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Epileptic Detection Based On EEG Signal Using Graph Index Complexity & Average Weight Degree

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Abstract:
EEG signal suffers from some problem which leads to difficult during diagnosis of diseases. This paper is presented a new approach for diagnosing epilepsy disease through EEG signals are using Weighted Visibility Graph(WVG) for build complex networks and then extracting two feature weight index complexity and average weight index of the network which characterized by its ability to detect seizure cases depending the amount of change in the EEG.
the suggested method has been tested with a publicly available benchmark database. So evaluation of performance of proposed the method the experimental results with Support Vector Machine SVM classifier gave us 100% accuracy for classifying healthy VS epileptic seizure signals and also when testing every feature as separate way average have get 97% accuracy.

1.INTRODUCTION:

Epileptic is the chronic neurological syndrome most common of world [1]. An activity of a big set of neurons in the brain can be portrayed as exaggerated, synchronized activity [2]. It is characterized by involuntary body movements (seizures), a loss of consciousness, and a predominance over the bowel or bladder function [3]. Partial epileptic seizures take place when there are a special spot area of the brain experiences suffer from immoderate or concurrent electrical discharge, in other hand the public epileptic seizures arise when the whole brain suffer from an experiences excessive or concurrent electrical discharge. As a result, successfully diagnosing and anticipating epileptic seizures remains a difficult task [4]. On account of the unstable and anarchic nature for EEG signals, detecting epilepsy from electrical features of EEG data acquired from the brains in cases of seizures is a difficult task to researchers and neurologists [2], [5]. The most commonly utilized signal to clinically analyze brain activities is the electroencephalogram (EEG), which contains information on the electrical activities produced by cerebral cortex nerve cells. The identification of epileptic form discharges in the EEG is also a crucial part of epilepsy diagnosis [6]. Because EEG data is in the form of a time series, epilepsy is usually detected by employing time series analysis techniques, which can be either linear or non-linear. Non Linear ways involve the determination of entropy, correlation dimensions, and Lyapunov exponents [7]. Nowadays, new methods based on complex networks have been proven by a significant number of

research, which show that complex networks may be used to represent the complexity of EEG signals and discern the differences between them [8].
It builds a network based on the proximity of locations in the Poincare section of time [9], Another type of method [10] introduces the concept of visibility graph by building the natural visibility graph (NVG) and later the horizontal visibility graph (HVG) algorithm [10].

In,2015 [11], Because it is slow to transform huge time series, the Visibility Graph Algorithm was improved in this study to improve its transformation efficiency by using a Divide &Conquer (DC) technique to raise the computation performance.
In, 2016 [12] After converting EEG data for the Weighted Visibility Graph(WVG). Modularity and average weighted degree that represented two critical aspects of a network are recovered as features from the WVG.
In, 2020 [13], n this paper, there are statistically analyze the characteristics of AD networks and control networks through calculating eight different topological characteristics. they are clustering coefficient, average weighted degree, graph index complexity, network entropy, degree distribution index, modularity, local efficiency, and average path length.
In our research, while using complex networks, it is unimportant to utilize a massive data to clarify the changing of time series of EEG data, the reason a quantification of graph complexity does not require a large number of nodes. Segmentation of time series provides extra information significant and might be considered as a part of whole data set [14]. So, we had divided each channel into four parts, each part have 1024 data point then it divided into 32segment and each segment contain 32 data point. Each segment has converted to graph based on NVG algorithm so as to from each channel had created 128 graph which is described in section (3). After converting EEG signals to WVG, two significant network features are selected: Average Weight Degree and Graph Index Complexity. These two characteristics are chosen because they provide extremely noticeable information about the time series and identify the effect of sudden fluctuations in EEG data. Finally, the collected feature set is put to the test using the SVM method, one of the most widely used machine learning approaches. The following is an outline of the paper's later sections:
Section 2 contains a detail of the dataset that'susing in the experiment, as well as the approach that was proposed. Part 3 has a full overview of the experimental approach and outcomes, while section 4 has a feature extraction from each graph. Section 5 includes the conclusions as well as recommendations for future research.

2. METHODOLOGY

The algorithm's rationale is to design a limited N-vision crossover line that is the same length as the visible lines connecting the two network nodes. Every node in the time series corresponds to a graph node, and each node is connected to other nodes within its constrained crossing line to form a complicated network. Figure 1 depicts a flow diagram of the proposed methodology (1). The dataset as well as the various steps of the process are detailed in the following sections.

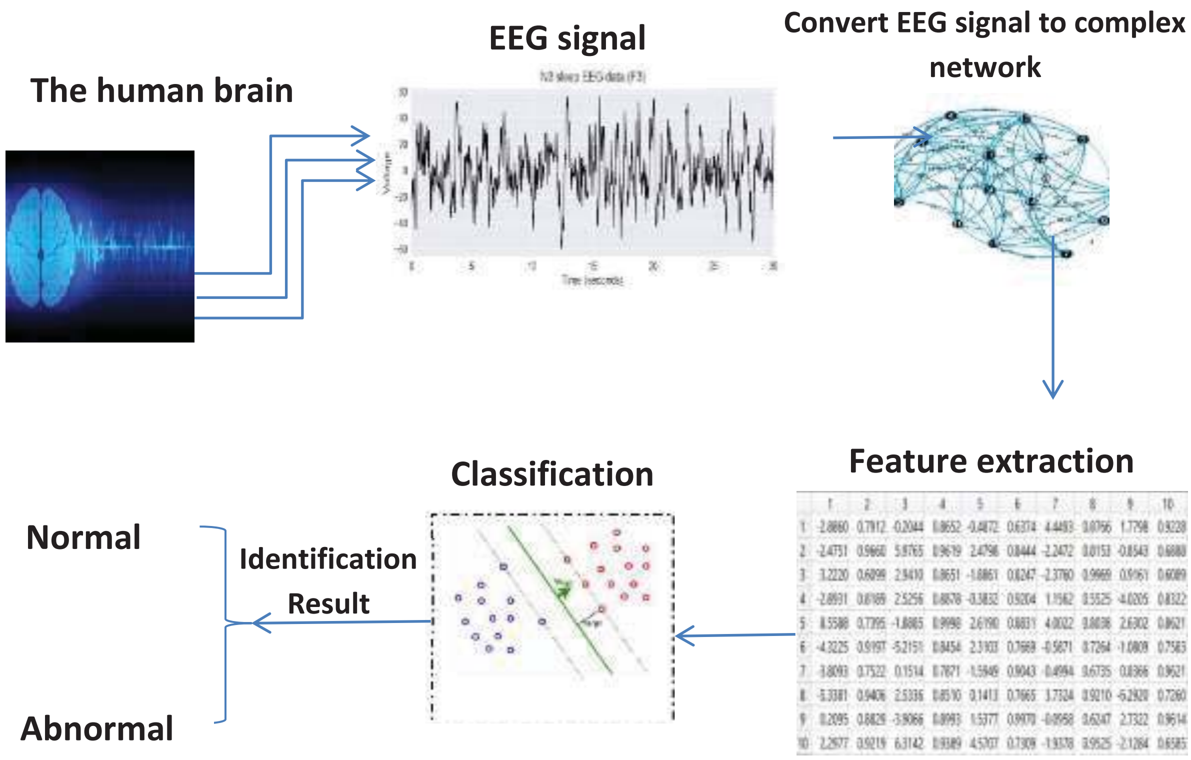

FIGURE 1: flow chart of the proposed methodology

A. EXPERIMENTAL DATA

The data which it are used in the paper are available online . Epilepsy 's data are produced by the department of epilepsy at Bonn University in Germany (http://epileptologie-bonn.de/cms/front content.php? idcatD 193&langD3).

this paper worked on five sets(A, B, C, D, and E) that make up the EEG database. Each set consist of 100 channels of EEG signals captured in 23.6 seconds. The 10-20 technique of electrode implantation is used to record EEG signals. The same 128-channel amplifier device was used to capture EEG, with an average common reference. The data was digitized at a rate of 173.61 samples per second with a 12-bit resolution.. The band-pass filter is adjusted between 0.53 and 85 Hz.. [15], There are 4097 sample data points in each channel of EEG signal. However, we subdivided each channel using 32 data sample points per segment to reduce computation time, as shown in table 1

TABLE 1: Summary of University of Bonn (UoB), Germany[16]

Subject Information	Healthy Subject		
	Set A	Set B	
Patient state	Awake with eyes open(normal)	Awake with eyes close (normal)	
Electrode type	surface	Surface	
NO.of epoch	100	100	
Electrode placement	International 10-20system	International 10-20system	
Subject Information	Epilepsy patient		
	Set C	Set D	Set E
Patient state	Seizure free(interictal)	Seizure free(interictal)	Seizure activity(ictal)
Electrode type	Intracranial	Intracranial	Intracranial
NO .of epoch	100	100	100
Electrode placement	Opposite to epileptogenic zone	Within epileptogenic zone	Within epileptogenic zone

B. WEIGHT VISIBILITY GRAPH (WVG) CONSTRUCTION

Weighted Visibility Graph (WVG) for EEG data are built through followings step:-

- Consider A represent a time series $x(t_i)$ while i=1,2,3,…..N, N: sampling point and time (t_i=1,2,3,…N;
- Define graph G=(N,E) graph for time series where

N={n_i} i=1,2,3,….N are nodes and E=e_i are edges

Build Natural Visibility Graph : while sample is considered to be a node define and for connecting two nodes so they can see each other, namely, a straight visibility line exists between them. for do that should validate following criterion [17]

Let ta of length N, two points (ta,ya) and (tb,yb) are be naturally visible when to be over there intermediate point time series(tc,yc) such that ta < tc <tb

$$Y_c \le Y_b + (Y_a + Y_b)\,\frac{t_c - t_a}{t_b - t_a} \qquad (1).$$

- The weight for NVG to construct WVG can be obtained by using time points t_i, i = 1, 2, ...N. An edges identify the linking between two time points. in addition the edge has weight which are calculated through the following formula [18]:

$$W_{ij} = arctan\frac{x(t_i) - x(t_j)}{t_i - t_j}, i < j \qquad (2)$$

W_{ij} :the weight of the edge between node n_i and node n_j.

all the weights values of edges are calculated by radian function (arctan function) because this function display discover the sudden mutation in Electroencephalography signal. [12], as it illustrates in Table 2 which clarify the edge between the nodes and weight values for first 10 data points.

TABLE 2: Example of edges and weight between first 10 data points of EEG time series data of tab

Edges	Weight(w)	Edges	Weight(w)	Edges	Weight(w)	Edges	Weight(w)
E12	**1.4940**	**E34**	**1.5506**	**E67**	**1.5232**	**E910**	**1.532**
E13	**1.5495**	**E41**	**1.5375**	**E610**	**1.5153**	**E106**	**1.5153**
E14	**1.5375**	**E42**	**1.5561**	**E76**	**1.5232**	**E107**	**1.5481**
E15	**1.5565**	**E43**	**1.5506**	**E78**	**1.5208**	**E108**	**1.5342**
E16	**1.5537**	**E45**	**1.5516**	**E79**	**1.5182**	**E109**	**1.532**
E21	**1.4940**	**E51**	**1.5565**	**E710**	**1.5481**		
E23	**1.5477**	**E52**	**1.5546**	**E87**	**1.5208**		
E24	**1.5561**	**E54**	**1.5516**	**E89**	**1.5396**		
E25	**1.5546**	**E56**	**1.5508**	**E810**	**1.5342**		
E31	**1.5495**	**E61**	**1.5537**	**E97**	**1.5182**		
E32	**1.5477**	**E65**	**1.5508**	**E98**	**1.5396**		

3.FEATURE EXTRACTION:

Following the creation of a graph from each EEG segment, the second stage involves eliciting representative features from each graph; this step is critical to any successful recognition system. In the categorization of epileptic EEG $_{\text{signals}}$, extracting the proper feature set is a difficult task. In this paper we extract two feature from each graph : average weighted degree and graph index complexity.

- Average Weighted Degree:-

averge weight degree consider one of the bested statistical feature. It can be defined as the average of total the incident linkages weights on all the network's vertices. By analyzing edge weight values, average weighted degree aids in identifying the impact of abrupt variation in EEG $_{\text{signals}}$.[19]

(3) [13] $$Wd = \frac{1}{N}\sum_{i \in G_i} S_i$$

- Graph Index Complexity

The greatest eigenvalue of an adjacency matrix of a weighted or unweighted graph can be used to quantify Graph Index Complexity, which shows the variety or heterogeneity of edge distribution over all nodes. defined as follow[20][21]:-

(4) $$C_r = 4c(1-c)$$

where

(5) $$C = \frac{r - 2\cos(\pi/(N+1))}{N - 1 - 2\cos(\pi/(N+1))}$$

C_r : varies between 0 and 1

4. CLASSIFICATION:

Classification algorithm can be categorized into two kind binary and multi-class classifier. In biomedical area, classification problem has multi class nature[22], such as Supper Vector Machine(SVM).

A. CLASSIFICATION ALGORITHM

SVM algorithms work by transforming input data into a higher-dimensional space and then constructing an optimum separating hyper-plane (OSH) between the two classes in the transformed space [23]. A typical SVM takes a collection of input data and guesses which of two classes the data belongs to. An SVM representation of the examples as points in space, mapped so that the separated categories' examples are separated by a distinct gap as broad as possible [24].

B. CLASSIFICATION ACCURACY, SENSITIVITY AND SPECIFICITY

For the performance evaluation were used three matric accuracy, precision and recall which are calculated as follow[23]:-

$$accuracy = \frac{TP+TN}{TP+FN+FP+TN}(\%) \qquad (6)$$

$$precision = \frac{TP}{TP+FP}(\%) \qquad (7)$$

$$(8) \qquad Recall = \frac{TP}{TP+FN}(\%)$$

C. RESULT AND DISCUSSION:

The suggested method tested by using the standard data: Bonn university epileptic EEG data, in order to ensure that the presented study is valid. The suggested mechanism is put on the test on four various groups of test statuses, as shown in table (3). As we mentioned in section 1, about the importance of dividing EEG time series before converting it into a complex network, which adds speed in the formation of the network. for that reason, we divided each channel. Whereas every channel of every collection contains 4097 data points for 23.6 second. In this paper each channel is divided into 128 segment with size of each equal to 32 data point. Now, we can construct graph for each segment by using a weighted visibility graph algorithm which is described in section2 and a complex network with seizure activity exhibits varied weighted edges values, an edge weight based algorithm aids in the detection of rapid fluctuations for epileptic detection.

In feature extraction step we extract two feature Average Weighted Degree and Graph Index Complexity. in Fig.2 illustrate box plot diagram of Average Weighted Degree, as it is obviously that the average weighted degree of sets patients (C, D and E) have the highest values as compared with healthy volunteer’s sets (A and B).

Fig.3 illustrate the box plot diagram of graph index complexity, clearly is that when compared the set E to the other sets (A, B, C and D), it has the highest value.

The result of classification by using SVM algorithm between (A vs E) when we take each feature separately or take them together we get accuracy equal to 100%and other test result shown in Table 4.

Finally, Table 5 displays a comparison of the proposed method's classification accuracy with other approaches using the identical EEG $_{\text{dataset}}$ to show a new technique that’s more precise for epileptic seizure exposure than the others.

TABLE 3: The classification description of different groups of problem along with their EEG data sets

Test case	Data group	Classification problem description
Test I	set A vs set E	Healthy persons with eye open vs Epileptic patients during seizure activity
Test II	set B vs set E	Healthy persons with eye close vs Epileptic patients during seizure activity
Test III	set C vs set E	Hippocampal seizure free vs Epileptic patients during seizure activity
Test IV	set D vs set E	Epileptic seizure free vs Epileptic patients during seizure activity

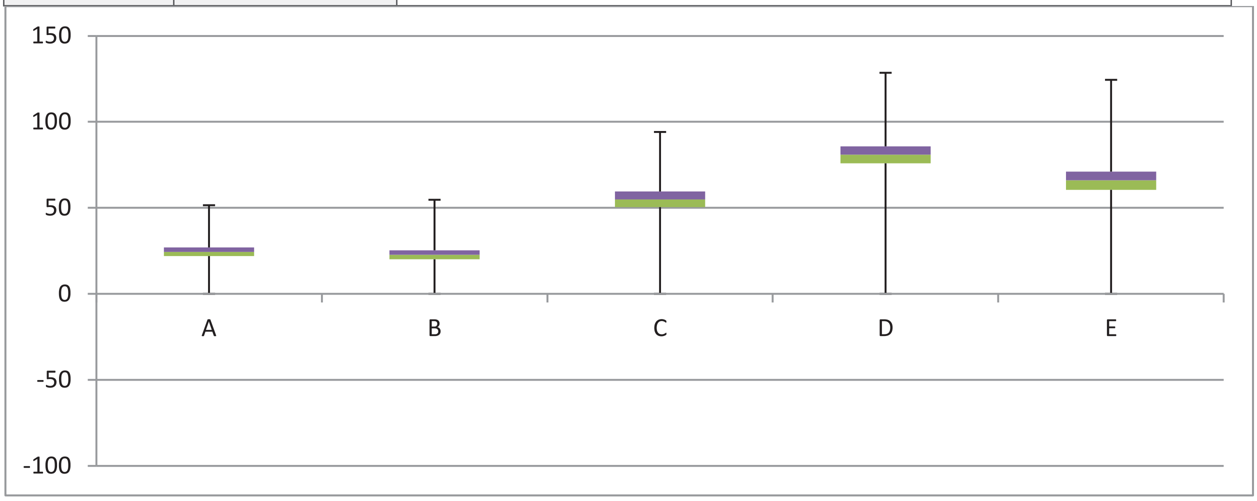

FIGURE 2: Boxplot of the average weight degree features set of different sets of EEG signals.

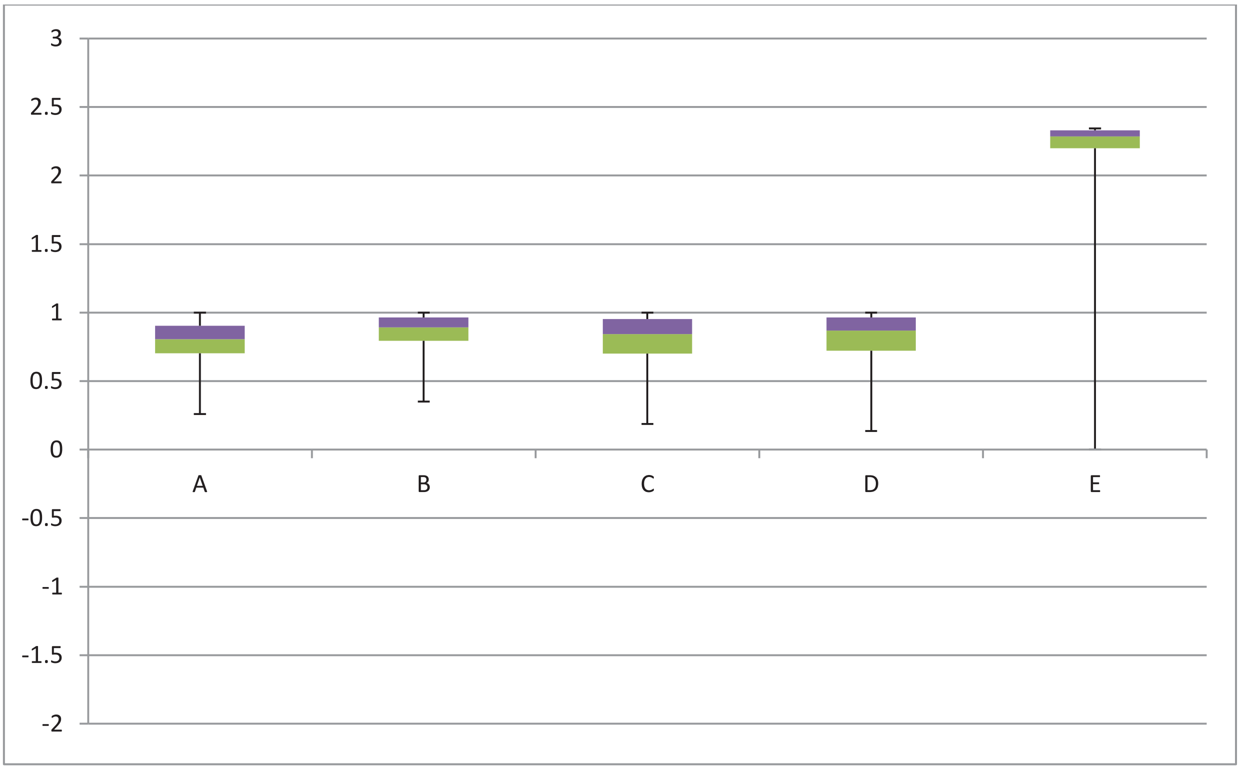

FIGURE 3: Boxplot of the graph index complexity features set of different sets of EEG signals.

TABLE 4: The performance classification of different test cases of EEG data set

Data Group	Performance for average weighted degree features set of WVG			Performance for graph index complexity features set of WVG			Performance for combined feature vector set of WVG		
	Accuracy %	precision %	recall %	Accuracy %	precision %	recall %	Accuracy %	precision %	reca ll %
set A vs set E	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
set B vs set E	**100**	**100**	**100**	**97.92**	**100**	**100**	**100**	**100**	**100**
set C vs set E	**91.67**	**100**	**100**	**97.92**	**100**	**100**	**100**	**100**	**100**

TABLE 5: Comparative analysis of the accuracy of the proposed work with existing work that used the same data set for their experimentation

Data	Authers	Features	Accuracy %
A VS E	**Guohun Zhu et al.,2014**	**2**	**99**
	Supriya Supriya , 2016	**2**	**100**
	our proposed method	**2**	**100**
B VS E	**Guohun Zhu et al.,2014**	**2**	**97**
	Supriya Supriya , 2016	**2**	**97.25**
	Our proposed method	**2**	**100**
C VS E	**Guohun Zhu et al.,2014**	**2**	**98**
	Supriya Supriya , 2016	**2**	**98.25**
	Our proposed method	**2**	**100**
D VS E	**Guohun Zhu et al.,2014**	**2**	**93**
	Supriya Supriya , 2016	**2**	**93.25**
	Our proposed method	**2**	**100**

5.CONCLUSION:

the paper describes a new way for detecting epileptic problem from EEG brain signals, which involves process converting EEG time series data into a Weighted Complex Network and extracting two features. By using SVM method have achieves 100 percent classification performance in terms of accuracy, precision, and recall. When analytic through using WCN theory, the average weight degree and graph index complexity were shown to be the most promising features for revealing the unobserved information of brain functions of EEG time series. This paper also investigates how distinct nodes of an EEG weighted complex network react with one another with varying degrees of strength. As a result, when using complex network theory to find out epilepsy from EEG signals, the edge weight serves as a crucial floor for detecting abrupt fluctuations during seizure activity. This technology, we believe, can be hired to diagnosis another brain illness from EEG patterns.

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