86.25% and overall G_mean 89.46%.

Table2. Autism Classification using KNN Confusion Matrix

Signal	Autism(%)	Typical Control (%)
Autism	94.2	15.0
Typical Control	5.8	85.0

Finally, Table 3 illustrates the simulation results of the classification algorithm of autism with SVM. In accordance with the attained confusion matrix, SVM classifier acquires all time higher classification performance when analyzed with KNN and ANN. It accomplishes

an overall sensitivity 98.33%, overall accuracy 92.50%, overall specificity 86.66%, overall F_measure 92.91%, overall precision 88.05% and overall G_mean 92.31%.

Table 3. Autism Classification using SVM Confusion Matrix

Signal	Autism(%)	Typical Control (%)
Autism	98.3	13.3
Typical Control	1.7	86.7

Table 4. Autism Classification Performance Summary

S.No	Parameter	ANN	KNN	SVM
1	Accuracy	88.80	89.60	92.50
2	Sensitivity	90.83	94.16	98.33
3	Specificity	86.66	85.00	86.66
4	Precision	87.20	86.25	88.05
5	F_measure	88.97	90.03	92.91
6	G_mean	88.72	89.46	92.31

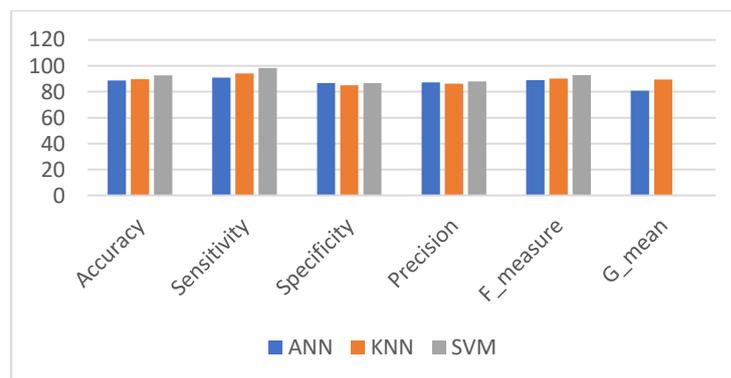


Fig. 3. Comparison of performance parameters (Bar Graph)

The comparison shows that the SVM classifier-based autism classification algorithm shows predominately more adequate classification accuracy over ANN and KNN. Besides, all the SVM classifier's performance parameters also offer more satisfactory results when compared with ANN and KNN.

From Table 5, the propounded method achieved a high accuracy rate compared to work from the literature. Besides, novel decomposing techniques and features, in propounded scheme exhibit substantial enhancement.

TABLE 5. Comparison of Various EEG Based ASD

Author	Extracted Features	Classifier	Results
W. H. Tager-Flusberg, Tierney, and C. Nelson [5]	- mean - pvalue -standard deviation -mean multiscale entropy (mMSE)	Support Vector Machine (SVM)	80-90%
Djema. R., A. Alsuwailem, K. AlSharabi and S. Ibrahim [6]	-mean -variance -(SD)Standard deviation -skewness -kurtiosis	Artificial Neural Network (ANN)	90%
Vij A. Sheikhan, M. Noroozian, H. Behnam, P. Golabi and M. R. Mohammadi [3]	-mean -standard deviation -coherence	KNN	82.4%
M. J. Alhaddad, H. M. Malibary and M. I. Kamel [7]	-spectral spread -statistical features -spectral flatness	FLDA	90%
T. RoopaRechal	-spectral spread -statistical features -spectral flatness	ANN KNN SVM	88.80% 89.60% 92.50%

IV. CONCLUSION

In this study, the proposed method initially performs VMD to extract the spectral and statistical features of various autistic and typical signals. A significant method is developed for extracting features of EEG signals, and calculated a total of 44 features with four level decomposition of testing and training datasets. The best approach to fuse the diagnosing of autism by various machine learning algorithms such as ANN, KNN, and SVM is exhibited. In each algorithm accuracy, precision, specificity, sensitivity, F_measure and G_mean observed. Among this, SVM classifier attains highest classification accuracy over KNN and ANN. Hence, the SVM classifier is better in diagnosing the autism.

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