PREDICTION OF EPILEPTIC SEIZURE CLASSIFICATION USING THIRD-ORDER CUMULANTS AND SPARSE AUTOENCODER

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ABSTRACT

Epilepsy is one of the serious neurological diseases in the world. Indeed, early detection of epileptic seizure will extend the life span of epileptic patients. In this regard, a lot of efforts has been done to predict epileptic seizures based on electroencephalography (EEG) signals. In literature, there are many feature-based seizure classification methods quoted. No method is proved perfectly in capturing a standard set of feature with the dynamics of signals. In this research, a new strategy is proposed based on ant colony organization (ACO) pro-processing and third-order cumulants (ToC) for capturing the perfect feature set. Besides second-order statistical features also derived for pre-processed EEG signals. All these features are inputted for a sparse encoder which selects optimal features to obtain good accuracy. This paper describes an automated seizure classification into a focal and non-focal epileptic seizure. The proposed strategy experiments for different labels and all cases shown stunning performance in seizure classification into focal and non-focal EEG signals, and it will be useful for neurologists for rapid and robust prediction of epileptic seizure surgery.
Keywords: *Electroencephalography, Epilepsy, Focal, Non-Focal, Sparse Encoder, ACO, ToC*

1. INTRODUCTION

Causes of aberrant brain disorders produced by an epileptic disease are quite prevalent and present numerous symptoms, e.g. loss of consciousness, strange behaviour and confusion in the brain. In many situations, these symptoms lead to falls and tongue bites. It is not an easy process to detect a probable attack in advance. Most seizures come suddenly, and it was a challenge for many researchers to identify means of detecting a prospective seizure before it happened. The application of classification algorithms, the approach utilized in this study, can be utilized to establish whether or not someone has a seizure.

Epilepsy is a progressive neurological disease that affects 65 million individuals worldwide [1,2]. It is influenced by irregular cortical neuronal discharge. Epilepsy patients' social lives and psychological well-being are significantly impacted by the recurrence of epileptic seizures [3]. As a consequence, it is essential to identify and treat epilepsy patient appropriately. The most often used techniques for diagnosing epilepsy are positron emission tomography (PET) [5], magnetic resonance imaging (MRI) [8], electroencephalogram (EEG) [4]and single-photon emission computed tomography (SPECT) [6, 7]. Signs of EEG are often used in these approaches because of less price and ease of acquisition [9]. Epilepsy treatment can be aided by an accurate and quick diagnosis of epileptic seizures. When treating epilepsy patients, the most important thing to remember if the epileptic seizure is non-focal or focal. Since focal or non-focal seizure in the brain is called epileptic seizures. Even though central seizures happen in a specific space of the cerebrum, non-central seizures happen outside the epileptogenic zone [10]. Epilepsy is generally treated in any one of the following ways: medically or surgically. Drug-resistant patients are surgically controlled [11]. However, this procedure is used to treat patients who are experiencing focal epileptic seizures. As a result, determining the focal of epileptic seizures signs in EEG are critical in surgery [12]. As a result, epileptic seizure forms are often detected using EEG signals.

Many traditional methods concentrate on classification using feature extraction to differentiate non-focal and focal epileptic seizures. Numerous entropy tests [13, 14, 15], a variety of Hilbert–Huang transform [21], Transformations on wavelets[15, 16, 18, 19, 20], reconstruction components (RCs) hybrid approaches [23], decomposition of empirical mode [15], dependent on sliding mode-singular continuum analysis [22], the logarithm of the diagonal slice of a third-order cumulant [24] and nonlinear measures [22, 25], are Numerous clustering and classification methods used to evaluate the accuracy of non-focal and focal epilepsy seizures, including k-means clustering, radial basis function, k-nearest neighbours, neural networks, Adaptive Neuro-Fuzzy Inference System, support vector machines and Naive Bayes[21, 22, 23, 25]. Both of these methods, collectively referred to as manual feature extraction, require considerable computing resources and time. As a consequence, the real-time execution of these dynamic processes is incredibly complicated [26].

Numerous classification techniques, including linear prediction [27], autoregression (AR) models [28, 29], and spectral estimation [30], are common methods for seizures discrimination using EEG signals. These signals display nonlinear behaviour, which the algorithms described above are incapable of analyzing properly. As a result, various time-frequency (TF) methods were proposed for analyzing the non-stationary signals of EEG[31, 32, 33]. The TF techniques simultaneously divide the considered signal on frequency and time axes, revealing the energy distribution across the signal's separate frequency. The transform of wavelet is often needed to investigate the properties of electroencephalogram (EEG) signs concerning their time variation. It computes a non-stationary signal's scale-time variant decomposition by allowing for the capturing of the signal's transient operation. Numerous researchers have suggested various wavelet transform versions, including the discrete wavelet transform (DWT) [34, 35, 36], the mixed band wavelet transforms (MBWT) [37], the multiwavelet transforms (MWT) [38], the analytical wavelet transforms (EWT) [43], the dual-tree complex wavelet transforms (DT-CWT) [39, 40], the analytic TF and the wavelet packet entropy (WPE) [41, 42], versatile analysis The author's classified seizures automatically using EEG signals using a combination of machine learning algorithms [44, 45, 46]. Many of the architecture listed in the literature are addressed two issues that are feature dependence and computational complexity. A 13-layer profound CNN method is proposed by Acharaya et al. [44] for the classification of seizures, furthermore, a three-layer CNN is proposed by Zhou et al.[45] for the same reason.

Husseni et al. [46] classified seizures using a long short-term memory (LSTM) and recurrent neural network (RNN). By the number of layers in the network, the model becomes well-trained, which results in higher prediction accuracy. However, it increases computational complexity as a result of overfitting and exacerbates the vanishing gradient issue.

Hybrid machine learning [23, 57]methods used to detect epileptic seizures were presented robust machine learning classification techniques applying different feature extraction strategies to detect epileptic seizures [46]. The complexity of the manual examination demands approaches for automatic seizure detection, which emulates professional visual evaluations. The acceptability of these algorithms in a clinical environment is dependent on a low false positive detection rate and a high sensitivity. Traditionally, the typical frequency bands for brain activity need an EEG frequency study. By utilizing Fourier's or Wavelet transform, traditional approaches shift signals into the frequency domain and extracted essential characteristics that explain seizures, typically employing the descriptors of the time domain. These hand-made characteristics subsequently provide the input for training a classifier that differentiates between seizures and non-seizures.

The limits of the use of domain-based methodologies are that because of the acquisition artefacts and the non-stop nature of the EEG, its statistical parts might change with time and subjects, they are prone to fluctuations in seizure patterns. The rest of this paper arranged as follows. Section 2 describes the proposed strategy along with pre-processing. Section 3 explains the discussion of experimental results. Section 4 concern the conclusions.

2. PROPOSED METHOD

The proposed strategy is a data-dependent algorithm. The strength of this algorithm is extracting complete significant features sustainability of that features. The best preprocessing methodology namely ant colony optimization (ACO) is considering eradicating unused information in the EEG signal. Indeed, to capture underlying nonlinear signal dynamics used ToC. And it is most sufficient to reduce the complexity of EEG signal. There are many issues in deep neural networks namely: vanishing gradient, overfitting and complexity. These issues restrict the performance of the model [47, 48].

All these issues are resolved by simply changing the network architecture. In this paper, three layered- sparse autoencoder is suggesting for classifying the class of seizure as focal or non-focal. It is simply to avoid overfitting and reduce the dimensionality of data that permits error of loss function into deeper nodes. This property of the proposed model will solve loss in the problem of gradients[49]. The proposing sparse encoder with ACO is described in figure1.

The proposed model is implemented using the Colab tool with Python programming language. As it is taking 5 EEG signals as raw input and preprocessed using third ordered cumulants and by that a feature selection algorithms like term-frequency, fast Fourier transforms, eigenvectors and auto-regression applied with ant colony optimization.

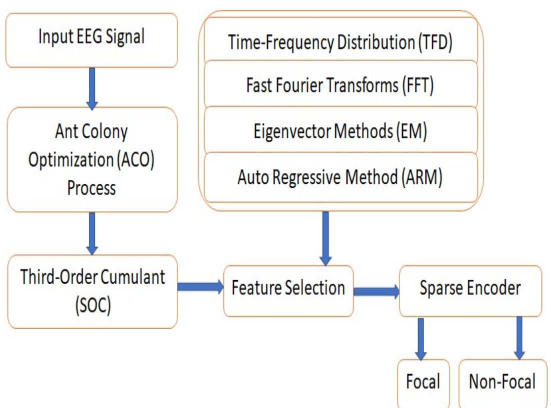

Figure1: Block Diagram Of The Proposed Strategy

Before mentioning the proposed algorithm, we review the third-order cumulants (ToC), Autoregressive method (ARM), Eigenvector methods (EM), Fast Fourier transform (FFT), Time-frequency distribution (TFD), autoencoder and softmax classifier.

2.1 Preprocessing: Ant Colony Optimization (ACO)

Numerous algorithms focused on bees, ants and swarm individuals have been developed for various complex and optimization problems to generate robust computational time and cost[50, 51]. Initially, Dorigo et al. (1996) proposed ant colony optimization (ACO), which was inspired by ant populations. Created the basic method Ant system (AS) Deneubourg et al. (1990). Numerous scholars have been inspired by the action of ant colonies, including ELITIST AS, ANT-Q Gambardell and Dorigo (1995), and Hoos(1996), Colorni et al. (1992).ACO has many applications like biomedical data processing; brain rhythms detection with periodogram patterns, feature selection of QEEG data classification, classification of had motion detection and clustering analysis of ECG arrhythmias and so on. This ACO is developed as part of swarm intelligence (SI) motivated by the friendly conduct of the bugs and different creatures. Ant colonies are a highly structured social organization and they can perform complex tasks.

Despite the simplicity of their individual's capacities, they can outperform complex tasks. Hence "ant algorithm" is used as a basic source of research in the design of new algorithms for optimizing solutions. The basic principle of these Ant algorithms is self-organization in food searching, classification of breeding, division of labour and transport cooperation. Ants can put a chemical (pheromone) in the earth while searching for food, this can helps other ants to communicate indirectly. The idea of this algorithm is artificial stigmergy is used to coordinate reaming artificial agent societies. The recent application of SI algorithms is biomedical data processing such as ECG and EEG. In this work, ACO is used for pre-processing EEG signal for acquiring more perfect features. The first problem which is solved by using this ACO is the travelling salesperson (TSP) problem where we need to start from one point and again reach the same point.

2.1.1. Ant System (AS)

Formally, TSP is represented with weighted complete graph G = (Ve, Eg) Ve is the group of nodes representing places and Eg is arced between the places. The arc (p,q) Ɛ E is assigned weight d_{ij}, where p,qƐV. The objective of TSP is to find the minimum length path between p and q. The optimal solution is permutation Ψ of the index of places {1,2,…n} to f(Ψ) is smallest where f(Ψ) is denoted by

$$f(\Psi) = \sum_{i=1}^{n} d_{\Psi(p)\Psi(p+1)} + d_{\Psi(n)\Psi(n)} \quad (1)$$

In ACO, k is the number of ants representing different places. Every ant constructs a feasible solution using a proportional random rule which decides the nearest place. The likelihood P with the ant kk that is at present in city p and decided to go q

$$P_{pq}^{kk} = \begin{cases} \frac{[\pounds_{pq}]^{\gamma}\,[\pi_{pq}]^{\gamma\gamma}}{\sum_{l \varepsilon N_p^{kk}}[\pounds_{pq}]^{\gamma}\,[\pi_{pq}]^{\gamma\gamma}} & if\ q\ \mathcal{E} N_p^{kk} \\ 0\ Otherwis \end{cases} \quad (2)$$

Where, $\pi_{pq} = 1/d_{pq}$, γ and $\gamma\gamma$ denote the comparative effect of the pheromone and artificial knowledge, correspondingly, and N_p^{kk} denotes the group of neighbouring locations that the ant kk has not to visit while in the area, and the likelihood of selecting a Location outside N_p^{kk} is 0. The evaporation of pheromones is measured using Eqn.3.

$$\pounds_{pq} \leftarrow (1-\rho)\pounds_{pq}\,, \forall\,(p,q)\mathcal{E}\,L \quad (3)$$

So L =A and o< $\rho < 1$ is representing the pheromone evaporation rate, ρ is used to keep away from the bad decision decided previously. After vanishing, every one of the insect's stores pheromones in the bows they have crossed on their visit:

$$\pounds_{pq} \leftarrow (1-\rho)\pounds_{pq} + \sum_{kk=1}^{k}\Delta\,\pounds_{pq}{}^{kk}\forall\,(p,q)\mathcal{E}\,L \quad (4)$$

$\Delta\pounds_{pq}{}^{kk}$is total amount deposited at arc(p,q) by the ant kk, $\Delta\pounds_{pq}{}^{kk}$ is calculated by Eqn. 5

$$\Delta\pounds_{pq}{}^{kk} = \begin{cases} \frac{Q}{L_{kk}}\ if\ (p,q)\ \mathcal{E}\ L_{kk} \\ 0\ Otherwise, \end{cases} \quad (5)$$

L_{kk}, represents the length of the path and Q is the constant.

As mentioned in the above ant colony optimization algorithm, the signs got from EEG, given an SSVEP-based BCI system. After obtaining, signals from EEG, the cathodes O1 and O2, which are straightforwardly identified with the visual handling of the mind signals, are chosen. These signs are post-handled utilizing the proposed ACO calculation to acquire a streamlined sign (ACO-O1O2). The below figure2 shows the ACO inward activity.

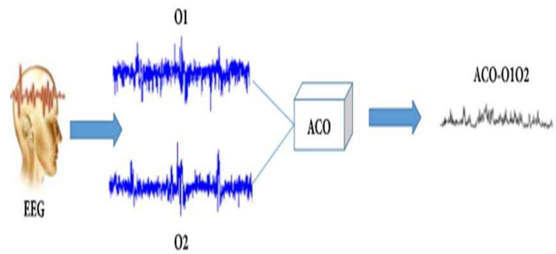

Figure2: ACO Description

2.2 Cumulants

As per Kravtchenko-Berejnoi, V. et al. 1995, let {x1, x2, …,xn} real variables and r = k1 + k2 + … + kn their moments.

$$Mom\left[x_1^{k_1}, x_2^{k_2}, x_3^{k_3}, \dots x_n^{k_n}\right]$$
$$= E\left[x_1^{k_1}, x_2^{k_2}, x_3^{k_3}, \dots x_n^{k_n}\right]$$
$$= (-j)^r \frac{\partial^r \phi(w_1,w_2,w_3,..w_n)}{w_1^{k_1}, w_2^{k_2}, w_3^{k_3}, \dots w_n^{k_n}} \quad (6)$$

Where $\emptyset(w_1, w_2, w_3, ..w_n) = \Delta E\{e^{j(w_1x_1,\ w_2x_2,\ w_3x_3 \dots w_nx_n)}\}$ is their joint character function. Another form of characteristic function is defined as the natural algorithm of $\emptyset(w_1, w_2, w_3, ..w_n)$ *is* given by :

$$\Psi(w_1, w_2, w_3, ..w_n) = \ln[\emptyset(w_1, w_2, w_3, ..w_n)] \quad (7)$$

As per Nikias and Petropulu, the Taylor expansion of the second characteristic function about zero is

$$Cum\left[x_1^{k_1}, x_2^{k_2}, x_3^{k_3}, \dots x_n^{k_n}\right] = E\left[x_1^{k_1}, x_2^{k_2}, x_3^{k_3}, \dots x_n^{k_n}\right] = (-j)^r \frac{\partial^r \Psi(w_1,w_2,w_3,..w_n)}{\partial w_1^{k_1}, \partial w_2^{k_2}, \partial w_3^{k_3}, \dots \partial w_n^{k_n}} \quad (8)$$

As per Nikias and Petropulu, the moments of random variable x_1 is

$$m_1 = E\{x_1\}.m_2 = E\,\{x_1^2\}\,.m_3 = E[\,x_1^2] \quad (9)$$

Cumulants of moments by

$$c_1 = m_1.c_2 = m_2 - m_1^2\,.c_3 = m_3 - 3\,m_2m_1 + 2\,m_1^3 \quad (10)$$

The third-order cumulants are defined for x_1, x_2, x_3 is

$$c_3^x(\tau_1,\tau_2) = m_3^x(\tau_1,\tau_2) - m_1^x[m_2^x(\tau_1) + m_2^x(\tau_2) + m_2^x(\tau_1-\tau_1)] + 2.(m_1^x) \quad (11)$$

The Gaussian distributed processes are equal to 0 of higher-order cumulants, which means $C_i^y\,[l_1, l_2, \ldots l_{i-1}] = 0\ i \geq 3$. These higher-order cumulants provide two pieces of information namely high order correlation and Gaussian process.

- The ToC used to analyze the minimum phase signals
- The ToC can identify the linear/non-linear, Gaussian / non-Gaussian system and phase coupling etc.
- The ToC has various symmetric as well as lots of redundant and repeated information. As for these higher-order cumulants, we consider lower oblique attributes for further analysis. This information has full distribution and is more efficient from a computational perspective.

2.3 Autoencoder

Sparse Autoencoders are autoencoders that use sparsity to create a context constraint. The loss function is designed in such a way that activations within a layer are penalized. Sparsity constraints may be implemented using L1 regularization or a KL variance around predicted average neuron activation and an optimal distribution p.

In essence, the sparse autoencoder is an unsupervised follower but it uses supervised methods. It applies the suitable bias vector and weight matrix to the input vector at the output terminal [52]. The autoencoder is composed of 2 components: a decoder and an encoder. Both will retain their distinct activation functions (Ψ) and biases (φ). In the case of a hidden layer (HL), the input vector of the encoder (x ƐЂ) is assigned to the HL (h ƐЂ) in the following manner:

$$h = \Psi\,(W.x + b) \quad (12)$$

Where 'h' is a latent variable and w and b denoted as bias vector and weight matrix correspondingly, that have been randomly initialized. The backpropagation method is used to update this parameter iteratively. Similarly, the decoder maps (h ƐЂ) to an approximate input vector representation ($\bar{x}$ƐЂ), i.e.

$$\bar{x} = \varphi\,(w'.h + b') \quad (13)$$

Where w' and b' are bias vector and weight matrix at the decoder side. The cost of error function Φ(e) of the encoder is denoted as [53]

$$\Phi(e) = \frac{1}{2}\|x - x'\|^2 + \Omega\,(h, x) \quad (14)$$

$$= \frac{1}{2}\left\|x - \varphi\,\left(w'\left(\Psi\,(w.x + b\,)\right) + b'\right\|^2 + \Omega\,(h, x) \quad (15)$$

Where $\left\|x - \varphi\,\left(w'\left(\Psi\,(w.x + b\,)\right) + b'\right\|$ loss is function and $\Omega\,(h, x)$is regularization. Here regularization is reflected weight decay parameter and it is defined as

$$\Omega(h, x) = \lambda \sum_{i=1}^{p} \|\nabla x_i\,.\,h_i\|^2 \quad (16)$$

Where ∇x_i is the different parameter of node 'i' for random variable x. Even x changes, the entire model does not affect that much as the effect of regularization [54].

As per the suggested sparse three-layered autoencoder for classifying EEG signs in Fig.3. The oblique ToCcoefficients are taken at the first hidden layer and reduced cost values which are generated from the first layer are taken at the second layer and optimal reduced cost values are taken at the third layer. The Kruskal–Wallis test [55] test has considered along with p values. The features significance will decide by p-value where the lower the p values higher the significance. The lower p-value layer does not extract significant features from the input. The most refined features are extracted at the third layer. In this regard, p values of the subsequent hidden layer is a lot lesser than the primary hidden layer similarly third hidden layer has much lesser than the second hidden layer.

The entire seizure ToC coefficients are divided as training and testing in 75% and 25% ratio respectively. In this proposed stratify softmax classifier is considered for classifying unknown EEG signal.

2.4 Softmax Classifier

Cross-entropy loss is used for the Softmax classification. The name of the Softmax classifier is derived from the Softmax function used to transform raw class scores into normalized positive values that add up to one, to allow a cross-entropy loss.

The primary objective of the current approach is to distinguish binary seizure groups. This softmax classifier is used at the proposed network's output layer. This classifier computes the

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probability distribution for each label and uses the calculated probability distribution to predict the out label (most probable label).

The results of the softmax classifier for label k in terms of the binary class named input data X and weight matrix W [54].

$$p(Y = k|X) = \frac{\exp(W_k^T.X)}{\sum_{i=1}^{N} \exp(W_k^T.X)} \quad (17)$$

$$= \frac{1}{\sum_{i=}^{N} \exp[(W_i - W_k)^T.X} \quad (18)$$

Where N is number classes and the . is dot product of vectors.

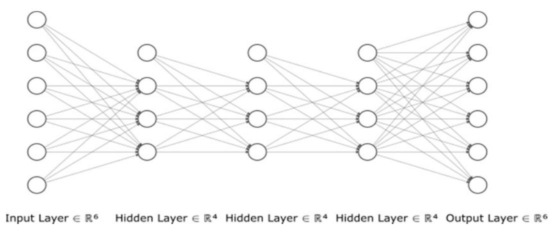

Figure3: Three-Layer Architecture Generated By The Autoencoder

** Seizures characterization dependent on higher request measurements and deep neural organization

2.5 Time-Frequency Distribution (TFD)

Wavelet transforms are mother wavelets which are having a variety of frequencies with a slight change in the signs [56]. To get the required Hz band, this paper used exploited method, in this EEG signal is hanged from 173.61 Hz to 120 Hz primarily. By applying fourth level wavelet transforms, the EEG signal is decomposed into sub-bands; here we consider coefficients for each sub-band. The ideal factual attributes were separated from the determined wavelets coefficients specifically theta, delta, alpha, gamma and beta. In this work, we utilized Daubechies request 6 (DB6).

For the cases where the characters in signal frequency differ with the moment, it is a généralization and refining of the Fourier analysis. As numerous signals of interest – including voice, music, images and medical signals – have shifting frequency features, time-frequency analyzes are widely used.

A discrete sign can be addressed with the accompanying condition in l2 (Z),

$$f(n) = \frac{1}{\sqrt{M}} \sum_k W_\theta[j_0, k], \theta_{j0,k}[n] + \frac{1}{\sqrt{M}} \sum_{j=j0}^{\alpha} \sum_k W_\theta[j, k], \Psi_{j,k} \quad (19)$$

Where $W_\theta[j_0, k], \theta_{j0,k}[n]$ is a discrete function defined in M.The coefficients are obtained by the inner product rule.

2.6 Fast Fourier Transforms (FFT)

Fourier's time function transform is a complicated frequency function, its magnitude (absolute value) reflects the quantity of this frequency present in the original function and its argument is to counteract the fundamental sinusoid phase in that frequency. The Fourier transformation is not only temporary but is usually referred to as the time domain as the domain of the original function. There is also an opposite Fourier transform that synthesizes, as seen by the Fourier inversion theorem, the initial equation from its frequency domain representation.

To analyze EEG signal, use the estimation of power spectral density (PSD). In this, we get four frequency bands that contain characteristics waveforms of EEG [57]. From PSD, we estimate the sequence of autocorrelation which are found by the non-parametric method [58]. The in a row sequence $x_i(n)$ is denoted as

$$x_i(n) = x(n + iD), n = 0,1,2..M - 1 while\ i = 0,1,2\ L - 1 \quad (20)$$

In i^{th} sequence, iD is the starting point and L is the length of 2M data segments. The resulting output as follows:

$$P_{xx}^{(i)}(f) = \frac{1}{MU} \left| \sum_{n=0}^{M-1} x_i(n) w(n) e^{-j2\pi f} \right| \quad (21)$$

In function of windowing, U denotes the normalization factor in the way that

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2\ (n) \quad (22)$$

Then w(n) is the function of windowing. The middling of this new version gives Welch's power spectrum as below:

$$P_x^{ww} = \frac{1}{L} \sum_{i=0}^{L} P_{xx}\ (f) \quad (23)$$

2.7 Eigenvector Methods (EM)

Eigenvalues and eigenvectors play an important role in linear transformation analysis. Originally used to investigate the principal axes of rigid body rotational motion, eigenvalues and eigenvectors now have a broad variety of applications, including stability analysis, vibration analysis, atomic orbitals, face recognition, and matrix diagonalization.

The techniques are used to signal calculation frequencies and control from artefacts conquered ones. The potential of Eigen decomposition is to correlate even artefacts to corrupted signal. This paper used the minimum-norm method and MUSIC method [59].

2.7.1 MUSIC Model

The MUSIC Model of Motivation is a research-based model to understand the interactions between variables that influence people's motivation to participate in tasks such as classes and class assignments. Many motivational concepts and ideas have been established by researchers all over the world. However, an improved paradigm of inspiration tailored for teachers that could be linked to specific strategies and observable results was missing. The MUSIC model answered this challenge by combining the most relevant scientific concepts into a multidimensional model that students, professors, and instructional designers would appreciate.

This method aims to eradicate false zeros using spectra's average of whole eigenvector [60]. The result is as follow:

$$P_{MUSIC}(f) = \frac{1}{\frac{1}{K}\sum_{i=0}^{K-1}|A(f)|^2} \quad (24)$$

2.7.2 Minimum Norm Model

This model is to separate zeros false from real zeros from the unit circle. From this, we can calculate the most significant commotion subspace vector from one or the other clamour or fundamental sign subspace. The base standard elites a straight mix of the complete commotion subspace eigenvectors [61]. This technique is characterized by

$$P_{min}(f,k) = \frac{1}{|A(f)|^2} \quad (25)$$

The L1-norm loss function is also known as least absolute deviation (LAD), least absolute errors (LAE). It is minimizing the sum of the absolute differences between the target values and the estimated values.

The L2 norm is also known as the least-squares error (LSE). It is minimizing the sum of the square of the differences between the target values and the estimated values.

2.8 Autoregressive Method (ARM)

A statistical model is autoregressive if it predicts future values based on past values. Autoregression is a time series model that uses previous measurements as an input to a regression equation to forecast the next step. It is a basic concept that can lead to precise forecasting of several problems in time series. The autoregressive effects explain the stability of the buildings from time to time. More specifically, the self-recording effects describe the continuity of human variations from time to time.

To estimate EEG signal PSD using a parametric method, the ARM method is suitable. Here there is no spectral leakage, unlike the non-parametric method. Assessment of PSD is achieved by calculating the coefficients using Yule-Walker Method [62].

2.8.1 Yule-Walker Model

The Yule-Walker Process block calculates the input power spectral density by the Yule-Walker AR method. This technique, also called the autocorrelation approach, adapts to the windowed input data of an autoregressive (AR) model. It achieves this by limiting in the least quadratic sense the forward prediction error.

The least-square of forwarding error coefficients are calculated by using Eqn. 26.

$$\begin{vmatrix} r(0)_{xx} & r(-1)_{xx} \ldots\ldots & r(-p+1)_{xx} \\ r(1)_{xx} & r(0)_{xx} & r(-p+2)_{xx} \\ . & . & . \\ r(p-1)_{xx} & r(p-2)_{xx} & r(0)_{xx} \end{vmatrix} x \begin{bmatrix} a(1) \\ a(1) \\ . \\ a(p) \end{bmatrix} \quad (26)$$

Where r_{xx} can be found using the following Eqn.

$$r_{xx}(m) = \frac{1}{N}\sum_{N=0}^{N-m-1} x^*(n)x(n+m), m \geq 0 \quad (27)$$

AR coefficients are as follows:

$$p_{xx}^{BU} = \frac{\sigma_{wp}^2}{\left|1+\sum_{k=}^{p} a_p(k)e^{-j2\pi fk}\right|^2} \quad (28)$$

$$\sigma_{wp}^2 = E_p^f = r_{xx}(0)\prod_{k=1}^{p}[1-|a_k(k)|^2 \quad (29)$$

The input must be a column vector. This input represents a frame of consecutive time samples from a single-channel signal. The block outputs a column vector containing the estimate of the power spectral density of the signal at Nfft equally spaced frequency points. The frequency points are in the range [0, F_s), where F_s is the sampling frequency of the signal.

A seizure is a sudden, uncontrolled electrical disturbance in the brain. Based on their intensiveness there are two types of seizures, convulsive and non-convulsive. By having abnormal EEG, we mean that the patient is in a state called non-convulsive status epilepticus. This is a very mild type of seizure where the patient becomes drowsy. A family member or a close friend is only able to tell this by looking at the patient with attention. Seizures affecting only a part of the brain/hemisphere are called Focal/Partial Seizures. They either affect the whole hemisphere or only a particular lobe of a particular hemisphere of the brain.

The extant research-related literature has been evaluated. It emphasized various operational approaches, such as image processing, extraction and the relevant machine classifiers and deep learning. It also highlighted several operational strategies. To obtain the greatest seizure classification accuracy, these issues should be addressed. Here in this paper, we would like to find the given data is a seizure or not by using hybrid algorithms third-order cumulant, ant colony optimization, statistical methods and sparse encoder, so the higher accuracy is going to be obtained.

3. PROPOSED SEIZURE CLASSIFICATION ALGORITHM

The International League Against Epilepsy (ILAE), 2017, was published in March 2017 and the most recent description of seizures and epilepsy. With good clarification of the terminologies and some new seizures, this new grouping is better structured. Better seizure and epilepsy are diagnosed and managed as categorized as separate medicines that are typically useful with different cases of seizure and clustered into related entities.

Seizures are referred to as intermittent manifestations and indicators of pathological neuronal behaviour of a brain neuronal community. If epilepsy is described as a persistent brain disease with a lasting disposition to repetitive unprovoked seizures, neurobiological, neurological, psychological and social implications. Epilepsy diagnosis involves at least two unsuccessful convulsions that occur more than 24 hours apart. The syndrome is characterized by irregular investigations in a familiar pattern as a characteristic seizure.

The proposed algorithm shown in the figure1 block diagram for seizure EEG signal classification is as follows:

1. Consider the raw EEG signals and apply ACO pre-processing method for getting accurate EEG signal
2. The lower oblique attributes are derived using TOC and used for further processing.
3. Extract features from pre-processed EEG signals using TFD, FFT, EM and ARM methods.
4. Generate three hidden layers using a sparse autoencoder. The optimal features which are derived from TOC, TFD, FFT, EM and ARM are considered as input for the first layer. The subsequent layer extracts refined weights and forwards them to the output layer.
5. By applying a softmax classifier at the output layer, classify EEG signal as focal and non-focal seizures.

4. EXPERIMENTAL SETUP

4.1. Description of EEG Dataset

The Bonn University EEG database [63] is widely used, which is publicly available and labelled as A, B, C, D, and E. There is much published work using the Bonn dataset for epilepsy detection. They concern three main classification problems: the two-class seizure detection problem focuses on the classification between nonseizures and seizures; the three-class epileptic classification problem focuses on the grouping of three different EEG categories (normal, interictal, and ictal); and the five-class recognition problem focuses on the classification of five distinct types (A, B, C, D, and E). This database

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consists of five diverse subsets (set A–E) denoted as Z, O, N, F, and S. Set A and B are composed of surface EEG recordings of healthy volunteers in the wakeful state with eyes open and eyes closed, respectively. On the other hand, Sets C, D, and E are gathered from patients with epilepsy. Thereinto, Sets C and D were recorded during seizure-free intervals. Set C was recorded from the hippocampal formation of the opposite hemisphere of the brain. Set D was recorded from within the epileptogenic zone. Set E only included seizure activities.

4.2. Domain Setup

The dataset is experimented with Python Programming language and evaluated on Google Colaboratory notebook. Datasets are grouped with different combinations for exploring a general classification model, which is classified into two classes (nonseizures and seizures), three categories (normal, interictal, and ictal), and five classes (A, B, C, D, and E). To choose better model parameters, we considered eight models with different configurations.

5. RESULTS AND DISCUSSIONS

The seizure types included in the classification are: (i) focal motor: epileptic spasms, hyperkinetic and automatism - in this new classification, seizures like myoclonic, tonic, tonic-clonic, clonic and atonic which were considered only generalized are now included in focal onset seizures; (ii) focal non-motor: emotional or behavioural arrest; (iii) generalized: epileptic spasms, myoclonic-atonic, myoclonic-tonic-clonic, and absence with eyelid myoclonia.

To evaluate the proposed model's accuracy, we used the standard EEG dataset of Bonn university [63]. This database contains information about average, seizure-prone, and seizure-free individuals. It is divided into five groups: S, O, N, F and Z each of which contains Hundred of one-channel signals of EEG with a length of 23.6s. There is, in reality, a pool of 128 EEG signals. These signals rate sampled at 173.61 Hz with a resolution of 12 bits and a BPF of 0.53-40 Hz. These calculations will exclude a small number of objects. The four cases studied in this analysis were classified into two binary, three, and five types of EEG signals, as follows: Z – S – Z – S – Z – S – Z – Case number two: ZOFN – SC ZO – FN – SC are 3Z – O – F – N – S.

The multilabel confusion matrix calculates class-wise or sample-wise multilabel confusion matrices, and in multiclass tasks, while the confusion matrix calculates one matrix between every two classes, three classes and 5 classes as shown below figures 4.a, 4.b, and 4.c.

103	379
349	1469

Figure4.a: Confusion Matrix for 2 labels

223	625	523
145	1562	541
201	652	1232

Figure4.b: Confusion Matrix for 3 labels

On the x-axis, we have the predicted labels and on the y-axis, we have the true labels of the test set's samples. a perfect classifier would result in a confusion matrix where we have values only on the diagonal for a 2X2, 3X3 confusion matrix and similarly for 5X5 labels.

569	256	356	514	521
546	1245	521	541	456
652	541	1324	521	254
523	521	621	1204	254
523	652	521	541	1201

Figure4.c Confusion Matrix for 5 labels

Figure4(4.a, 4.b, 4.c): Confusion Matrix (CM) for 2, 3, and 5 labels

In this paper, the ACO method is used as pre-processing to extract efficient features. After pre-processing a signal dataset, extract the features using the ToC based data-dependent strategy.

On another hand, statistical features are derived for the entire seizure dataset. The features derived from ToC and statistical features are together given to a sparse auto-encoder automated seizures classification. From ToC non-linear dynamics of the signal are acquired, indeed for seizure(S) it contains a high value and in the case of non-seizures (N, F, O and Z) class the values are different.

5.1 Performance Measures

The confusion matrices (CM) for two labels, three labels, and five labels are shown in Fig.4. The proposed model demonstrated superior labelling precision of 98.12 percent for binary classification (2 labels), 97.32 percent for three labels, and 96.21 percent for five labels when used to discriminate seizure-label EEG signals. random accuracy (RA), kappa value (KV), absolute

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accuracy (TA), precision (SPE), and Sensitivity (SEN) are the efficiency metrics considered [66]. Many of these measures are expressed in terms of true-negative (TN), true-positive (TP), false-negative (FN) and false-positive (FP) and with the following definitions:

$$SEN = \frac{TP}{TP + FN}$$

$$SPE = \frac{TN}{TN + FP}$$

$$TA = \frac{TP + TN}{TP + FP + TN + FN}$$

$$RA = \frac{(TN + FP) * (TN + FN) + (FN + TP) * (FP + TP)}{(TP + FP + TN + FN)^2}$$

$$kv = \frac{TA - RA}{1 - RA}$$

The values of all the above parameters total accuracy, precision, recall, random accuracy and kappa value are given in Table 1 display the superiority of proposing a strategy. Table 1 gives the performance measurements values of the proposed strategy. And Table 2 gives the previous research work along with respective methods, classes and accuracy (%).

Table 1: The Performance Of Measurement Parameters Of Proposed Model

Classes	TA(%)	SEN(%)	SPE(%)	RA	K
Z-S	98.12	98.87	98.54	0.56	0.998
ZO-FN-S	97.32	97.24	97.54	0.45	0.885
Z-O-F-N-S	96.21	96.54	95.63	0.42	0.756

The same classification is visualized in the following figure4

Figure 4: Performance Measurement Of Classes Of The Proposed Model

6. COMPARATIVE ANALYSIS

The findings achieved for the use of several classifiers and some parameters for certain classifications are described in this part for the classification of a seizure epileptic dataset. The deployment of a huge data collection with several (features) properties, 178 is one of the obstacles faced. The function reduction may be used for near predictions of elliptical seizure instances with some specified features as described in the extraction function.

Table 2: Accuracy Values Of Existing Methods And Respective Methods

Methods	Methods and features	classes	Accuracy (%)
Panigrahi and Patidar (2017) [64]	TQWT	Z-S	97.75
		ZO-FN-S	96.35
		Z-O-F-N-S	95.62
Acharya et al. (2018) [65]	13 layers deep CNN	Z-S	88.70
		ZO-FN-S	86.32
		Z-O-F-N-S	85.32
Zhou et al. (2018) [66]	3-layers CNN	Z-S	93.36
		ZO-FN-S	92.35
		Z-O-F-N-S	91.56
Proposed model	ACO+ToC+Statistical + Sparse Encoder	Z-S	98.12
		ZO-FN-S	97.32
		Z-O-F-N-S	96.21

Patidar and Panigrahi [64] used least square SVM (LS-SVM) classifier and tunable Q-wavelet transform (TQWT) with 97.75% for 2-labels, 96.35% for 3 labels and 95.62% for 5-labels, classification accuracy for seizure and non-seizure EEG signals.

Acharya et al. [65] used 13- layer deep CNN model and obtained 88.70% for 2-labels, 86.32% for 3-labels and 85.32% for 5 –label discrimination accuracy for seizure and non-seizure EEG signals. He applied resultant attributes and z-score normalization algorithm are engaged to a deep-CNN structure with five max pooling, three fully connected layers.

Zhou et al. [66] acquainted a three-layer CNN with characterize seizure pre-ictal, and ictal classes. This model has a pooling layer and a completely associated layer. In his work, the time and recurrence upsides of EEG signals are straightforwardly inputted to the three-layer CNN. The discrimination values of this model are 93.36% for 2-labels, 92.35% for 3-labels and 91.56% for 5-labels for discriminating seizure EGG signals. The comparison of proposed and existing models in terms of accuracy is given in figure5. where the proposed model showed good performance when compared with exited models.

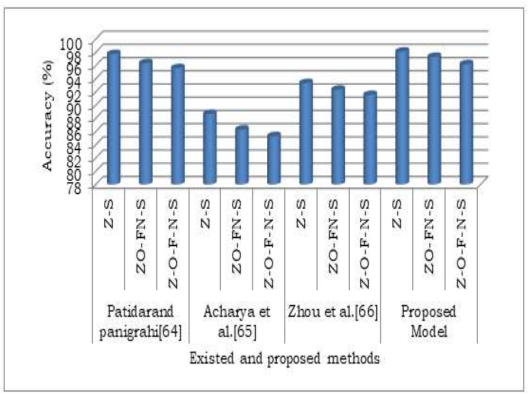

Figure5: The Accuracy Of Existing And Proposed Models

The proposed algorithm has the following additional points

- This method is the most robust feature independent - Robust are statistics with good performance for data drawn from a wide range of probability distributions, especially for distributions that are not normal.
- It can reduce humane error and automated - Automation reduces the chance for human error, helping to ensure consistency, adherence to processes, compliance and increased security by eliminating mistakes that lead to misconfigured systems.
- It gets extract most discriminative features for seizure classification
- A Systematic Mapping of Feature Extraction and Feature Selection Methods of Electroencephalogram Signals for Neurological Diseases Diagnostic Assistance

Selected categories of patients, like the elderly or those with learning disabilities, may be encouraged to start treatment after a first seizure, but this is still a controversial issue. Some situations may indicate deferral of treatment (e.g., pregnancy) while others, for example, patients performing potentially dangerous activities, may favour initiation of treatment. In either case, the patient should be involved in the decision process.

EEG is an essential part of the diagnostic evaluation of epileptic seizures both in children and in adults. If the EEG during wakefulness is normal, sleep EEG can be recommended, but its diagnostic yield is still uncertain. An EEG should be performed within 24 h after a seizure, particularly in children

5. CONCLUSION

The strength of this algorithm is extracting complete significant features sustainability of those features by Ant Colony Optimization algorithm, third-order cumulants (ToC), Autoregressive method (ARM), Eigenvector methods (EM), Fast Fourier transform (FFT), Time-frequency distribution (TFD), autoencoder and softmax classifier. The proposed model was analyzed and evaluated by a series of tools such as confusion matrices, error rates, and classification reports. Each modification produced changes in the results mostly improved accuracy and widely varying performance times. The objective of this study was to decrease the misclassification rate in seizure detection using an autoencoder model extracted features which were achieved.

We evaluated the performance of the algorithms using the standard metrics of seizure detection problems: accuracy, specificity and sensitivity, and also included those of detection problems: precision, recall or sensitivity, F-measure, which is defined as the area under the precision-recall (PR) curve built with different confidence thresholds according to the probability of belonging to the ictal class.

Electroencephalogram(EEG)is a non-invasive tool used to monitor the electrical activities of the brain. EEG signal analysis has several applications in the medical field. It is widely used

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for clinical diagnostics and advances in the Brain-Computer Interface (BCI) area.

For several years, it has been a struggle to achieve an epilepsy quality classification. Several models have been presented in each model with various descriptors and terms which would permit patients and healthcare providers to consider their symptoms, but do not lack substantial restrictions leading to a post-survey analysis.

This paper is focused on classifying non-focal and focal seizure signals of EEG using a sparse encoder with help of ACO and ToC for acquitting perfect features. This proposed strategy experiments in three cases like 2-labels, 3-labels and 5-labels namely: Z-O-F-N-S, Z-S, ZO-FN-S. For 2-labels, 3-labels and 5-labels, the classification accuracy of the proposed strategy is 98.12%, 97.32% and 96.21% respectively. Thus, this automatic and robust mechanism has been offered to assist neurologists.

To conclude, the performance of the models have been verified again with some images never seen by the systems using the classifier and achieved satisfactory results. This classification model would greatly help in better communication about epilepsy types among clinicians, the non-medical community, and researchers.

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