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Optimized One-Dimension Convolutional Neural Network for Seizure Classification from EEG Signal based on Whale Optimization Algorithm

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Abstract: Epilepsy is a chronic disorder that causes sudden, recurring seizures and early detection of seizures is needed for prompt treatment to reduce the higher risk. An electroencephalogram (EEG) can detect epilepsy based on traces of electrical activity and wave patterns in the brain. However, analyzing EEG signals takes a long time and is operated by neuroscientists. In this paper, we propose automatic seizure detection using a one-dimension convolutional neural network (1D CNN) and the approach of whale optimization algorithm (WOA). The EEG signal is trimmed every three seconds, and features are extracted using discrete wavelet transform (DWT). The WOA approach was used to optimize the number of layers and neurons in 1D CNN. The experimental results show that the proposed model can improve CNN's performance in detecting seizures with an accuracy of 99.76%, respectively. The proposed method is suitable for the children's hospital boston – massachusetts institute of technology (CHB-MIT) dataset.

Keywords: Epilepsy, Electroencephalography (EEG), Discrete wavelet transform (DWT), Convolutional neural network (CNN), Whale optimization algorithm (WOA).

1. Introduction

Epilepsy is a neurological disorder that affects approximately 50 million people worldwide, of which 80% reside in developing nations [1, 2] epilepsy is a failure of the brain in which patients typically experience seizures that are accompanied by no outward signs or symptoms. In addition, epilepsy is dangerous since it can raise the risk of other diseases such as dementia, cardiovascular disorders, depression [2]. An electroencephalogram (EEG) is typically used in clinical diagnostics because of its ability to record brain wave patterns and identify even minute traces of electrical activity in the brain. The diagnosis of epilepsy is performed manually by examining EEG patterns, which is a method that is both time-consuming and prone to inaccuracy [3]. Therefore, the process of evaluating recorded EEG brain signals causes a significant strain on neuroscientists and affects the effectiveness of their work. These restrictions have prompted efforts to create and develop automated systems to assist neurologists in identifying seizure and non-seizure EEG brain signals. These automated systems will help neurologists distinguish between the two types of EEG brain signals [1].

There have been several research done in the past that used EEG data to carry out automatic detection of epilepsy. These studies classified EEG data into two class as well as three categories. A one-dimensional pyramidal CNN, an Adam optimizer, and a dataset obtained from BONN University were used in the method that Ullah I, presented for diagnosing epilepsy. After the convolution layer, the suggested model includes one more layer, which is referred to as the batch normalization (BN) layer. This layer helps give fast convergence while eliminating special initialization of a parameter. In their particular example, they carried out two experiments, the first of which divided participants into two categories (seizure and non-seizure), while the second of which divided participants into three categories (normal, ictal, and interictal). The overall accuracy for the 2 class classification is found to be 96.1%, while the overall accuracy for the 3 class classification is found to be 98.1%. In neither instance was any application of classification hyperparameter optimization discovered by the classifier [1]. Xiaoyan Wei suggested using a three-dimensional CNN and compared it to a two-dimensional CNN in a situation where the classification that was carried out was a three-class classification. These three classes include pre-ictal, interictal, and ictal. When a 3-dimensional CNN is utilized, the accuracy that is achieved is 92.37%, however when a 2-dimensional CNN is utilized, the accuracy that is achieved is 89.91%. Xiaoyan Wei's classification work also does not make advantage of CNN's hyperparameter tuning feature [3]. Wei Z proposed the identification of epilepsy coming from CHB-MIT, which was then processed into a time-domain waveform. Additionally, Wei Z introduced the use of merger of the increasing and decreasing sequences (MIDS) and data augmentation to improve classification performance using CNN. The accuracy that was acquired for the experiment that used MIDS was 82.37%, whereas the accuracy that was gained for the experiment that used augmentation data was 84.00 %. The classification that was done by Wei did not make use of parameter optimization, which is the reason why the accuracy that was reached is still less than 90% [4]. To classify two different datasets, namely the BONN university and CHB-MIT datasets, Li and Chen made use of the fast fourier transform (FFT) to get matrix generation, the principal component analysis network (PCANet) to get hidden features in the matrix generation generated by FFT, and the super vector machine (SVM) to label each feature generated by PCANET. The BONN dataset has an accuracy of at least 99%, but the CHB-MIT dataset has an accuracy of 98.47%. Within the scope of this study, the classification model does not incorporate optimization [5]. Using the CHB-MIT dataset, which has an average accuracy of 99.44%, Nath Bairagi diagnoses epilepsy using discrete wavelet transform (DWT), and then distinguishes two types, namely seizures and non-seizures, using artificial neural network (ANN). The sequential window algorithm (SWA), which is used to increase the false detection rate, is one of the things that makes Nath Bairagi's method better (FDR) [6]. In order to diagnose epilepsy in the datasets from CHB-MIT and Seoul national university hospital (SNUH), Chulkyun Park utilized 1D and 2D CNNs. On the CHB-MIT dataset, accuracy was measured at 86.60%, whereas on the SNUH dataset, accuracy was measured at 90.50%. Within the scope of this investigation, they do not make use of classification hyperparameter optimization [7]. The accuracy of Jana G's research, which involved identifying epilepsy by employing CNN 1D with input information in the form of a spectrogram, came out to be 77.56%. There was no evidence identified of the employment of a classification hyperparameter optimization technique [8]. The CHB-MIT dataset was used to test Aayesha's method for identifying epilepsy, which uses a classification that is divided into two groups, namely fuzzy and traditional. Aayesha's method was carried out with CHB-MIT dataset. Utilized DWT in order to extract features. Both the standard method of k-nearest neighbor (KNN) classification (with an accuracy of 91.09%) and the fuzzy method of fuzzy rough nearest neighbor (FRNN) classification (with an accuracy of 92.76%) yielded the best results in terms of accuracy. In this particular investigation, classification hyperparameter tuning was not utilized in any way [9]. Mengni Zhou proposed the use of the fast fourier transform (FFT) for feature extraction and the convolutional neural network (CNN) for the classification model on the CHB-MIT and Freiburg datasets for the classification of three classes: interictal, ictal, and preictal. On the Freiburg dataset, the resulting accuracy is 92.30% and on the CHB-MIT dataset, it is 93.00%. The classification makes no use of hyperparameter optimization [10]. Rajendra Acharya U. proposed using 13-Layer CNN to detect epilepsy in the Bonn dataset. Achieved an accuracy rate of 88.67%. Neither was hyperparameter optimization discovered in this investigation [11]. In the absence of hyperparameter optimization study, researchers achieve a level of accuracy in the region of up to 80%.

The optimal classification accuracy can be obtained by tuning the hyperparameters of the classifier. Several researchers have employed meta-heuristic optimization techniques to adjust these hyperparameters. In addition, several new metaheuristic optimization techniques have been developed, such as stochastic komodo algorithm (SKA) [12], fixed-step average and subtraction-based optimizer (FS-ASBO) [13], multi leader optimizer (MLO) [14], mixed leader based optimizer (MLBO) [15], three influential members based optimizer (TIMBO) [16], random selected leader based optimizer (RSLBO) [17], squirrel search optimizer [18], puzzle optimization algorithm (POA) [19], and ring toss game-based optimization algorithm [20].

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However, those algorithms have not yet been applied to optimize the hyperparameters of the classification model. On the other hand, the whale optimization algorithm (WOA) [21] has been applied in some studies to optimize the hyperparameters of the CNN model, as reported in [22, 23]. Both of the aforementioned studies demonstrate how WOA can significantly improve CNN's classification performance. In this study, we proposed a CNN optimization strategy using the whale optimization algorithm (WOA) to detect epilepsy. The proposed method is utilized to select the number of filters, number of neurons in the hidden layer, and dropout employed in the hidden layer of CNN. Discrete wavelet transform (DWT) is employed for feature extraction. This research seeks to detect EEG signals by distinguishing between seizure and non-seizure signals.

The following is the order in which each section of this paper is presented: Section 2 presented work related to this study. The materials and methods that were utilized in this research are discussed in section 3. Section 4 provides an analysis of the findings of the research as well as the discussion. In the final section, the conclusions are discussed.

2. Materials and method

2.1 EEG dataset

This study makes use of a dataset from children's hospital boston – massachusetts institute of technology (CHB-MIT), which is accessible online. This data comprises of 24 recordings of EEG signals originating from 22 patients, with the 23rd recording being the recording of the first patient and a time interval of approximately 1.5 years between records. The twenty-fourth record was added in 2010. Each case (chb01, chb02, etc.) consists of nine to forty-two continuous edf files from a single patient. In most situations, these signal recordings capture EEG signals with a duration of one hour; however, in chb10, they are captured with a duration of two hours, whereas in chb04, chb06, chb07, chb09, and chb23, they are captured with a duration of four hours. All signals are sampled at a rate of 256 samples per second with a resolution of 16 bits. Positioning and naming of electrodes for signal recording also adhere to the international 10-20 system. The file record contains 664 lists of edf files, and the list of files with one or more seizures is stored in a file named RECORDS-WITH-SEIZURE. Describe the recorded file pertaining to the presence or absence of seizures.

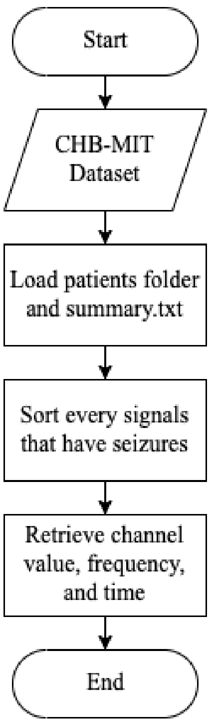


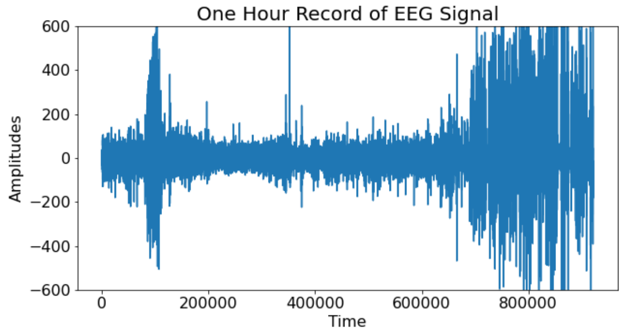
Figure. 1 Data information extraction flow chart

2.2 Preprocessing

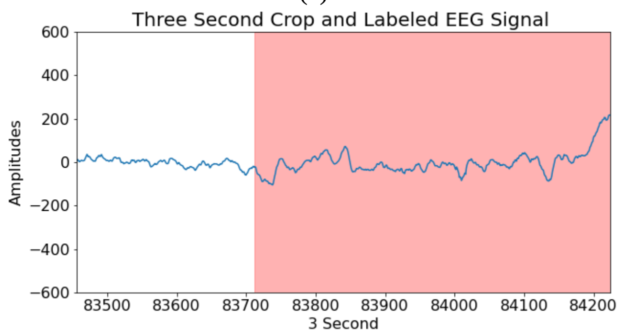
The raw data from the CHB-MIT dataset is processed first, with the information contained in each patient extracted via a file ending in summary.txt in each patient's folder. The data collected includes which signal a seizure occurred at, when it happened, and which channel was used.

Some patients were recorded with 24 or 26 channels, however the majority of patients were captured with 23 channels. Because the number of channels used by each patient varies, the selected channels in this research are 18 channels, and these channels are used to classify each patient. F8-T8, F3-C3, T8-P8, P8-O2, T7-P7, FP1-F7, F7-T7, FP2-F4, CZ-PZ, C3, P3, C4-P4, FZ-CZ, P7-O1, P3-O1, P4-O2, FP2-F8, F4-C4, and FP1-F3 are the channels utilized [24]. The flow of the data information extraction procedure is depicted in Fig. 1.

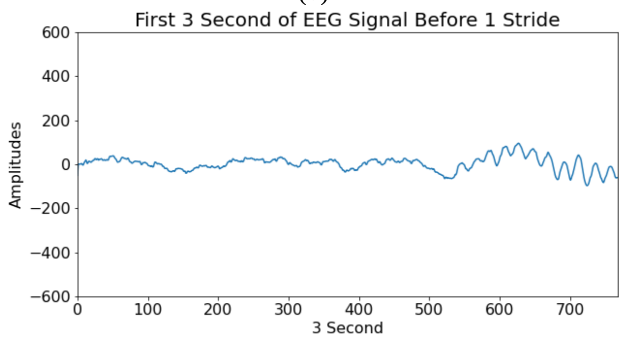
Each file that showed seizures in each patient was then chopped every 3 seconds with a stride of 1 and labeled with seizure and non-seizure locations depending on the time received from the summary.txt. Fig. 2 (a) illustrates an EEG signal recording from one subject for one hour. Fig. 2 (b) shows an EEG signal recording that was cropped for 3 seconds and labeled in red for the seizure region. A stride is the number of seconds between signal cuts. In this scenario, a one-second stride is employed, with the first cut beginning from the 0th second to the 2nd second and the second cut beginning from the 1st second to the 3rd second. Fig. 2 (c) and (d) show a signal cut with one stride.



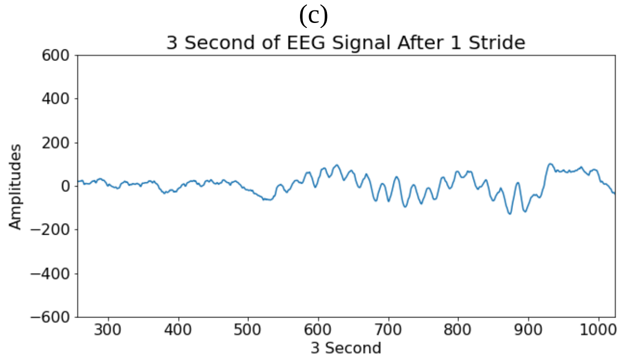
(a)



(b)



(c)



(d)

Figure. 2 Different EEG signals condition: (a) one hour EEG signal record, (b) three seconds crop and labelled EEG signal, (c) crop before first stride, and (d) crop after first stride

2.3 Feature extraction

A wavelet is an oscillation with a wave-like amplitude that starts at zero, can rise or decrease, and can return to zero several times. The EEG signal dataset may be represented using wavelets in this work, but utilizing raw wavelets that are directly categorized without feature extraction results in unacceptable accuracy. Jana G previously suggested a 1-dimensional CNN model with a spectrogram foundation for identifying epilepsy, with an average accuracy of less than 80% without the use of feature extraction [8]. A wavelet is an oscillation with a wave-like amplitude that starts at zero, can rise or decrease, and can return to zero several times. The EEG signal dataset in this research may be represented using wavelets, but utilizing raw wavelets, which are categorized directly without feature extraction, can result in inadequate accuracy. Jana G previously suggested a 1-dimensional CNN model with a spectrogram foundation for identifying epilepsy, with an average accuracy of less than 80% without the use of feature extraction [24]. DWT can partition the signal into many sets, each of which is a time series coefficient describing the evolution of the time signal in the proper frequency range. The use of DWT in obtaining EEG signal characteristics is proposed in this study.

The wavelet transform's capacity is highly dependent on the mother wavelet (t), which is used to generate a time-frequency representation (TFR) that matches the original waveform. The following Eq. (1) depicts the mother wavelet. The scale employed here is s, and the translation parameter is u. DWT employs two distinct functions, namely the scaling and wavelet functions. Because these two functions output two filters and two down-samplers in each phase, low and high pass filters are employed. Using the down-sample output, the high and low pass filters may examine details and approximations for the former.

$$\psi(t) = \frac{1}{\sqrt{s}}\, \psi\left(\frac{t-u}{s}\right) \tag{1}$$

The DWT can capture small changes in the EEG signal by expressing it in the multi-scale time-frequency domain with the approximation (A_i) and detailed ($D_i, i = 0,1, \dots l-1$) coefficients, where l is the decomposition level [25]. There are various extant wavelet families, including Haar, Daubechies, Biorthogonal, Symlets, Coiflets, Reverse Biorthogonal, and Discrete Meyer, however only the Daubechies family will be tested in this work because EEG signals are commonly dissected using this wavelet family [25]. It was also tried varying the decomposition level between levels 1 and 6. For feature extraction, the coefficients A_i and D_i were employed to represent sub-band EEG signals in the frequency range 0-32 Hz. This wavelet coefficient correlates to multiple sub-bands in the EEG signal, including delta (1 - 4 Hz), theta (4 - 8 Hz), alpha (8 -

15 Hz), beta (15 - 30 Hz), and gamma (30 Hz), 60 Hz).

We can use the wavelet transform to describe the EEG signal with discrete wavelet coefficients. The significance of these signals increases when they are described by statistical information. This statistical property minimizes signal dimensionality [26]. The coefficients generated by DWT are extracted for statistical characteristics and crossing frequency features in this study. Five statistical features are extracted: the 5th percentile, the 25th percentile, the 50th percentile, the 75th percentile, and the 95th percentile. The total number of features recovered from the DWT coefficients is $5(l + 1)$, where l is the decomposition level. In addition to statistical characteristics, crossovers in extracted coefficients result in zero crossing frequency (ZCF). When the two coefficient vectors shift from positive to negative or vice versa, the ZCF is the frequency at which this occurs. In some cases, the signal is just above or below the horizontal axis, indicating that there is no ZCF. As a result, in addition to ZCF, the mean crossing frequency (MCF) is calculated, which is the frequency of the two elements of the mean cross of the coefficient vector (m). The extraction of the crossover frequency characteristics yields $2(l + 1)$, where l is the decomposition level. The total number of features acquired from feature extraction is $5(l + 1) + 2(l + 1)$. The Numpy library is utilized in the implementation of percentiles, ZCF extraction, and MCF extraction in this study [27].

Section 2.2 of this study describes the application of DWT on preprocessed EEG recordings. Only the Daubechies wavelet family was used. The decomposition level is selected heuristically and ranges from 1 to 6. In order to achieve the optimum classification performance, the wavelet family and decomposition level are combined. The DWT coefficients are then extracted again for statistical and intersection frequency characteristics.

2.4 One-dimensional convolutional neural network (1D-CNN)

A convolutional neural network (CNN) is a biologically inspired classification algorithm for image classification and pattern detection. [22]. Several research used CNN with varying dimensions to detect epilepsy, with promising results [1, 3, 4]. This study proposes using CNN 1D to classify two class of EEG signals.

The architecture of a simple CNN is typically described using the diagram in Fig. 3. The convolution layer processes data from the input layer with the help of a kernel/filter to build a feature map,

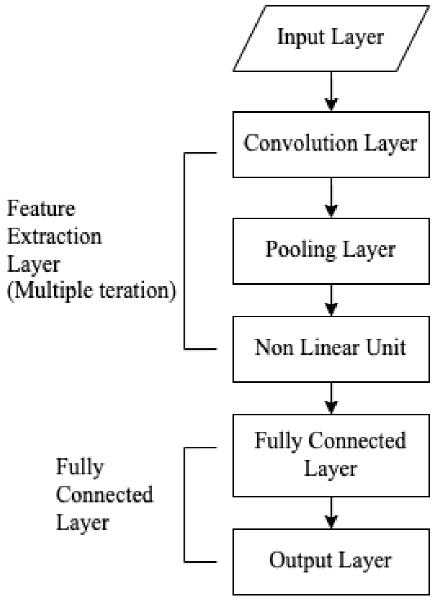


Figure. 3 Basic CNN architecture

where this map feature reflects the raw features. Down sampling is performed at the pooling layer to minimize the size of the map features. The features analyzed by the rectified linear unit (ReLU) unit will be fed into a fully connected layer, which will perform the classification process on the data. In general, the output layer has a soft-max estimate, which aids in multiclass classification but is not usually employed when the classification is simply ternary.

The convolution layer is made up of numerous convolution filters that, during the convolution step, will convolute the input and stride data [4]. The CNN utilized in this study is a 1D CNN since the input data is in the time domain, and 1D convolution works very well with data in this domain. This is due to the kernel shifting in one dimension in 1D convolution. This layer is created by convoluting the preceding layer with the kernel K receptive field Rf and into c, which is equal to the previous layer's number of channels or map features. In the convolution process, the layer $X = \{x_{ij}: 1 \le i \le c, 1 \le j \le z\}$ is transformed to layer $Y = \{y_{lm}: 1 \le l \le K, 1 \le m \le K\}$ using Eq. (2), where c is the number of channels in the layer X, and z is the number of neurons in each channel.

$$y_{lm} = \sum_{d=1}^{c} \sum_{e=1}^{Rf} k'_{d,e} \ x_{d,e+m}, \qquad (2)$$

Each channel has m neurons, and the total number of channels in the layer is K. The convolution layer generates the same number of channels as the number of kernels. Various kernels extract various types of discriminatory features from the input data [1]. This layer down samples the map feature, and the

1D kernel is utilized in this research to determine the maximum value based on the pool size of the map feature. The FC layer converts the representation of features studied in the preceding layer to label space.

An activation function that maps the outcome value between 0 and 1 or -1 and 1 is used to obtain the output of a neural network, such as "yes" or "no." The activation function itself is classified into two types: linear and non-linear. The linear produces a linear graph by using the formula $f(x) = x$, however the non-linear can help the graph to seem like a parabolic shape, which can assist the model adapt to varied data and differentiate the output. The -linear activation function is a common activation function in neural networks. There are several types of activation functions, including the sigmoid or logistic, the tanh or hyperbolic tangent, the rectified linear unit (ReLU), and the leaky ReLU. The sigmoid has a graph that looks like a s and the formula $\phi(z) = \frac{1}{1+e^{-z}}$. Because the sigmoid function has a value between 0 and 1, it is widely employed in models to predict output as a probability, with the likelihood of anything being between 0 and 1. Tanh has a graph similar to a sigmoid, although it works best when the range of tanh is between -1 and 1. Tanh has the benefit over sigmoid in that it can map negative inputs as negative and zero inputs as near zero on the tanh graph. Because it is utilized in practically all CNNs and deep learning, ReLU is the most widely used activation function in the data world. As in Eq. (3), ReLU is 0 when $x < 0$ and x when $x \geq 0$. Because a threshold can supply a ReLU activation value, ReLU has a lower computational and faster convergence speed. The difficulty with utilizing ReLU alone is that any negative values are turned to zero, reducing the model's capacity to effectively train the data.

$$f(x) = \max(x, 0) \tag{3}$$

Finally, leaky ReLU is a solution to the ReLU issue. In leaky ReLU, $f(x) = ax$ produces a graph that can overcome negative values, resulting in a leaky graph. This leak contributes to the expansion of the ReLU function set.

2.5 Whale optimization algorithm (WOA)

WOA is a herd intelligence-based optimization algorithm that simulates the predation behavior of humpback whales when hunting for food. Fig. 4 depicts the simulation of the unique behavior of humpback whales in building a bubble network when foraging. The humpback whale's foraging strategy is as follows: once the whales have located their prey, they begin to form a network of bubbles along a spiral path and migrate upstream to prey. WOA activity can be classified into three stages: swarming prey, bubble network attack, and hunting prey [28].

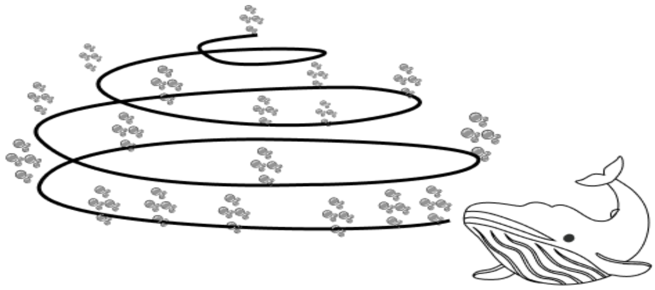


Figure. 4 Humpback whale bubble-net foraging

The first stage is swarming the prey; because the whales do not know the specific location of the prey at first, they swarm around it. If the current optimal position is the target prey, each individual whale in the group advances to it. The following Eqs. (4) and (5) expresses this behaviour:

$$\begin{aligned} X(t+1) &= X^*(t) - A \cdot D \\ D &= |C \cdot X^*(t) - X(t)| \end{aligned} \tag{4}$$

The current iteration count is t, $X^*(t)$ is the prey's position vector or the current optimal solution, $X(t)$ is the current ideal position, and $A \cdot D$ is the surrounding step size. In Eq. (5), $rand$ is a random number between 0 and 1, and a is the control parameter, which decreases linearly from 2 to 0 with increasing iterations.

$$\begin{aligned} A &= 2a \cdot rand - a \\ C &= 2 \cdot rand \end{aligned} \tag{5}$$

The mathematical formula is stated at Eq. (6).

$$a = 2 - \frac{2t}{T_{max}}, \tag{6}$$

T_{max} represents the maximum number of iterations. In the second stage, the whale begins to form a network of bubbles by swimming in a limited encirclement along a spiral path towards prey. WOA divides this behavior into two categories: shrinking and crowding processes, and spiral update positions. The convergence factor a in Eqs. (5) and (6) yields the shrinkage and crowding mechanism. The spiral update position is derived by computing the distance between individual whales and their current best location, and then simulating the whale catching its prey in a spiral. This can be stated mathematically as Eq. (7).

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t),$$
$$D' = |X^*(t) - X(t)|, \quad (7)$$

Where D', b, l denotes the distance between the i-th whale and the current ideal position, a constant coefficient defining the spiral's logarithm, and a random number between -1 and 1. The spiral envelope and contraction envelope done with the same probability to produce this synchronization model. If $|A| \geq 1$ in the third stage of hunting for prey, the whale is randomly selected to replace the current optimal solution, which can boost the algorithm's global exploration capability, shift the whale away from the current reference target, and necessitate the search for a better prey to replace it. The following is the mathematical model :

$$X(t+1) = X_{rand} - A \cdot D$$
$$D = |C \cdot X_{rand} - X(t)| \quad (8)$$

In Eq. (8), X_{rand} is the location vector of a whale chosen at random.

WOA will be utilized in this study to establish the number of filters, neurons for each hidden layer, and use of dropout hidden layers on CNN that produces the best accuracy. The steps for applying WOA in CNN hyperparameter optimization are as follows.

1. To get $A_0, D_0, D_1, \ldots, D_{(l-1)}$, the EEG signal is feature extracted using DWT with l level of decomposition.
2. To obtain the feature set F, extract $5(l+1)$ statistical features and $2(l+1)$ crossing frequency features from the coefficients $A_0, D_0, D_1, \ldots, D_{(l-1)}$.
3. The following WOA in CNN classification:
   a. Loop as much as maximum iteration T_{max}.
   b. Generate random hyperparameter X in the 0th iteration as many as the number of whales.
   c. Train 2-class CNN (C_i) with hyperparameter X.
   d. Calculate fitness value obtained from CNN
   e. If $t = T_{max}$ then the optimal position is now $X^*(t)$.
   f. Using the formula 4,7,and 8 to generate a new hyperparameter X.
   g. Back to 3.c. until $t = T_{max}$.

Fig. 5 depicts the flow of the preceding steps. First, using DWT, the F feature set is extracted from each class of EEG signals. Then, set the number of whales and the maximum number of iterations. WOA chooses hyperparameter X at random. CNN classification uses hyperparameter X to calculate fitness value. The hyperparameter X is then updated using Eqs. (4), (7), and (8) based on the condition the iteration currently on. The loop will run until $t = T_{max}$, at which point the current optimal position $X^*(t)$ will be obtained.

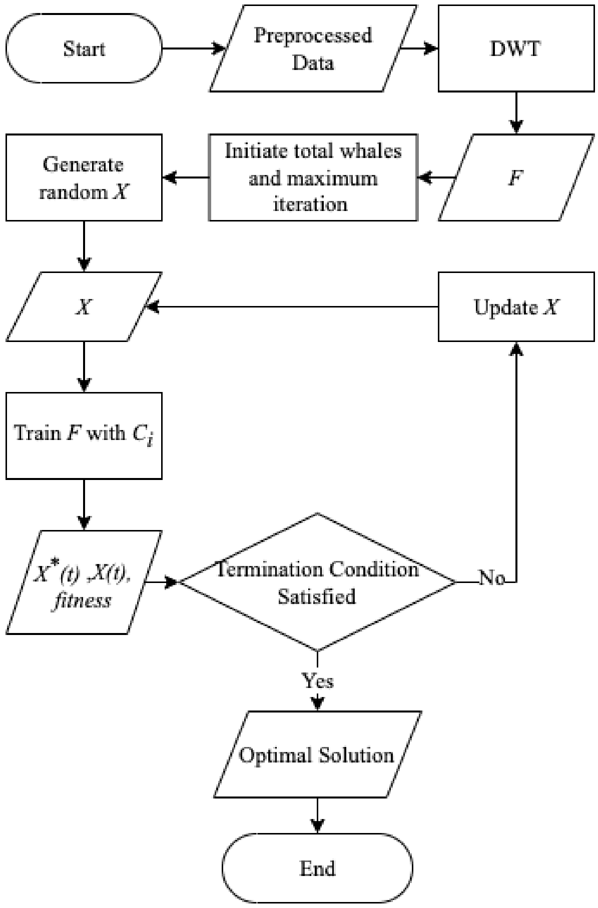


Figure. 5 WOA flowchart

2.6 Experimental setup

Many laboratory experiments have been conducted to validate the proposed EEG signal classification method for detecting epilepsy. The first experiment involved classification without the use of feature extraction, oversampling, as well as CNN parameter optimization with WOA. In the second experiment, classicization was performed using feature extraction without oversampling and CNN parameter optimization with WOA. In the third experiment, classification was performed through feature extraction with DWT and oversampling without CNN parameter optimization with WOA. The final experiment involved classifying the proposed model. All experiments divide the EEG signal into two classes: class 0 and class 1. In scenario 2, an experiment is performed to determine the best combination of wavelet families and decomposition levels for classification performance.

This experiment was carried out on a high-end computer equipped with an AMD Ryzen 5 3600 CPU, an Nvidia GTX 1650 graphics card, and 16 GB of RAM. Some python libraries are also on the method used, namely Numpy [27], PyWavelets [29], and Tensorflow [30]. Stratified shuffle split is also utilized, which combines kfold and split with 1 iteration for each optimization achieved by WOA. The amount of training and test data is divided into 70% and 30%, respectively, with 90.543 training data and 38.805 test data.

3. Result and discussion

3.1 Classification with CNN

In the first scenario, an experiment was carried out to categorize EEG signals into two classes, seizures and non-seizures, with the raw data of the EEG signal being directly entered into the CNN model. However, as mentioned in the Preprocessing step, the EEG input is cut every 3 seconds initially. The accuracy ranged from 10% to 30% in detecting seizure signals, and it was 99% in both classes. Table 1 displays the classification experiment results. The accuracy of the resulting seizures is relatively low based on the findings of the categorization only with CNN. However, the classification accuracy for both classes gets high results.

Table 1. Classification result only with CNN

Experiment number	Accuracy (%)	
	Seizure	All
1	20.44	0.994694
2	25.33	0.994816
3	16.94	0.994725
4	**37.64**	**0.994037**
5	15.75	0.994663

3.2 Classification with feature extraction

The accuracy of the application of DWT and the combination of levels and wavelets utilized in the decomposition of the EEG signal is shown in Table 2. Only the Daubechies family was employed in the studies, with a combination of levels ranging from 1 to 6. The best seizure accuracy was 87.59%, while the accuracy of seizure and non-seizure identification was 99.06% during which the db2 family and a decomposition level of 5 were used. There were 36 features extracted from the best seizure accuracy produced by feature extraction with the db2 family and decomposition level 5. The accuracy of the seizure generated by Table 2 rose significantly after feature extraction, however the classification accuracy of both classes was similar to the accuracy generated by the classification without feature extraction.

Table 2. Accuracy results for classification using wavelet

Mother wavelet	Decomposition level	Accuracy (%)	
		Seizure	All
Db1	1	81.44	99.33
Db1	2	84.12	99.38
Db1	3	81.64	99.52
Db1	4	86.51	99.43
Db1	5	75.35	99.56
Db1	6	86.90	99.59
Db2	1	85.27	99.46
Db1	2	81.12	99.31
Db1	3	82.29	99.57
Db1	4	81.96	99.49
Db1	5	**87.59**	**99.06**
Db1	6	85.56	99.67
Db3	1	81.87	99.50
Db3	2	69.33	99.32
Db3	3	79.47	99.56
Db3	4	78.97	99.60
Db3	5	84.24	99.49
Db3	6	57.39	99.31

3.3 Classification with feature extraction and oversampling

As a result, in the third experiment, the number of whales and maximum iteration were increased, and the resulting accuracy increased by 15.24%. The parameter search reached convergence in the 25th iteration in the fourth experiment with a maximum iteration were increased, and the resulting accuracy increased by 15.24%.

The parameter search reached convergence in the 25th iteration in the fourth experiment with a maximum iteration of 35 times where the parameters produced were always the same, namely only the number of the first filter with the number 2.0 but the resulting accuracy was only 88.20% the same as the previous experiment. This suggests that a large number of iterations does not always improve seizure accuracy. The seizure accuracy in the last two experiments was greater than 90%, namely 91.28% and 91.84% when the number of WOA iterations was

Table 3. Classification experiment results with WOA

Whales	Iteration	Best number of filters			Best number of neurons			Best Dropout			Accuracy (%)	
		1	2	3	1	2	3	1	2	3	Seizure	All
4	4	228	464	441	231	1493	458	0	0	0	72.95	99.12
10	5	852	553	775	704	1654	419	0	0	0	73.13	99.14
9	10	113	2	657	389	1352	0	0	0	0	88.20	99.02
7	35	2	0	0	0	0	0	0	0	0	88.20	98.61
10	15	5	46	231	236	70	135	0	0	0	89.29	98.50
7	25	0	64	23	0	0	208	0	0	0	91.28	98.96
7	10	882	975	385	2048	2048	1511	0	0	0	**91.84**	**99.76**

Table 4. Accuracy comparison between scenario

Methods	Accuracy (%)	
	Seizure	All
CNN	36.18	99.42
CNN + DWT	87.59	99.06
CNN + DWT + Oversampling	90.53	99.47
CNN + DWT + Oversampling + WOA	**91.84**	**99.76**

25 and 10, respectively, with a total of 7 whales.

Because of the imbalanced amount of data between the seizure signal data and the non-seizure signal data, an over sampler was utilized in the third scenario to equalize the seizure signal data. The seizure data is oversampled using a balanced data generator. When compared to the classification without oversampling, the resulting accuracy increased noticeably. With the db2 wavelet family, 5 layers of decomposition, and oversampling, seizure accuracy is 90.53% and total accuracy is 99.47%. Based on these findings, it is fair to conclude that using oversampling improves CNN classification accuracy.

3.4 Classification with feature extraction, over-sampling, and hyperparameter optimization

There were seven experiments and iterations to determine the number of whales shows in Table 3. The seizure detection accuracy was 72.95% in the first experiment with the same number of whales and iterations, i.e. 4. Accuracy The seizures obtained in the first trial were small. It can be concluded that the number of whales and maximum iterations are both small, resulting in a small seizure accuracy.

Table 4 shows a comparison of the accuracy of each scenario. According to table 4, the accuracy generated by WOA optimization indicates that WOA can improve classification performance without optimization. However, the number of whales and the maximum iteration should be considered when using WOA.

3.5 Comparison with existing method

There have been numerous methods for classifying epilepsy using the CHB-MIT dataset with various classes. Table 5 compares our method to methods developed by other authors using only the CHB-MIT dataset. The proposed method outperforms several state-of-the-art methods for detecting epilepsy from EEG signals, specifically for the study in [4, 6-10, 31-39]. It can be seen that the accuracy of the method that only uses CNN without feature extraction is lower than the accuracy of the method we propose, whereas the accuracy of the method that uses feature extraction such as DWT and FFT is higher than 90%. Our method outperforms the classification method based on FRNN and DWT by 7%. Nath Bairagi's method for detecting epilepsy uses ANN and DWT as feature extraction and SWA to improve the performance of ANN classification, yielding an accuracy of 99.44%, 0.32% less than our proposed method. As can be seen in Table 5, the proposed method outperforms both CNN and non CNN classifiers in epilepsy detection from EEG signals. However, the proposed method was only evaluated using EEG signals from CHB-MIT dataset with two classes.

4. Conclusion

In this study, an epilepsy detection system is proposed, which classifies epilepsy into two classes: seizures and non-seizures. The proposed method employs the CNN model with WOA parameter optimization. This model is intended to improve seizure detection accuracy. The classification results of this study, on the other hand, are highly dependent on the wavelet family used in the feature extraction process using DWT. As a result, several experiments were conducted to determine the combination of the wavelet family and the level of decomposition that resulted in seizure accuracy and accuracy of both classifications of 87.59% and 99.06%, respectively,

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Table 5. Classification results with other existing methods

Author	Methods	Class	Acc (%)
[4]	CNN + WGANs	Interictal vs. Ictal vs. Preictal	84.00
[6]	ANN + DWT + SWA	Seizure vs. Non-Seizure	99.44
[7]	1D and 2D CNN	Seizure vs. Non-Seizure	85.60
[8]	1D CNN + Spectrogram	Seizure vs. Non-Seizure	77.56
[9]	FRNN + DWT	Seizure vs. Non-Seizure	92.76
[10]	CNN + FFT	Interictal vs. Ictal vs. Preictal	93.00
[31]	Hybrid Transformer	Seizure vs. Non-Seizure	91.80
[32]	Gradient Boosting Decision Tree (GBDT)	Seizure vs. Non-Seizure	92.50
[33]	CNN 2D	Interictal vs. Ictal vs. Preictal	94.00
[34]	Slow Component Analysis (SCA)	Seizure vs. Non-Seizure	94.41
[35]	LSTM	Seizure vs. Non-Seizure	96.40
[36]	DWT + RUSBoosted Tree Ensemble	health control vs. seizure free vs. seizure active	97.00
[37]	DWT + SVM	Ictal vs. Preictal	97.43
[38]	CNN + DWT + SSA	Seizure vs. Non-Seizure	99.15
[39]	CNN + SVM	Seizure vs. Non-Seizure	99.57
Proposed Method	**CNN + DWT + WOA**	**Seizure vs. Non-Seizure**	**99.76**

when using the db2 wavelet family with five decomposition levels. As can be seen, the seizure accuracy has not yet reached 90%. Because the number of seizure signals is less than the number of non-seizure signals, this occurs. Oversampling was used to balance the data imbalance between the two classes, and the seizure accuracy obtained was 90.53% and the classification accuracy for the two classes was 99.47%. This accuracy can be improved further by optimizing the CNN hyperparameter, which in this paper is WOA. The accuracy of detecting seizure signals was 91.84% and the accuracy of both classes was 99.76% using WOA. WOA improved seizure accuracy by 1.31%. The CNN optimization parameters using WOA are 882, 975, and 385 for the number of filters 1 to 3, 2048, 2048, 1511 for the number of neurons in hidden layers 1 to 3, and 0 for dropout 1 to 3. The findings were compared to other research methods that used the same dataset, namely CHB-MIT. Classification methods that do not use feature extraction achieve accuracy of 70-85%, whereas those that do use feature extraction achieve an average accuracy of more than 90%. The accuracy generated by the ANN classification with DWT and SWA extraction features is the closest to the accuracy of our proposed method. Overall, it can be concluded that using WOA to optimize CNN hyperparameters can improve epilepsy detection accuracy.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Dwi Sunaryono, Riyanarto Sarno, Joko siswantoro and Rahadian Indarto Susilo; methodology, Dwi Sunaryono and Joko Siswantoro; validation, Dwi Sunaryono, Joko Siswantoro, and Shoffi Izza Sabilla; formal analysis, Dwi Sunaryono, Joko Siswantoro and Shoffi Izza Sabilla; investigation, Dwi Sunaryono and Joko Siswantoro; writing—original draft preparation, Dwi Sunaryono and Rafif Ridho; writing—review and editing, Dwi Sunaryono, Joko Siswantoro, Shoffi Izza Sabilla and Rafif Ridho; Dwi Sunaryono and Rafif Ridho; supervision, Joko Siswantoro, Agus Budi Raharjo and Shoffi Izza Sabilla.

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