Epilepsy Identification Based on VMD, RELIEFF Algorithm and Machine Learning Classification Techniques

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Abstract: Epilepsy identification is done by visual observation of electroencephalography (EEG) signals, which is more sensitive to bias and time consuming. In most of the previous research of epileptic seizure detection suffers from unsuitability and low power for processing large datasets. To eliminate aforementioned problems a computerized detection method is required to aid medical professionals. In this paper, a new technique is proposed to identify the epilepsy based on VMD, RELIEFF algorithm and machine learning approach. To investigate the proposed method performance a public EEG dataset is adopted from university hospital bonn, Germany. The technique starts with the VMD, which is used to extract the features from each EEG signal. And then RELIEFF algorithm is adopted to identify the best features. Finally to categorize the normal and epilepsy EEG signals a machine learning classification (ANN, KNN, and SVM) approach is used. The results demonstrate that the adopted method (VMD+RELIEFF+SVM) can achieve a better accuracy, shows that a commanding method to identification and classification of epileptic seizures.

Index Terms: Variational Mode Decomposition, RELIEFF algorithm, ElectroEncephlogram, Machine Learning Method.

I. INTRODUCTION

Epilepsy is a neurological disorder (any disorder of nervous system). The cause of most cases, epilepsy occur as a result of brain injury, strokes or abnormal activity of brain cell (i.e., produce four times larger signal than of normal). It causes seizures, loss of awareness sometimes or neuronal activity in the cortex of the brain. The majority of epileptic cases are increasing across the world extremely from time to time. In many situations, epileptic disorders or seizures can handle with medication (anti-epileptic) nearly 70% of situations or sometimes with surgery or neuron stimulation.

Electroencephalogram (EEG) is often used to confirm epilepsy. It is method of monitoring and recording electrical activity of the brain. During the test electrodes are placed along the scalp. The normal pattern of brain waves will be changed, even when an individual is not having a seizure but an epilepsy. It is possible to diagnose epileptic seizure by examination of the recorded signal using efficient techniques. The fig. 1 (https://www.brainlatam.com/products/eeg-electrode-caps) shows the EEG electrode placement. Epilepsy patients reveal two stages of unusual activities with their EEG signals i.e., ictal and interictal. Ictal is the record of an EEG while a seizure is occurring (waveforms with sharp & spikes). Interictal is the period between the seizures (transient waveform i.e., spiky & sharp). By examination of long duration of EEG signals, experienced neurologists with conventional method reveals epilepsy. But this procedure requires long duration of time and vulnerable to diagnosis of errors. Hence to overcome these limitations a Computer-aided detection (CAD) of epileptic EEG signals can be used.

Fig. 1.EEG electrode placement

The electrical signal of brain cells usually has very small amplitude which is in the range of 100 microvolts. The frequency is in between 0.44 Hz and 80 Hz. Normally, EEG signals are classified into five sub-bands, namely delta (0.5-4Hz), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz) and gamma (30-60Hz). Table 1 shows the amplitude and frequency range for each type of waves [2].

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Table-I: Band Frequency and Amplitude

Band	Frequency (Hz)	Amplitude
Delta	0.5 – 4	Maximum
Theta	4 – 8	Medium
Alpha	8 – 15	Minimum
Beta	15 – 30	Very small
Gamma	30 – 60	Smallest

In this paper, a new epilepsy identification technique based on VMD, RELIEFF, and machine learning classification approach is proposed. Variation mode decomposition (VMD) is a new adaptive signal decomposition technique which decomposes any real-time signal into band-limited functions or variation modes and extracts the features. The main purpose of feature extraction is to obtain the unique properties hidden in the EEG signals. The suggested method also employed a RELIEFF algorithm to choose the best features of the EEG signals. Finally, machine learning classification approach is used to classify the EEG signals.

The remainder of this paper is organized as follows. In Section II literature review of existing works are presented. Section III presents detail discussion about the used techniques (i.e, VMD, RELIEFF, ANN, KNN and SVM). With the extracted features performance of each classifier with respect to their confusion plots for finding performance parameters discussed in section IV. The obtained experimental results are also discussed in this section. Finally, concluding remark of the proposed method is presented in Section V.

II. RELATED WORK

In this section, epilepsy identification and classification of EEG signal processing relevant literature are discussed briefly.

A technique proposed by Juarez-Guerra et al. [3] to design an epilepsy seizure detection using EEG signals. In their technique, to filter the artifacts both FIR and IIR were used, and after that to split the signal into five sub bands they used wavelet analysis. Finally to extract features DWT and MODWT analysis were applied. By using Feed-Forward Neural Network classification, they achieving an exactness of 93.23%.

Yinxa Liu et al. [4] developed a seizure detection method based on Wavelet method. In this method signal divided into 5 sub-bands and for further process only 3 sub-bands selected. Then, features like fluctuation index, relative energy, COV (coefficients of variation) and relative amplitude extracted and given to SVM (support vector machine) for classification. In paper [5] Authors proposed a technique to detect epilepsy based on multichannel EEG signal. In the beginning, to filter the EEG signal Pass-band filter (0.1-7Hz) has been used. By applying the approximate entropy, statistical features were obtained like energy, total variation, and standard deviation. Different (SVMs) techniques were used to classify and detect the epilepsy. The results shows that Grid SVM had better performance compared to the rest with higher accuracy.

A technique proposed by Dawood Dilber et al. [6] using wavelet transform to extract the frequency domain and time domain features for classification and detection of epilepsy

seizure. To differentiate epileptic and non-epileptic the proposed method used machine learning approach such as DAT and SVM and it achieved an accuracy of 70%, and 93% respectively.

A method was proposed by Md. Mamun o Rashid et al. [7] to split EEG signals DWT was used to extract statistical features from the signal. After that, the extracted features fed to a Neural Network machine learning to determine epileptic and non-epileptic signals.

III. PROPOSED METHOD

The intention of this work is to adopt a method which can identify epilepsy by processing of EEG signals. The suggested method uses VMD, RELIEFF, and machine learning algorithms. In the next section, a brief explanation and underlying mathematical expression are provided for the used techniques.

A. Variational Mode Decomposition

Variational mode decomposition (VMD) is a new adaptive signal decomposition technique and it decomposes any real time signal into a band limited functions or variational modes (u_k). Each mode occurred concurrently and exhibit the sparsity property for reconstruction of an input signal. VMD decomposes a real time signal into k modes (u_k) around its center frequency (ω). Hilbert transform and frequency shifting property are useful parameters in formulation of an optimization problem. The formulation of a constrained variational problem as [8],

$$\min_{\{u_k\},\{\omega_k\}}\left\{\sum_k \left\| \partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \quad (1)$$

$$\sum_k u_k = f$$

The quadratic penalty factor and Lagrangian multiplier (λ) are converts into (2) from (1), The unconstrained optimization problem is expressed as (2);

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

The alternate direction method of a multiplier (ADMM) is an optimization method to solve (2) lagrangian function ℓ, it estimate modes around its own center frequencies. The wiener filter is embedded in a VMD to update each mode $u_k(\omega)$ optimally in a spectral domain.

Steps for decomposition of EEG signals by using VMD algorithm are provided below.

Step-1: predefine K which is the number of modes.

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

Step-3: For $n = n+1$, repeat loop until $k=1: K$ for $\omega \geq 0$. It keep on change $\hat{u}_k(t)$ in the spectral domain is ,

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

$$(3) \quad \hat{u}_k^{n+1}(t) = \text{Real}\{\text{ifft}(\hat{u}_k^{n+1}(\omega))\} \quad (4)$$

Update ω_k with

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

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

Step-4: Assign $k=k+1$, repeat until k equals K and n iteration of the loop

Step-5: λ(Lagrange multiplier), updated for all ω≥0 based on dual-ascent

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

Step-6: Repeat the above steps 2 to 5 until to obtain the modes by satisfy the convergence condition.

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

Here ∈ ,^ and τ represents the tolerance Fourier transform and time steps of dual ascent convergence respectively. Ifft ( ), Real ( ) are represents the inverse Fourier transform and real part of analytic signal. In VMD, the selection of a parameter is a first task, a number of modes (*K)*, and alpha.

The mode decomposition of normal and epilepsy EEG signals are in Figure 2a, Figure 2b shown respectively. It signifies that the mode increases also its frequency increases.
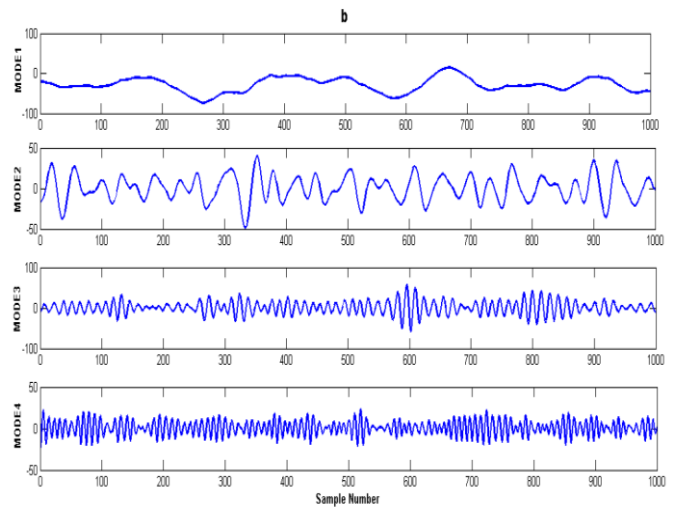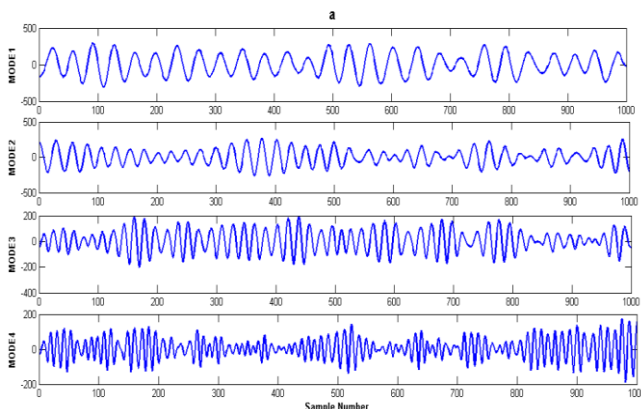

Fig. 2.VMD of four modes (a) Epilepsy signal (b) Normal EEG signal examples

B. Feature extraction:

1) Statistical features:

For an N sample EEG signal *y[n]* gives the magnitude spectrum of *Y[m]*.

Statistical features:

Mean: It is the average of an N sample EEG signal; it can be defined .

an: It is the average of an N sample EEG signal; it can be defined [16],

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

Standard deviation (SD): The dispersion of data from it's a mean value of a signal is a standard deviation. It is derived as,

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

Coefficient of variation (COV): It is ratio of SD to mean of the EEG signal is a coefficient of variation. It can be expressed as,

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

Entropy (H): It is defined as the measuring of randomness in EEG signals. For an EEG signals with N number of samples (y_1, y_2, y_3,…. Y_N) is expressed as,

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

Inter quartile range (IQR): It is the change between 75th and 25th percentile of samples, It measures variability in a data set is given by ,

$$IQR = Q_3 - Q_1 \quad (12)$$

Here, Q3 and Q1 are third and first quartile respectively.

Skewness: It measures the symmetry shape of the distribution of a signal, It can be derived as

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

NegEntropy: The differences between gaussian entropy H(Ygauss) and differential entropy H(Y) having mean μ and variance σ^2 of EEG signals. It is expressed as,

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

Kurtosis: It is a one of the statistical moment; it gives the time series data peaked nature. Kurtosis can be derived as [17]

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

2)Spectral features :

Spectral flatness (SF): Spectral flatness can be define as the ratio of magnitude spectrum of geometric mean to the arithmetic mean, It can be expressed as ,

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

Spectral spread (SS): Average deviation of a magnitude spectrum around its spectral centroid is called as spectral spread. It can also be assumed as instantaneous bandwidth, It can be mathematically expressed as ,

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

It is a ratio of sum of a weighted magnitude spectrum to normalized by an unweighted sum is called as spectral centroid (SC),

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

Spectral decrease (SDec): It measuring the amount of decrease of a spectral envelope of a signal with respect to frequency, it is denoted as,

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

C. K-Nearest Neighbor Classifier (KNN):

KNN is one of the finest learning algorithm, until the classification whole calculation differs in which function approximated locally only. KNN algorithm is one of the simplest Machine Learning algorithms. In order to catalogue the unknown instance with class label as that of known neighbor and to locate the nearest neighbor in instance set. Classification with an instant classifier can be straight forward task. Class membership is the output in KNN classification to classify, the training and testing datasets of epileptic EEG classification are applied to KNN and the documentation of classification result is done.

D. Artificial Neural Network (ANN):

In machine learning and cognitive science a family of statistical learning models are said to be artificial neural networks and are inspired by biological neural networks. Using machine learning process, the training dataset is used to train ANN, for epileptic seizure classification using ANN the test EEG dataset is used for testing the performance.

E. Support Vector Machines (SVM):

For Classification of healthy EEG signal, SVM classifier is fed with above features. In two-class problem, decision function is given by

$$g(x) = sign[w^T f(x) + b] \qquad (20)$$

Optimization problem can be expressed as

$$\text{Minimize} \qquad J(w,b,e) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{N}e_i^2 \qquad (21)$$

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

Here x_i is N input with i^{th} feature vectors and y_i is class label of 1 or -1 for x_i. b is called bias term and γ is called parameter of regularization. α_i is known as lagrangian multiplier, its SVM classifier solution is obtained as

$$g(x) = sign\left[\sum_{i=1}^{N}\alpha_i y_i K(x, x_i) + b\right] \qquad (22)$$

Kernel is needed for SVM classifier for training. In this Gaussian RBF kernel is the efficient one. RBF kernel can be represented as

$$K(x, x_i) = f^T(x)f(x_i) = e^{\left(-\|x - x_i\|^2 / 2\sigma^2\right)} \qquad (23)$$

Parameter σ is an optimization kernel width.

F. RELIEFF

RELIEFF is an algorithm which is popularly used for filtering feature selection in a very effective manner. It has high end application to binary classification problems with discrete or numerical features.

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Inductive machine learning problems typically use greedy search, however we use Relief algorithm for heuristic guidance of inductive learning algorithms.

The fundamental thought of RELIEFF is to gauge ascribes giving to how well their qualities separate among the cases that are close to one another. For given an example, RELIEFF scans for its two closest neighbors: one from a similar class called closest hit (indicated by H) and the other from the distinctive class called closest miss (meant by M). The first calculation of RELIEFF [9] arbitrarily chooses n training cases, where n is the client characterized parameter. The method is as fallows.

1. set all weights W[A] = 0.0;
2. for i=1:n
3.   randomly select an instance R;
4.   find nearest hit H and nearest miss M;
5.   for A = 1: #all_attributes
6.   W[A] = W[A] – diff(A,R,H)/n
7.   + diff(A,R,M)/n;
8.   end;
9. end;

The weights W[A] estimates the standard of attributes. the premise of the formula for change the weights is that a decent attribute ought to have identical worth for instances from identical category (subtracting the distinction diff (A; R; H)) and will totally differentiate between instances from different categories (adding the distinction diff (A; R; M)).

The capacity diff(Attribute,Instance1,Instance2) figures the distinction between the estimations of Attribute for two occurrences instance1 and instance2. For discrete qualities the thing that matters is either 1 (the qualities are extraordinary) or 0 (the qualities are equivalent), while for ceaseless properties the thing that matters is the genuine distinction standardized to the interim [0; 1]. Standardization with n ensures all loads W[A] to be in the interim [-1; 1], be that as it may, standardization with n isn't required if W[A] is to be utilized for relative correlation among traits.

The all out separation is basically the aggregate of contrasts everything being equal. Truth be told unique RELIEFF utilizes the squared distinction, which for discrete credits is proportionate to diff. In every one of the investigations, there was no generous contrast between results utilizing diff or squared distinction. On the off chance that N is the quantity of all preparation occurrences, at that point the unpredictability of the above calculation is O (n x N x #all_attributes)

In this paper, an efficient method based on VMD, RELIEFF and machine learning approach is designed, developed and implemented for classification of the epileptic seizures. Matlab platform has been used to implement and simulate the proposed classification algorithm and the achieved simulation results are presented in this section. The EEG dataset is adopted from the Bonn University Hospital of Freiburg [10]. It contains five individual subsets (set A-E) named as Z,O,N,F and S. Each subset consists 23.6s duration of 100 single channel EEG signals. The data has a sampling rate of 173.61 Hz and digitalized with 12-bit analog to digital resolution. Set A and set B are captured extra cranially whereas remaining

collected intracranial with a standardized 10-20 electrode system. Set A was recorded from the healthy patients when eyes open, set B was recorded from the healthy patients when eyes close, Set C and set D were recorded when patients are in seizure free intervals, Set E consists of epileptic seizure signals and these signals show ictal activity.

To evaluate the proposed methods performance, accuracy, sensitivity, specificity, precision, F_measure, and G_mean classifier performance parameters are used.

$$Accuracy = \frac{TP+TN}{(TP+FN)+(TN+FP)} \quad (24)$$

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (25)$$

$$Specificity = \frac{TN}{TN+FP} \quad (26)$$

$$\Pr ecesion = \frac{TP}{TP+FP} \quad (27)$$

$$F\_measure = \frac{2(\Pr ecesion \times Sensitivity)}{(\Pr ecesion + Sensitivity)} \quad (28)$$

$$G\_mean = \sqrt{(Specificity \times Sensitivity)} \quad (29)$$

The obtained simulation results of an epileptic seizure classification algorithm using ANN are presented in Table 2.

TConfusion Matrix Of Epileptic Seizure Classification Using ANN With RELIEFF

Signal	Epilipsy(%)	Normal(%)
Epilipsy	97.5	2.5
Normal	11.7	88.3

From the obtained confusion matrix, it can be observed that the classification algorithm using ANN with RELIEFF achieves an overall accuracy of 92.91%, overall sensitivity of 97.50%, overall specificity of 88.33%, overall precision of 89.31 %, overall F_measure of 93.22% and overall G_mean 92.80%.

Simulation results of an epileptic seizure classification algorithm using KNN with RELIEFF are presented as follows in Table 3. According to the confusion matrix obtained, t is observed that the classification algorithm using KNN with FMFS achieves an overall accuracy of 93.33%, overall sensitivity of 96.67%, overall specificity of 90.00%, overall precision of 90.62 %, overall F_measure of 93.54% and overall G_mean 93.27%.

Table-II: Confusion Matrix Of Epileptic Seizure Classification Using KNN With RELIEFF

Signal	Epilipsy(%)	Normal(%)
Epilipsy	96.7	3.3
Normal	10.0	90.0

Finally, the simulation results of SVM with RELIEFF based epileptic seizure classification algorithm are illustrated in Table 4. From the confusion matrix of SVM+ RELIEFF based epileptic seizure classification algorithm, it is observed that later approach achieves all-time high classification performance compared to the previous techniques. It achieves an overall accuracy of 96.66%, overall sensitivity of 98.33%, overall specificity of 95.00%, overall precision of 95.16 %, overall F_measure of 96.72% and overall G_mean 96.65%.

Table-III: Confusion Matrix of Epileptic Seizure Classification Using SVM With RELIEFF

Signal	Epilipsy(%)	Normal(%)
Epilipsy	98.3	1.7
Normal	5.0	95

Table-IV: Performance Summary of An Epileptic Seizure Classification

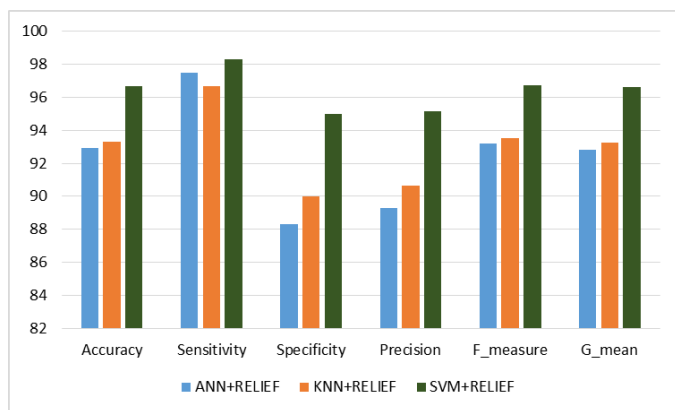| S.No	Parameter	ANN+ RELIEFF	KNN+ RELIEFF	SVM+ RELIEFF
1	Accuracy	92.91	93.33	96.66
2	Sensitivity	97.50	96.67	98.33
3	Specificity	88.33	90.00	95.00
4	Precision	89.31	90.62	95.16
5	F_measure	93.22	93.54	96.72
6	G_mean	92.80	93.27	96.65

Fig. 3.Bar graph comparison of performance parameters

IV. CONCLUSION

In this paper, methods for Identification of epilepsy in EEG signals have been discussed. The adopted method used VMD for feature extraction the obtained features are passed to RELIEFF algorithm to select the best features. The machine learning techniques namely, ANN, KNN, and SVM are employed to in this work for the detection of epilepsy. The ANN+RELIEFF achieved 92.08% accuracy and KNN+RELIEFF achieved 93.33% of accuracy whereas, SVM+RELIEFF achieved 96.66% accuracy. From the overall obtained result it can be concluded that SVM, RELIEFF with

VMD is able to provide highly improved performance compared to the other two methods.

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