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ENHANCED SALP SWARM ALGORITHM BASED ON CONVOLUTIONAL NEURAL NETWORK OPTIMIZATION FOR AUTOMATIC EPILEPSY DETECTION

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ABSTRACT

Epilepsy is a neurological disorder that occurs due to abnormal activity in the brain. Symptoms can vary, such as uncontrolled movements, muscle stiffness, difficulty breathing, loss of consciousness, and even death. Therefore, the multichannel electroencephalogram (EEG) is very important to understand the pattern of seizure occurrence and non-seizure in epilepsy. In this paper, we determine an automatic epilepsy detection method using enhanced Salp Swarm Algorithm (SSA) CNN-based of EEG signals. The signal is transformed into Low Pass Filter (LPF) and High Pass Filter (HPF) with one level, frequencies, and scales using Wavelet Transform. Enhanced SSA was used to determine the number of neurons and the appropriate number of convolution layers in the CNN algorithm for classifying two classes (epilepsy and epilepsy with seizure) using the CHB-MIT dataset from Children's Hospital Boston. The results of the study show that the proposed method produces the highest accuracy of 99.15% and 89.04% of average accuracy. This result is obtained with a computation time on testing data of 0.0001 seconds using a high-end computer. Enhanced SSA was proven to increase the performance of CNN of 81.13%. The proposed method can be used in the automatic detection of epilepsy.
Keywords: *Epilepsy, CHB-MIT, Wavelet Transform, Convolutional Neural Network, Salp Swarm Algorithm*

1. INTRODUCTION

Epilepsy is a kind of neurological disorder that may manifest at any age and causes dead. This neurological illness is caused by the discharge of excessive electrical charges on brain neurons, which leads to aberrant brain activity. The symptoms may include jerky limb movements, muscular stiffness, trouble breathing, and even transient loss of consciousness. According to statistics from the Epilepsy Foundation, there are now 65 million persons with epilepsy in the world. Epilepsy affects as many as 3.4 million Americans, a number that continues to rise by 150.000 every year[1]. WHO (World Health Organization) statistics indicate that 80% of epileptics live in low and middle income countries[2]. Unquestionably, epilepsy is more prevalent in poor nations than in industrialized nations. There is currently no particular medication or treatment for epilepsy. The medicine administered to the patient is not intended to treat epilepsy, but rather to control its symptoms. Therefore, it is vital to have an appliance for early detection of epilepsy so that persons with epilepsy may be treated

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promptly and effectively to prevent potentially deadly circumstances.

The electroencephalogram (EEG) is a test used to diagnose epilepsy in individuals. EEG is performed by connecting electrodes to the patient's scalp and recording electrical activity by constantly monitoring the voltage in the neurons of the brain over a while. The output of the Electroencephalogram (EEG) is a paper printout of a graphic picture, which is subsequently inspected and evaluated to diagnose epilepsy. Nonetheless, the analytical procedure demands a great deal of time and resources. The findings of the manually performed epilepsy analysis were susceptible to human error. Therefore, We want an automated detector that can assist patients in properly diagnosing epilepsy. Based on a study by Shoeibi et al. comparing different Deep Learning approaches, it has been shown that deep learning techniques are capable of processing more complicated data and have great performance, hence reducing the time required for epilepsy analysis[3]. Several further types of study have used automated detection, Using Empirical Mode Decomposition (EMD) for feature extraction and Deep Neural Network for classification producing an accuracy value of 98.60%[4]. Signh has created an epilepsy detection tool that uses machine learning and the cloud. The EEG data is transferred straight to the cloud over a 4G or wifi network, where it is analyzed using Fast Walsh Hadamard transformation and higher-order spectra (HOS) for feature extraction. Using the random forest algorithm, the three-class classification process (normal, interictal, and ictal) obtained an accuracy of 99.40%, sensitivity of 99.40%, and specificity of 99.66%[5].

This article presents a technique for classifying EEG epileptic diseases based on the Salp Swarm Algorithm (SSA) for optimizing hyperparameter through Convolutional Neural Network. Salp Swarm Algorithm is a metaheuristic scheduling method devised by Mirjalili that was inspired by the salp life mechanism in nature. Salp resembles jellyfish in that it is translucent and lives in colonies (Swarm). Moving toward a food source, salp develops a chain. It is known that the SSA method may generate superior hyperparameters than other algorithms such as DE and PSO[6]. In this work, the hyperparameters of CNN were optimized using the SSA technique. On the Bon dataset, a 13-layer Deep Convolutional Neural Network (CNN) is used to categorize EEG signals into three classes: normal, preictal, and seizure. The accuracy, specificity, and sensitivity of the final results were 88.67%, 90.00%, and 95.00% respectively[7]. Using manual feature extraction and a convolutional neural network to explore three classifications. Manually comparing the frequency and time domains to extract features. Without optimization, the detection accuracy of epilepsy is 62.30%[8]. The research of class 2 epilepsy detection without CNN optimization had an accuracy of 85.60%[9]. The detection research of two classes using DWT for feature extraction and ANN without optimization yielded a 93.00% accuracy[10]. In this work, it is anticipated that the optimization of SSA for epileptic EEG classification using CNN can maximize the accuracy value.

The CHB-MIT dataset's electroencephalogram (EEG) signals are separated into two classes: normal and ictal. The algorithm used by the feature extraction approach is Discrete Wavelet Transform. The accuracy value produced by the epilepsy EEG categorization algorithm will be assessed. This paper's preparation consists of three chapters: chapter 2 describes the materials and techniques, chapter 3 describes the findings and discussion, and chapter 4 describes the conclusions. Salp Swarm Algorithm is a metaheuristic scheduling method devised by Mirjalili that was inspired by the salp life mechanism in nature. Salp resembles jellyfish in that it is translucent and lives in colonies (Swarm). Moving toward a food source, salp develops a chain. It is known that the SSA method may generate superior hyperparameters than other algorithms such as DE and PSO[6]. In this work, the hyperparameters of CNN were optimized using the SSA technique. On the Bon dataset, a 13-layer Deep Convolutional Neural Network (CNN) is used to categorize EEG signals into three classes: normal, preictal, and seizure. The accuracy, specificity, and sensitivity of the final results were 88.67%, 90.00%, and 95.00% respectively[7]. In the literature on classification of detection using CNN, no one applies optimization to provide a low accuracy value. Through CNN, the Salp Swarm Algorithm will be used in this study to discover the optimal hyperparameter for epilepsy detection. The number of neurons in each CNN layer filter serves as the hyperparameter that will be adjusted. As a result, the SSA optimization strategy can improve the accuracy of CNN's ability to detect epilepsy.

The CHB-MIT dataset's electroencephalogram (EEG) signals are separated into two classes: normal and ictal. The algorithm used by the feature extraction approach is Discrete Wavelet Transform. The accuracy value produced by the epilepsy EEG classification algorithm will be assessed. This paper's preparation consists of three chapters:

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chapter 2 describes the materials and techniques, chapter 3 describes the findings and discussion, and chapter 4 describes the conclusions

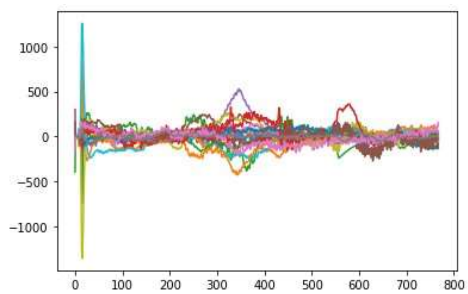
2. MATERIALS AND METHOD

2.1 Materials

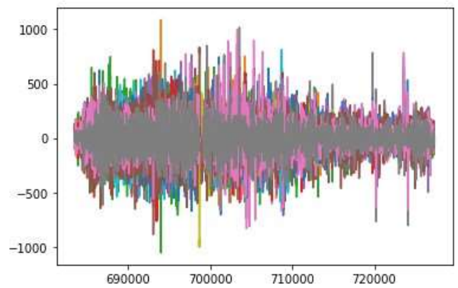
The system built consists of hardware, software, and CHB-MIT dataset. The hardware used is on high-end computer and low-end computer with windows operating system. High-end computer with the specifications used in this study having a 3.60GHz Intel (R) Core (TM) i9-9900K computer with 32GB RAM, NVIDIA GeForce GTX 1080 Ti GPU. Low-end computer has specifications a 1.60GHz Intel (R) Core (TM) i5-8265U computer with 8GB RAM, NVIDIA GeForce MX250.

2.1.1 Dataset CHB-MIT Scalp EEG

Children's Hospital Boston gathered data for the CHB-MIT Scalp EEG dataset. This file comprises of 22 pediatric participants with a diagnosis of severe seizures who were examined for many days after the cessation of medication delivery in order to classify the kind of seizure experienced. There are 22 participants in this data collection, including 5 men aged 3 to 22 years and 17 girls aged 1.5 to 19 years. Each file contains information on the age and gender of each subject. Each case (chb01, chb02, etc.) comprises of 9 to 42 continuous .edf files for each topic. The average time required to acquire records was 36 hours. In certain instances, the .edf file includes precisely 1 hour of digital EEG signal for chb04, chb06, chb07, chb09, and chb23, and 2 hours for chb10. The CHB-MIT dataset utilizes 18 seizure channels (FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP1-F7, F7 - T7, T7-P7, P7-O1, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ), whereas the The international standard of 10-20 electrode locations and naming is applied in this record[11]. Figure 2 displays recordings of the patient's normal and aberrant brain activity. Figure 1a shows the outcome of a typical recording made at 1:43 p.m. while the patient slept. Figure 1b depicts anomalous recording findings that were obtained 50 minutes later. Figure 2 demonstrates that it is difficult to determine with certainty the amplitude of the patient's brain activity. Each folder pulls information about time, frequency, and channel data. During the feature extraction phase, the data will be used for the signal cropping procedure.



(a) Normal



(b) Seizure

Figure 2. The visualization of EEG signal: (a) Normal, (b) Seizure

2.2 Proposed Method

2.2.1 Discete Wavelet Transform

Discrete Wavelet Transform (DWT) is a transformation function that separates a signal into its constituent parts. The resolution of each signal component corresponds to its appropriate scale[11]. In Figure 3, the EEG signal data is cropped in search of seizure-related data. The data is processed by severing the signal for three seconds, and each signal fragment is tagged. Figure 3 depicts the input of preprocessed EEG signal data during the early phase of signal decomposition. Low Pass Filter (LPF) and High Pass Filter (HPF) with one level, frequencies, and scales will be used to assess the signal decomposition procedure[12]. The signal that is processed through the LPF will generate an approximation coefficient (cA) that is a close approximation of the signal that will be decomposed at the subsequent level. While the HPF will create a detail coefficient (cD) of the EEG signal at its output. This research will use Discrete Wavelet Transform with Bioorthogonal 3.1 level 1 for decomposition by equation (1)

$$WTx(j,k) = \int x(t)\hat{\psi}_{j,k}(t)dt \qquad (1)$$

Where WTx is the feature generated in the feature extraction process, $x(t)$ is the preprocessed EEG signal data, j is the frequency in integers, k is the

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time in integers and $\psi(t)$ is the discrete wavelet basis function described by the equation (2). Where is a basic wavelet function such as Haar, Daibechies, Couiflet, Biorthogonal.

$$\hat{\psi}_{j,k}(t) = 2^{-j/2}\, \hat{\psi}(2^{-j} t - k) \quad (2)$$

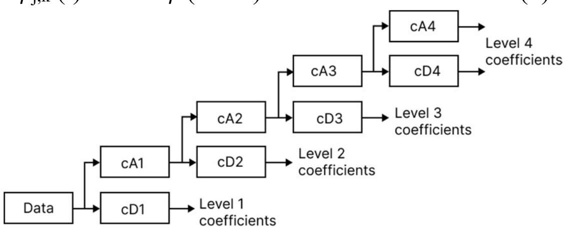

Figure 1. Visualization of DWT Level 4

2.2.2 Convolutional Neural Network 1D

Convolutional Neural Network 1D is the evolution of Multi-Layer Perceptron (MLP) with a deep learning algorithm capable of converting text processing data such as signal vectors[13]. The input data is a vector derived from the process of feature extraction, which will be processed by many hidden layers. Each hidden layer contains neurons, where neurons across adjacent layers have weight and bias values that will be applied to the input data as linear operations. The last layer in a series of linked layers is also known as the output layer or the categorization result of the input data.

In this work, the CNN design consists of an input layer, three convolution layers, a pooling layer, a fully connected layer, and an output layer[14]. The quantity of input data determines the number of neurons in the input layer. While 1 to 2048 initial initiating neurons are used in each convolution layer. Using the Salp Swarm Algorithm (SSA), the number of neurons and the number of convolution layers will be optimized with each iteration. In the convolution layer, a dot multiplication is performed between the vectorized input data and the kernel, which acts as a data filter to generate a feature map. Convolutional data are downsampled at the pooling layer level. The pooling layer has a size and stride 1 filter that will move over the whole feature map. The final output of the convolution will be flattened and joined in a completely linked layer. The most accurate model will be created alongside the best model.

2.2.3 Salp Swarm Algorithm

Salp Swarm Algorithm (SSA) is a metaheuristic scheduling algorithm devised by Mirjalili that is inspired by the mechanism of salp life in the ocean[6]. Salp has a translucent, jelly-like appearance and lives in swarms known as the Salp Chain. Researchers think that the distinctive behavior of swarming Salps is their means of moving and coordinating swiftly in search of food sources[15]. The SSA algorithm's mathematical optimization function was evaluated to determine the optimum solution to the optimization issue. According to the outcomes of these experiments, the SSA optimization method was able to optimally increase the original random and convergent solutions[16]. It is known that the SSA technique may generate better features than other algorithms, such as Dolphin Echolocation (DE) and Particle Swarm Optimization (PSO).

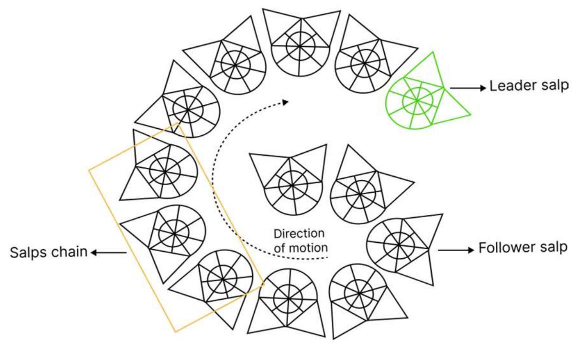

Figure 2. Visualization of Salp Swarm Algorithm

Figure 4 illustrates a Salp chain with a leader and a follower. The leading salp is known as the salp leader (green), while the other salp is known as the salp follower. The foraging position of Salp is specified in n-dimensional terms, where n is the number of identified issue variables. All salp locations are kept in a 2-dimensional matrix named m. In the livelihood space, x is supposed to be the food supply for the herd objective. In equation (3), the location of the Salp leader in the SSA algorithm may be modified.

$$S_j^i = \begin{cases} X_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \geq 0 \\ X_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \geq 0 \end{cases} \quad (3)$$

Where Mij is the initial location of Salp in the j dimension, Xj is the initial position of the food supply in the j dimension, ubj is the upper limit in the j dimension, and lbj is the lower limit in the j dimension. The variables c1, c2, and c3 are random number generators. The coefficient c1 is an essential parameter for balancing search and usage in the SSA algorithm, as described in equation (4)

$$C_1 = 2e^{-\left(\frac{4I}{L}\right)} \quad (4)$$

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Where l, L represent the current process iteration and the maximum number of iterations, respectively. The parameters c2 and c3s are created uniformly in the interval [0,1]. To find the next dimension location, j must move in either the direction of positive or negative infinity. It may be utilized in Newton's laws of motion to determine the location of the follower. Sij is the location of the Salp follower in dimension j if I is greater than or equal to 2, t is time, V0 is the starting velocity, and an is the acceleration according to the equation (5)

$$a = \frac{v_{final}}{v_0} \text{ where } v = \frac{x - x_0}{t} \quad (5)$$

Due to the fact that the optimization time is a process iteration, the iteration difference with variable l is the same and V0 = 0 is assumed. The salp position equation may be represented as equation (6)

$$S_j^i = \frac{1}{2}\left(S_j^i + S_j^{i-1}\right) \quad (6)$$

Where I >= 2 and Sij is the salvage follower's location on dimension j. In this research, SSA optimization will be used to estimate the optimal number of filters and neurons for CNN1D classification in order to get the highest accuracy. The most optimal number of hyperparameters will be determined by comparing accuracy outcomes from each iteration. The flow of the SSA optimization process via CNN can be seen in the following steps:

1. Fetch feature data from feature extraction process, set as hyperparameter on neural network
2. Initiation of the initial amount of salp where Si with i=(1,2,3,4,….,n) and the limit value of ub,lb is between 1-2048
3. When the optimum criteria conditions have not been met, the fitness value will be obtained to update the position of the leader of the salp by equation (3). Update the value of c1 by equation (4)
4. Update the position of the salp in the population:
   a. If the salp position = 1 then update the salp leader position by equation (3)
   b. If the salp position > 1 then the salp leader position is updated by equation
   c. Salp population will be updated according to the upper limit(ub) and lower limit(lb).
5. Update hyperparameter values
6. Updated salp optimization according to process (3)(4). Returns the iteration weight and threshold value for the next iteration
7. Entering the weight and threshold values from the process (6) and then repeating the hyperparameter optimization process until the iteration ends.
8. The final salp position will be used as the initial value of the model prediction on the training data
9. Perform the data test process and generate accuracy values.

Experimental Setup

The suggested approach of identifying epilepsy utilizing EEG data with two classifications, namely class 0 (normal) and class 1 (seizure), was validated using three experimental scenario. In the first scenario, epilepsy accuracy was compared using wavelet transformation Biorthogonal level 1 and cross-validation-based EEG signal classification. The second scenario compares the performance of classifying epileptic EEG signals using the Convolutional Neural Network 1D approach to other benchmarks. The third scenario involves the optimization of the Salp Swarm Algorithm for the computation time of EEG signal categorization.

There are more non-seizure data in the CHB-MIT dataset than seizure data. Consequently, k-fold cross validation is used in an effort to improve the degree of model performance in order to get the highest level of accuracy. The 10-fold cross-validation will balance the dataset by dividing the data into 10 partitions with a balanced class composition. 90% of the testing data in each partition will be iterated, while the remaining 10% will be utilized as training data to acquire accurate findings for epilepsy. Several libraries, including Numpy, PyWavelets, and Tensorflow, Keras are used in scenario testing .

3. RESULTS AND DISCUSSION

The developed and proposed system will be evaluated. The experiment was undertaken to evaluate the system's performance in a specified test environment. CHB-MIT dataset data were utilized for the experiment.

3.1. First Scenario Classification 2 Classes

In scenario 1, the accuracy of two kinds of EEG signals, namely seizure and non-seizure signals from the CHB-MIT dataset, is determined. Each seizure file pulls the time, frequency, and channel from the summary.txt file. The data was trimmed for 3 seconds using stride 1 and labeled with seizure and non-seizure categories. The cropping results will be retrieved using a bior 3.1 level 1 wavelet transformation. Convolutional Neural Network will be used to train the collected features to produce the optimal model for each n iteration. SSA will optimize the hyperparameter for each convolution to discover the optimal hyperparameter. Final findings include seizure accuracy, all accuracy (seizure and non-seizure accuracy), and average accuracy (average between seizure accuracy and all accuracy).

An experiment was previously conducted on the CHB-MIT dataset diagnosing epilepsy using CNN without without using optimization. The all accuracy was 99.07% and the average accuracy was 81.13%. The results acquired from all accuracy without using SSA optimization are comparable to the results obtained from all accuracy utilizing SSA optimization, which are 99.15% and 89.04%, respectively. We used hyperparameter optimization to identify the most optimal neurons during CNN convolution, which led to an increase in the detection of seizures with SSA optimization.

In Table 1, an experiment was conducted in which the starting number of iterations was 4 and the quantity of salp was 3, yielding an average accuracy of 81.50%. The following experiment yielded an average accuracy of 86.31% with 10 iterations and 7 salp. The average accuracy increases by 3.54% age points when the number of iterations and salp are increased.

3.2 Second Scenario Comparison With Existing Methods

In scenario 2, compare the suggested approach to its predecessor using the same dataset. The comparison's findings are shown in Table 2. Similar experiments have been done to categorize epilepsy EEG signals utilizing different signal decompositions using CNN as a classification engine, as shown in table 2 in section 3.2. It is clear that the strategy suggested in this study, which used SSA optimization, produced a bigger rise in the accuracy value than the method used in earlier studies. The addition of the SSA optimization method allows for the discovery of the optimal hyperparameter for a model's training on the CNN layer. To assess the model, SSA will change the hyperparameter or the number of neurons on each CNN filter.The accuracy of the suggested technique using SSA was 99.15%, which was greater than the accuracy of the case studies done by Park et al. and Zhou et al., which were 62.30% and 85.60% respectively. The approach for decomposing the signal used DWT bior 3.1 Level 1 and CNN for identifying two classes. Chen et al., Sallam et al., and Xiang et al. performed research with more precision than our studies. However, it employs a distinct approach of feature extraction and classifier.

3.3 Third Scenario Computational Processing Time

In scenario 3, computational time testing is performed on signal decomposition, feature extraction, data training, and data testing for the proposed technique. On both low-end and high-end machines, tests were conducted. Table 3 compares the amount of time required to calculate on low-end and high-end machines in getting the optimum accuracy of 99.15%. This demonstrates that the suggested technique may be utilized to create an automated system for detecting epilepsy in clinical practice.

4. CONCLUSION

In this article, we introduce and analyze the application of wavelet transform for feature extraction and the Salp Swarm Algorithm for hyperparameter optimization on CNN1D for identifying EEG Epilepsy data. The suggested strategy for categorizing the CHB-MIT dataset into two groups achieved an overall accuracy of 99.15% (seizure and non-seizure accuracy) and an average accuracy of 89.04%. The presence of SSA in the epilepsy classification process may enhance the performance of deep learning in the model learning process and raise the value of accuracy. Our suggested technique requires 0.0001 seconds to test the data necessary for classifying epilepsy. We feel our technology is very applicable to the automated identification of epileptic convulsions.

4.1 Acknowledgment

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4.2 Limitation of the study

There are some limitations that need to be limited for future research. First, the CHB-MIT dataset is the only one to which the suggested method is used to identify epilepsy. The outcomes are not always appropriate for use in studies utilizing datasets other than CHB-MIT. Second, the accuracy of using computers to identify epilepsy can vary depending

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on the computer specifications utilized, such as those for high-end and low-end computers as indicated in Table 3.

4.3 Conflicts of interest

The authors declare no conflicts of interest.

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Table 1. Classification Experiment Results with SSA

Number of Iteration (n)	Number of SSA	Accuracy (%)		
		Seizure	All	Average
4	3	0.6388	0.9912	0.8150
10	7	0.7350	0.9912	0.8631
20	10	0.7803	0.9915	0.8859
10	**10**	**0.7894**	**0.9915**	**0.8904**

Table 2. Some previous related studies in EEG signals classification.

Reference	Dataset	Signal Decomposition	Feature	Classifier	Accuracy (%)
[9]	CHB-MIT (normal, interictal, ictal)	Manual feature extraction (compare the frequency and time domains)	-	CNN	62.30%
[17]	CHB-MIT 2 kelas (normal dan ictal)	low-pass filter with cut-off frequency 30 Hz to the signal	-	CNN	85.60%
[18]	CHB-MIT 2 kelas (normal dan ictal)	DWT	-	ANN	93.00%
[19]	CHB-MIT 2 kelas (normal dan ictal)	The Stockwell Transform and DWT	PCA	SVM+Fuzzy	94.00%
[20]	CHB-MIT 2 kelas (normal dan ictal)	-	-	SVM+Fuzzy entropy	98.31%
Proposed Method	**CHB-MIT 2 kelas (normal dan ictal)**	**DWT bior 3.1 level 1**	**-**	**CNN+SSA**	**99.15%**

Table 3. The computational time needed by the proposed method

	Low end computer	High end computer
Signal decomposition	0.003 s	0.002 s
Feature Extraction	0.03 s	0.0218 s
Training Process	1766.607 s	1166.669 s
Testing Process	0.001 s	0.0001 s