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# WHALE OPTIMIZATION TECHNIQUE-BASED INTELLIGENT EPILEPTIC SEIZURE DETECTION AND CLASSIFICATION MODEL

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## Abstract

A novel epileptic seizure prediction approach for medically refractory epilepsy patients using Brain-Computer Interface (BCI), which is cloud based is developed in this work. Using this approach, the strategically implanted electrodes are influenced to effectively reselect the site of epileptogenicity, however owing to the immediacy of electrographic ictal behaviour, obtaining real time solution is a challenge. The Electrocorticographic (ECoG) and Electroencephalographic (EEG) signals are highly non-linear in nature resulting in wide ictal and normal pattern deviations. It is unfeasible to apply manually derived features for detecting seizure, since even a limited set of electrodes generate vast amount of data that takes longer time to process. Hence, by harnessing the capabilities of both deep learning and cloud computing, a seizure detection approach using BCI as Internet of Things (IoT) is designed and implemented in this paper. The process of feature extraction in addition to classification is carried out using Convolution Neural Network (CNN). The weights and biases of the CNN are optimized using Whale Optimization Algorithm (WOA). Using IoT, the storage, automatic computing and real time processing of the proposed approach is implemented. The electroencephalogram (EEG) has been widely used to detect epileptic seizures; however, it is still difficult to detect seizures from the EEG and necessitates the expertise of neurophysiologists. Real-time seizure detection is crucial for warning patients of imminent seizures, and it is possible using an Internet of Things (IoT)-based cloud platform. The electroencephalogram (EEG) has been widely used to detect epileptic seizures; however, it is still difficult to detect seizures from the EEG and necessitates the expertise of neurophysiologists. Real-time seizure detection is crucial for warning patients of imminent seizures, and it is possible using an Internet of Things (IoT)-based cloud platform. Thus, it is appropriate for choosing discriminative characteristics from a vast array of neurofeatures derived from EEG. The classification model is also built using the ELM framework, which leverages the DE algorithm for quick and effective learning. Findings indicate that the proposed NB-GWOA-DEELM model outperforms its rivals in categorising seizure states from EEG by avoiding over- and under-fitting and by performing more accurately.

**INDEX TERMS** Brain-Computer Interface, Cloud Computing, Convolutional Neural Network, Deep Learning, EEG Big Data, Epilepsy, Whale Optimization Algorithm (WOA).

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## I INTRODUCTION

A recently developed meta-heuristic optimisation system called WOA imitates the behaviour of humpback whales in the wild. The wrapper-based strategy is used in the proposed model to identify the best subset of features. This method was used to identify the optimum feature subset that preserves the fewest features while maximising classification accuracy. Epilepsy is a chronic nerve condition marked by unexpected and recurring attacks known as epileptic seizures, affecting more than 65 million people around the world, which amounts to at least 1% of the entire population of the world. The person with epilepsy experiences seizures at any time of the day or night with no apparent reason, while fatigue in addition to emotional stress leads to frequent seizure attacks. The first phase of specialized pharmacological treatment using Anti-Epileptic Drugs (AED) is effective in curing or even controlling nearly 70% of epileptic patients, whereas in case of refractory epilepsy, the treatment is carried out using surgical resection. The activities of the epileptic brain is disclosed completely using the EEG recordings, so it is used for successfully locating the seizure zones in addition to the prediction of seizure before its onset. In case of epileptic EEG signals, there are four different states of brain activities namely postictal, ictal, preictal and interictal. The brief period prior to the occurrence of seizure is known as preictal, the period during the occurrence of seizure is known as ictal, the state that subsequently follows the ictal period is known as postictal and the state that occurs between previously described states is known as interictal [1-5].The most prevalent neurological condition, epilepsy, is distinguished by recurrent abnormal brain activity called epileptic seizures [7]. It has an incidence rate of 5.8 per 1000 people in the developed world and 10.3 per 1000 to 15.4 per 1000 in poorer nations, making it the second most common neurological disorder after Alzheimer's disease and stroke that is evident on the global web [14]. Hence, it is precisely through the early detection and prediction of epileptic seizures that patients can seek more effective protection and treatment. The activities of the brain should be observed by electroencephalography (EEG) data that contain epilepsy indications in order to identify and forecast epileptic seizures clinically. The EEG is a very useful tool for understanding neurological conditions like epilepsy because it provides valuable data on a variety of mental and physiological states [11]. The EEG signals of epileptic patients contain two aberrant states of activity, termed interictal and ictal [1]. The term "ictal signals" refers to a physiological occurrence, such as a seizure, whereas the term "interictal signals," often known as "seizure free," refers to the interval between seizures that is indicative of an epileptic illness.

Intelligent algorithms are increasingly being used to enhance the precision of EEG-based seizure identification owing to the tremendous advancement seen in the field of machine learning in recent times [6]. These techniques include classification methods that encompasses fuzzy logic systems [7], neural networks [8], naïve Bayes [9] and Support Vector Machines [10]. Features are taken from raw EEG signals to train classification algorithms that can distinguish distinct states of epilepsy for seizure detection. Despite the development of feature extraction and classification approaches, obtaining effective features with vital information for precise seizure detection remains a difficult task. Deep learning, which is a machine learning approach has obtained immense attention in recent years as a remarkable feature selection approach. In deep learning, from huge quantity of simple expressions, complex representation of features are obtained using multi-level combinations. Among several deep learning approaches, CNN is one of most predominantly applied techniques [11-14]. The desired outcome is obtained by identifying the suitable features by analysing and modifying the weights of each layer of the neural network. The process of modifying the weights of CNN is carried out using WOA [15], which is inspired by the bubble net hunting technique used by humpback whales, effectively optimizes the CNN and enhances its efficiency.

An IoT based BCI system that provides safe storage along with computational resource for solving issues associated with big data caused due to implanted electrodes in epileptic patients is proposed. The process of feature extraction and classification is significantly executed using the application of Whale Optimized Convolution Neural Network (WO-CNN). Thus an effective seizure site location and seizure detection approach using big EEG data is developed in this work. An innovative method for handling optimisation issues is the Whale Optimisation Algorithm (WOA). Three operators are used in this algorithm to replicate how humpback whales hunt: by searching for prey, circling prey, and using bubble nets.

## II PROPOSED SYSTEM DESCRIPTION

One of the most prevalent neurological disorder that affects about 60 million people worldwide is epilepsy. The occurrence of unexpected seizures, which is a symptom of epilepsy is recognized with inconveniences experienced with cognitive functions, sensation, movement or loss of consciousness or awareness. In extreme situations, with the lack of proper diagnosis and treatment, epilepsy will result in brain damage. So the design of suitable seizure detection approach is considered crucial. The most effective analysis and diagnosis technique used for the treatment of epilepsy is EEG.

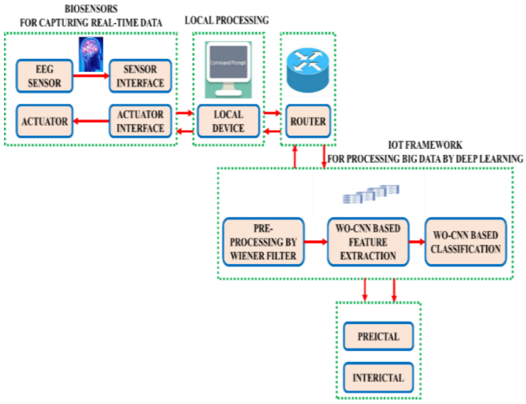



**Figure 1: Structure of the proposed IoT based BCI system for detection of epilepsy**

The structure of the proposed IoT based epilepsy detection approach is given in Figure 1. The EEG signals in general are highly influenced by numerous undesirable artefacts that comprises of heartbeat, muscle activity, eye blink, etc. The impact of these artefacts are eliminated in the pre-processing stage using the employment of weiner filter. The pre-processed EEG signals are then subjected to feature extraction using the optimized deep learning approach of WO-CNN. The classification of the obtained signals as preictal and interictal is also accomplished using WO-CNN, hence both the process of feature selection and classification is accomplished using WO-CNN. The EEG signals are initially recorded and transported to the IoT for processing using WO-CNN based deep learning method.

## III PROPOSED SYSTEM MODELLING

### A) PREPROCESSING USING WEINER FILTER

The electrical signal obtained from EEG, which is instrumental in detecting the behaviour and activity of the human brain is affected heavily by the existence of artifacts that hinders the accurate analysis of the EEG signals. Undesired signals called artifacts are caused by experimental errors, noise in the environment in addition to physiological distortions. Extrinsic artifacts include experiment error and environmental disturbances caused by external sources, whereas intrinsic artifacts include physiological distortions such as heart beat, muscle activity, eye blink, etc., caused by the body itself. In this work, we adopted wiener filter for successful removal of undesirable artefacts from the EEG signals.The structure of wiener filter for pre-processing EEG signals is given in Figure 2.

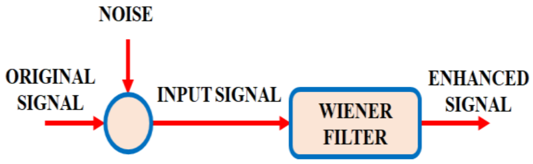



**Figure 2: Pre-processing using Wiener filter**

Spiral updating position: in this step, as illustrated in Fig. 2 the distance between the positions of whale and its prey is calculated, and then an equation of spiral is created between whale and prey locations to simulate. The degradation process of an EEG signal highly affected by artefacts in a wavelet domain is stated as,

$$X = S + N \quad (1)$$

Where, the pristine signal without artefacts is specified as S and the input EEG signal is specified as X. The terms N and $\sigma_n^2$ is used to specify the zero mean and an additive white Gaussian noise with a finite variance respectively. If the input EEG signal $X$ is of size $W \times H$,

$$X = [x_{ij}]_{W\times H} \quad (2)$$

Where, $i = 0, 1, \ldots, H-1$and $j = 0,1, \ldots, W-1$. The objective of the wiener filter is to get the best precise estimation of S from X. The wiener filter's simplified scalar relation is as follows,

$$S_{i,j} = \Psi_{i,j} x_{i,j} \quad (3)$$

$$\Psi_{i,j} = \frac{E\{S_{i,j}^2\}}{E\{x_{i,j}^2\}} \quad (4)$$

S is formulated as the linear combination of $\{x_{ij}\}$,

$$S = \Psi . X \quad (5)$$

$$\Psi = [\Psi_{ij}]_{W\times H} \quad (6)$$

The artefact free EEG signal is given as,

$$E\{S_{i,j}^2\} = E\{x_{i,j}^2\} - \sigma_n^2 \quad (7)$$

Where, $E\{x_{i,j}^2\}$ is expressed as,

$$E\{x_{i,j}^2\} = \frac{1}{|c_{i,j}|} \sum x_{m,n}^2 \quad (8)$$

Where, the coefficient set within a local window is represented as$C_{i,j}$ and its cardinality is$|C_{i,j}|$.

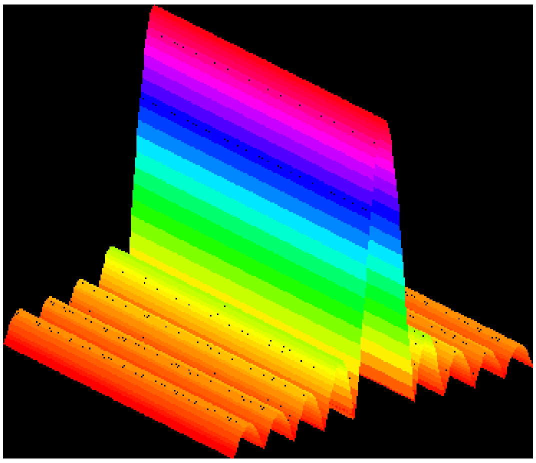
$$\Psi_{i,j} = \frac{(E\{x_{i,j}^2\} - \sigma_n^2)}{E\{x_{i,j}^2\}} \quad (9)$$

The EEG signals that are pure without the influence of noise, obtained from the process of pre-processing using wiener filter is then subjected to feature extraction using CNN. In a wrapper-based approach, the whale optimisation algorithm (WOA) is utilised for feature selection. The wrapper-based methodology's key characteristic is the application of the classification strategy as a guide to feature selection methods based on some optimised component; selected feature set. This study uses the KNN method of classification to maintain the quality of the chosen feature set. Based on the vast majority of the KNN category, KNN is employed as a classifier that matches the unknown case. Information on various brain activities can be found in the frequency-domain properties of EEG data. Hence, any EEG frequency band may be affected by both normal and pathological activities. Particularly, reports of epileptic seizure episodes have been made in the majority of EEG frequency bandwidths [6]. It has been stated in the literature [7] that the frequency domain characteristics of EEG data can be used to predict epileptic seizures. We determined the power spectrum density of the EEG channels for each window in this study and used the results as spectral features to categorise each window as preictal or non-ictal events.

The EEG signal was segmented using a 10-second time-domain frame with no overlap. Each segmented window was processed using a Fourier transform, and the results were separated into five clinically recognised frequency bands, namely. We used relative spectral power density to provide a fair comparison across all windows.

This is accomplished by dividing the power in band values by the combined spectral power of each window to normalise them. Finally, for each of M channels (M = 18 + M + 24), five relative in-band power spectral density features are recovered, yielding a total of 5M features (90 + 5M + 120). overlap. The most important technique for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter. From a signal processing standpoint, blurring due to linear motion in a photograph is the result of poor sampling. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Unfortunately, if the shutter speed is too slow and the camera is in motion, a given pixel will be an amalgram of intensities from points along the line of the camera's motion. This is a two-dimensional analogy to

$$G(u,v)=F(u,v).H(u,v)$$



It should be noted that the tools for restoring images discussed here function similarly in situations when there is blur from improper focus. The choice of H in this instance is the only distinction. The 2-d Fourier transform of H for focus blurring is the sombrero function, which is explained elsewhere. The 2-d Fourier transform of H for motion is a series of sine functions in parallel on a line perpendicular to the direction of motion. It should be noted that the tools for image restoration outlined here work similarly when there is blur due to incorrect focus. The only difference in this case is that H was chosen. For focus blurring, the sombrero function, which is described elsewhere, is the 2-d Fourier transform of H. The parallel sinc functions on a line perpendicular to the direction of motion make up the 2-d Fourier transform of H for motion.

The best method to solve the second problem is to use Wiener filtering. This tool solves an estimate for F according to the following equation:

$$\mathbf{Fest(u,v) = |H(u,v)|^2.G(u,v)/(|H(u,v)|^2.H(u,v) + K(u,v))}$$

The Original Whale Optimization Algorithm:

Seyedali and Andrew [22] have suggested the whale optimisation algorithm (WOA), a revolutionary meta-heuristic optimisation method that mimics the social behaviour of humpback whales. TIMThe bubble-net hunting policy serves as the basis for WOA as follows:

## B) CNN BASED FEATURE EXTRACTION AND CLASSIFICATION:

It is a remarkably challenging task to retrieve relevant patterns and features from the big EEG data for analysis and data querying.So the deep learning approach of CNN, which retrieves relevant patterns and features using hierarchical multilevel technique is adopted in this work. However, the application of CNN for EEG feature extraction is limited due to certain drawbacks that includes high computational time, minimum efficiency and trapping in local optima. Therefore WOA is selected as optimization algorithm for heightening the working of CNN. For the detection of seizures, the available pre-trained network is used instead of a newly trained networkto minimize the amount of labelled data trough transfer learning. The WOA optimisation algorithm is brand-new. It takes its cue from the way humpback whales behave in the wild. The hunting habit of these whales is typically their only means of survival. Although hunting tactics have been used in the past to address optimisation issues, the whale algorithm is special in that it can use a best or random agent in the search space to pursue the prey.

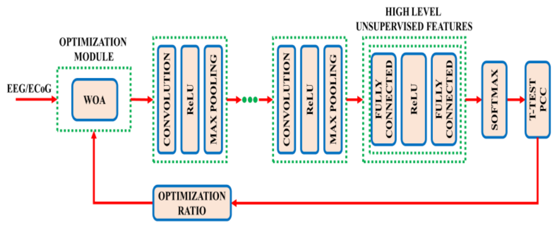



**Figure 3: Structure of CNN for Feature selection and Classification**

The structure of the CNN consists of multiple layers, where the first layer is used for defining the input dimensions. The central layers of the CNN comprises of several convolution layers which are coupled with max-pooling layers and Rectified Linear Units (ReLU) as seen in Figure 3. In every convolutional layer, neurons are linked as rectangular grids with the similar weights. Single output is derived by subsampling the convolution layer’s small rectangular blocks in pooling layer. The final layer of the CNN is designed to accomplish the process of classification of patterns in to interictal and parietal states of epilepsy. The basic features are filtered in the first layer of CNN and then by processing these basic features, features of higher level are developed by the deeper layers. Since a comprehensive signal is developed by incorporating several primitive features by the deeper layers, retrieval of relevant features is carried out before classification. The softmax layer is used for the process of classification and it operates based on the following equation,

$$\frac{P(c_r|)P(x|c_r)}{\sum_{k=1}^{K} P(c_k)P(x|c_k)} = \frac{\exp(a_r)}{\sum_{k=1}^{K}\exp(a_k)} \qquad (10)$$

The accuracy and performance of the CNN is enhanced further by optimizing the weights and biases of the CNN.

**Fitness Function:**

How to modify an optimisation algorithm's fitness function (objective function) in order to get the best result constitutes the majority of its work in general (or the nearest optimal solutions). As a result, we have modified the WOA's fitness function to take classification accuracy into account while doing searches. To do this, ten accuracy values for each search agent (whale) are collected using the K-fold cross-validation setup (k = 10), and Acc is set in this work to be between [0, 1]. The fitness value is then calculated by averaging the accuracy values.

$$f(w,t) = \sum_{k=1}^{N} \frac{Acc_{w,t,k}}{N}$$

Where f(w, t) the fitness function for whale w in iteration t, k is the obtained accuracy, N refers to the number of folds. With the use of the whale optimisation algorithm (WOA), this research attempted to choose the ideal feature set and acquire. When all features are included, classification accuracy is comparable or greater. WOA was used to tackle the feature selection problem using a wrapper-based approach. This issue was turned into an optimisation issue with the classification accuracy and the chosen number of features as the objective functions.

## C) WHALE OPTIMIZED-CONVOLUTION NEURAL NETWORK (WO-CNN):

The WOA, which is derived based upon the hunting procedure of the whales, is used for the evaluation of an ideal and perfect solution for a problem. The WOA algorithm keeps improving and updating the solution till a perfect solution is attained. The method of creating and updating WOA rules is distinct when compared to other meta-heuristic techniques. Whales generally capture their prey by trapping them in a network of bubbles.

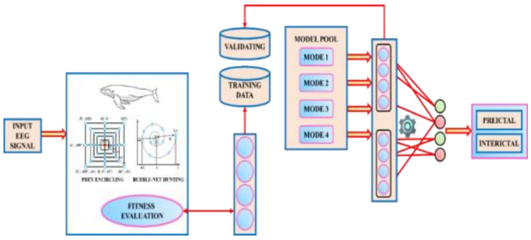



**Figure 4: Structure of WO-CNN**

The mathematical definition of the whale's bubble-net is as follows

$$X(t+1) = \begin{cases} X^*(t) - AD & p < 0.5 \\ D' e^{bl} \cos(2\pi t) + X^*(t) & p \geq 0.5 \end{cases} \quad (11)$$

$$D' = |CX^*(t) - X(t)| \quad (12)$$

$$A = 2ar - a \quad (13)$$

$$C = 2r \quad (14)$$

In order to identify the best feature subset that maximises classification performance, this research implements the WOA adaptively. The whales in WOA continuously modify where they are in relation to any point in the space beginning with the initial best search agent. They then strive to update their locations in relation to the optimal search agent, as shown in equations (1) and (2). (2). In the dataset, each individual answer is represented as a continuous vector of the same dimension. The values of the solution vector are continuous and limited to [0, 1]. values of the solution fitness evaluation are binary represented. The applied fitness function is ordinarily matching the classification performance and the number of selected features. This can be represented by the equation (10).

Where, the current iteration is specified as $t$, the distance between the beat solution (prey) and the $i^{th}$ whale is specified as $D'$. The random constants within [-1, 1] is specified as $l$, whereas the random constants within the terms $p$ and r refers to the random constants within [0, 1]. To mathematically represent bubble net hunting and prey encircling, an arbitrary population is first analysed, and the results are updated for each iteration. The structure of WO-CNN is given in Figure 4. The drawbacks of CNN for detection of epilepsy such as high computational time, minimum efficiency and trapping in local optima is subdued by the application of WOA for optimization. Biases and weights, which are the key parameters that are considered for CNN structure optimization is given as,

$$W = \{w_1, w_2, \ldots, w_p\} \quad (15)$$

$$A = \{a_1, a_2, \ldots, a_A\} \quad (16)$$

$$w_n = \{w_{1n}, w_{2n}, \ldots, w_{Ln}\} \quad (17)$$

$$b_n = \{b_{1n}, b_{2n}, \ldots, b_{Ln}\} \quad (18)$$

$l = 1,2, \ldots, L$ and $n = 1,2, \ldots, A$. Where, the number of layers and agents are represented as $L$ and $A$ respectively and the terms $l$ and $n$ refers to the number of layer and agent index respectively. The weight value of layer $i$ is specified as $w_{in}$. The optimizing parameters is given as,

$$w_n = \{W, A\} \quad (19)$$

These assignments are presented in Figure 5. The error value measured between system output and reference is given as,

$$E = \frac{1}{T} \sum_{i=1}^{k} \sum_{j=1}^{k} (d_{ji} - o_{ji})^2 \quad (20)$$

Where, number of output layers is described as $k$, number of training samples as $T$ and the CNN output value along with desired value are represented as $o_{ji}$ and $d_{ji}$ respectively. With the use of the whale optimisation algorithm (WOA), this research attempted to choose the ideal feature set and acquire. When all features are included, classification accuracy is comparable or greater. WOA was used to tackle the feature selection problem using a wrapper-based approach. This issue was turned into an optimisation issue with the classification accuracy and the chosen number of features as the objective functions. This algorithm's modelling uses three operators to imitate the behaviour of humpback whales during their hunting phases of exploration, encirclement, and bubble-net foraging. The following model and explanation illustrates the mathematical formulation:

Encircling the prey The whale algorithm begins this phase with the initial best search agent. It is presumptively the location of the prey, or very near it, and that the existing answers are the best.

By simulating encircling the prey, this modelling enables any agent to update its location in the vicinity of the current optimal solution. The movement in hypercubes will be made easier by the agents surrounding the best answer as it can go further in the search space for n dimensions.

Exploitation phase: This phase is also called the bubblenet attacking and it works by two approaches as follows: • Shrinking encircling mechanism: in this step, the value of →−a in equation is decreased and consequently the fluctuation range of −→A is also decreased by →−a . This implies that →−a is randomly placed in [−→−a, −→a ]. Where a is decreased from 2 to 0 over the optimization time. The randomness of →− A in [-1, 1], the new location of the search agent can be determined anywhere in between the agent past location and the current best location. Fig. 1 shows the possible locations from (X, Y ) towards (X∗, Y ∗) that can be accomplished by 0 A 1 in a 2-D space.

Exploration phase: In this phase, WOA achieves a global optimization. In Fig.3, whales search for its prey according to their positions to each other randomly. The −→A is set randomly from [-1,1] to oblige the search agent to move away from the reference whale. This means that →− A has to be either greater than 1 or less than the -1. Moreover, the updated position of a search agent here is done by randomly chose an agent that allows the WOA to perform global search

## IV RESULTS AND DISCUSSIONS

An IoT-based BCI system is proposed that provides secure storage and computing resources to address concerns with big data created by implanted electrodes of epileptic patients. The pre-processing of the EEG signal is done using weiner filter, which is followed by successful feature extraction and classification using WO-CNN. The research applies the public CHB-MIT Scalp EEG database that comprises of 24 EEG recordings collected from 23 patients for validation of the proposed epilepsy detection approach using MATLAB.

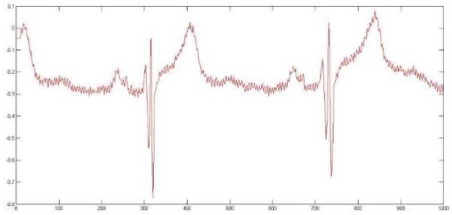


**Figure 5: Input EEG signal**

The input EEG signal for epilepsy detection is given in Figure 5. As seen in the figure, the image is affected by high level of noise contents. By the application of the Weiner filter, the unwanted artefacts that limits the proper examination of the EEG are removed and a signal of pristine quality is obtained as seen in Figure 6.

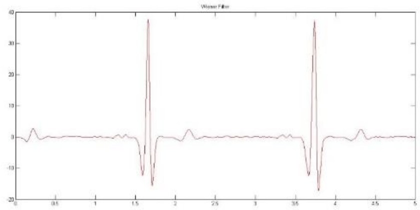
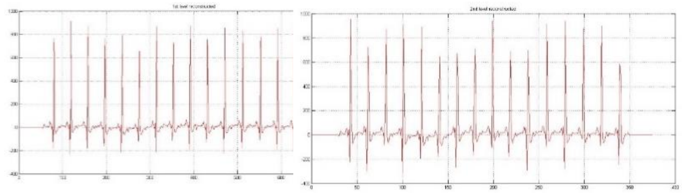
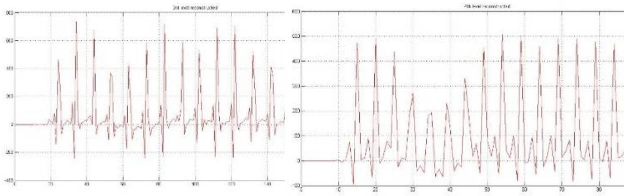


**Figure 6: Weiner filter output**



**(a)** **(b)**



**(c)** **(d)**

**Figure 7: WO-CNN based Feature extraction**

The process of feature extraction by which the temporal and spatial features of the EEG signal is extracted is obtained by considering the reconstructed signals as seen in Figure 7. Both the process of feature extraction and classification is done using WO-CNN. Based on the extracted output, the signals are classified as preictal and interictal stages of epilepsy as displayed in Figure 8.

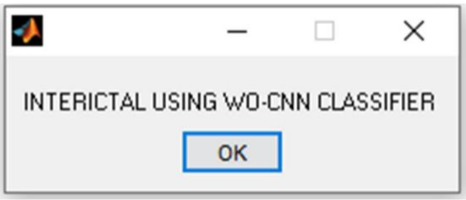



**Figure 8: Output of the WO-CNN classifier**

## V CONCLUSION

The effective processing and handling of big data is extremely useful in the management of complex medical diseases that need urgent medical assistance like epilepsy. A new IoT based BCI approach is proposed in this work, which addresses the issues of processing and storage of these big data, for the significant prediction of epileptic seizures. The artefacts that affect the quality of the EEG signals is eliminated greatly using the weiner filter. The limitations exhibited by manual feature extraction and classification approaches is subjugated with the application of CNN based unsupervised deep learning approach. An excellent metaheuristic algorithm in the form of WOA elevates the performance of CNN in terms of accuracy, computational time and efficiency. The proposed epilepsy detection technique is capable of analysing and processing huge quantity of EEG data. This technique has the remarkable advantage of assisting in providing timely treatment for control of epileptic seizure.

Through early identification of the seizure's characteristics, automatic seizure detection can aid in effective treatment and quick protection. In this study, a hybrid automatic detection method named WOA-SVM, which detects epilepsy using the Whale Optimization Algorithm (WOA) and Support Vector Machine with RBF in EEG signals, was proposed. Also, eight parameters from the EEG signals, including entropy, skewness, maximum, median, minimum, mean, energy, standard deviation, RWE, and variance, are retrieved and divided into a number of subbands using the discrete wavelet transform (DWT). WOA was modified for feature selection and SVM classifier optimisation parameters in the suggested method. Finally, the results of the experiments showed that the suggested method has a performance accuracy of 100% and can successfully distinguish interictal and ictal EEG of epileptic patients from the normal signals. It will be beneficial for future work to apply more advanced and reliable machine learning technologies for additional analysis and detection in the biological area. Results of the newly announced WOA feature selection algorithm are compared to those of previous optimisation techniques in the tables below. The average of 20 runs on the Matlab environment are used to calculate the findings. Table III and Table IV present the mean fitness for each optimisation strategy across the various datasets as well as the standard deviation. Table II, which shows the statistically worst case, makes it abundantly evident that the WOA outperforms all other features, demonstrating the viability of the wrapper-based method to feature selection. In general, WOA outperforms GA and PSO, proving its capacity to explore the space for the best feature subset. Moreover, it has the ability to prevent early convergence that could be brought on by falling

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