# Enhancing The Accuracy Of Epileptic Seizure Prediction Using Long Short-Term Memory Neural Network And Eeg Signal Processing

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## Abstract

***Purpose:*** *Epilepsy is a neurological disorder affecting approximately 1% of the global population. The primary tool for studying this disorder and detecting changes in brain electrical activity, which could indicate an impending seizure is the electroencephalogram (EEG). Unanticipated epileptic seizures can interfere with people's daily activities. As a result, monitoring and predicting such seizures in real time are of paramount medical significance.*

***Methods:*** *This paper presents a new method for enhancing the accuracy of Epileptic Seizure Prediction. In this research, first extract features from the brainwave data of epilepsy patients using the fast Fourier transform (FFT) and the discrete cosine transform (DCT) functions. These features are subsequently inputted into a long short-term memory (LSTM) neural network to forecast the likelihood of a seizure. Also, a new method for generalizing epileptic attack estimation algorithms is presented. In this method, for the training and testing of the LSTM neural network, all the data of people suffering from epileptic attacks are used in the form of data integration.*

***Results:*** *By examining and comparing the results of the conventional methods, and the proposed method, a 20% increase in the accuracy of the proposed algorithm with the DCT and FFT functions was observed versus other conventional methods.*

***Conclusion:*** *The proposed method demonstrates superior accuracy compared to previous techniques, showing its potential as an invaluable tool for medical professionals, especially during surgical interventions.*

Keywords: *Epilepsy; Electroencephalogram; Neural networks; long short-term memory (LSTM)*

## 1. Introduction

According to the World Health Organization, more than 55 million people worldwide have epilepsy [1]. For the disease of epileptic attack, no definite treatment method has been reported, and currently, this disease is controlled by medicine [2]. Patients with epileptic attacks have severe problems while driving, performing daily activities, and sleeping [3-5]. Estimating the occurrence of an epileptic attack is especially important for patients suffering from an epileptic seizure [6]. Nowadays, in most of the research related to brain signals, including in the diagnosis and estimation of epileptic attacks, the electroencephalography method is used more because of its simplicity and cheapness compared to other techniques [7-9]. Studying and checking brain signals without using computer methods is time-consuming and error-prone [10]. To estimate epileptic seizures, the signals of patients with epileptic seizures are divided into PRE-ICTAL and INTER-ICTAL classes to train deep neural networks [11]. Next, various types of classifiers such

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as support vector machine, sparse representation classification, k-nearest neighbor, and multilayer perceptron are used to classify the segmented signals [12,13]. Statistical parameters, such as standard deviation, mean, irregularity, elongation, skewness, and signal energy, were used in older methods to extract features [14-16]. In recent years, three-dimensional images from brain signals have been used to diagnose and estimate epileptic seizures [17]. Minxing Geng et al. detected epileptic attacks using the Stockwell-transform function, bidirectional long short-term memory neural network, pre-processing moving average filter, threshold judgment, multichannel fusion, and collar technique [18]. The fast Fourier transform (FFT) was commonly utilized before the deep neural network was adopted [19]. To estimate epileptic attacks, signal transfer between time and frequency domains was an important step [20, 21]. The Pearson correlation coefficient and the maximum information coefficient became standard techniques for heightened accuracy in such studies [22]. Zuyi Yu et al. integrated local mean analysis before using the deep neural network for feature extraction [23]. Harnessing both frequency and time-frequency traits, Waqar Hussain's team pinpointed the onset of epileptic events using a combination of a 1D convolutional neural network and a deep long short-term memory (LSTM) neural network [24]. Abdulnasir Yildiza et al. leveraged the time-domain transformation of brain signals and their class activation mapping [25]. Zuochen Wei et al. pinpointed primary features in the deep neural network through the peak and troughs of brainwaves, referred to as MIDS [26]. S. Raghu et al. prioritized the frequency spectrum as the main trait prior to employing the deep neural network [27]. J. Lian's team highlighted the significance of inter-channel signal connections [28]. D.K. Thara et al. predicted potential epileptic attacks using a short-long memory neural network complemented by a dimensionality reduction through a local averaging technique [29]. Epileptic seizure initiation was detected by harnessing features like sample entropy, its multivariate facets, and an extended memory neural network [30]. A review of related studies showed that incorporating a function before the deep neural network can enhance accuracy by about 20%, reaching an impressive 93.1%. However, surpassing an accuracy of 97% remained elusive in the mentioned research, prompting the need for a novel strategy. In this research, we process brain signals using the FFT and discrete cosine transform (DCT) methods before inputting them into the LSTM, aiming to improve the accuracy of automated epileptic seizure predictions.

## 2. Materials and Methods

The present study introduced two new methods based on brain signals and the LSTM neural network. In addition, to generalize the pre-epileptic seizure detection system and present a new algorithm, the data integration of five volunteers was used. Then feature extraction using the FFT and DCT functions is applied to the LSTM neural network to estimate epileptic attacks.

### *2.1 Data*

Brain signal data was sourced from the repository of the Massachusetts Institute of Technology (MIT, USA). This collection comprises records from 22 individuals captured across 23 channels with a sampling rate of 256 Hz. An in-depth breakdown of participant data attributes can be found in Table 1. Of the 22 participants, 17 were female, and five were male. However, data from only six of these participants was selected for the experiments. It is noteworthy that all

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subjects experienced epileptic seizures during the recording period. The age range was 2-19 years for females and 3-22 years for males. Each dataset marked distinct start and end times for seizure events, showing variance among participants. Brain signals, taken at one-second intervals, were divided into pre-ictal and inter-ictal. An equal number of samples from both groups was chosen for analysis. A comprehensive overview of the participant demographics is available in Table 1.

**Table 1.** the data characteristics of patients participating

| ID | SEX | Age | # of Seizure | Duration of Recordings | Duration of Seizure(min) |
|---|---|---|---|---|---|
| 1 | F | 11 | 7 | 40:33:08 | 7.37 |
| 2 | M | 11 | 3 | 35:15:59 | 2.87 |
| 3 | F | 14 | 7 | 38:00:06 | 6.7 |
| 4 | M | 22 | 4 | 156:03:54 | 6.3 |
| 5 | F | 7 | 5 | 39:00:10 | 9.3 |
| 6 | F | 15 | 10 | 66:44:06 | 2.55 |
| 7 | F | 14.5 | 3 | 67:03:08 | 5.42 |
| 8 | M | 3.5 | 5 | 20:33:08 | 15.32 |
| 9 | F | 10 | 4 | 67:52:18 | 4.6 |
| 10 | M | 3 | 7 | 50:01:24 | 7.45 |
| 11 | F | 12 | 3 | 34:47:37 | 13.43 |
| 12 | F | 2 | 40 | 23:41:40 | 24.58 |
| 13 | F | 3 | 12 | 33:00:00 | 8.92 |
| 14 | F | 9 | 8 | 26:00:00 | 2.82 |
| 15 | M | 16 | 20 | 40:00:36 | 33.20 |
| 16 | F | 7 | 10 | 19:00:00 | 1.4 |
| 17 | F | 12 | 3 | 21:00:24 | 4.88 |
| 18 | F | 18 | 6 | 35:38:05 | 5.28 |
| 19 | F | 19 | 3 | 29:55:46 | 3.93 |
| 20 | F | 6 | 8 | 27:36:06 | 4.9 |

| | | | | | |
|---|---|---|---|---|---|
| 21 | F | 13 | 4 | 32:49:49 | 3.32 |
| 22 | F | 9 | 3 | 31:33:08 | 3.4 |

### *2.2 Data pre-processing*

In LSTM neural networks, the brain signals of people with epilepsy enter the LSTM neural network directly to prediction epileptic seizures. In this study, initially, 268,800 samples were selected for the normal state (Inter-Ictal), as shown in Fig. 1. Then, to determine the samples of pre-epileptic seizures (Pre-Ictal), from the time of the main epileptic seizure with steps 1, 2, 3 ...200 seconds to the normal state, the sample data were determined for the Pre-Ictal case. For Inter-Ictal state 268,800 samples was selected, and for the Pre-Ictal state, the number of samples was variable. The first 256 samples and then 512 samples were selected for the Pre-Ictal mode. In the third stage, 1024 samples were used, and in the last stage, 38,400 samples (i.e., 150 × 256) were used. Next, using relations 1 and 2 the FFT and DCT features were calculated for the signals of both Pre-Ictal and Inter-Ictal states. Finally, after preparing the FFT and DCT characteristics of the brain signals, the above information was used to train and test the LSTM neural network.

$$X(W) = \int_{-\infty}^{\infty} x(t).\, e^{-JWt}.\, d_t \quad (1)$$

$$X_K = \sum_{0}^{N-1} x_n.\, COS\left[\frac{\pi}{N}\left(n + \frac{1}{2}\right) K\right] \qquad for\ K = 0,1,2, \ldots \ldots \ldots \ldots N-1 \quad (2)$$

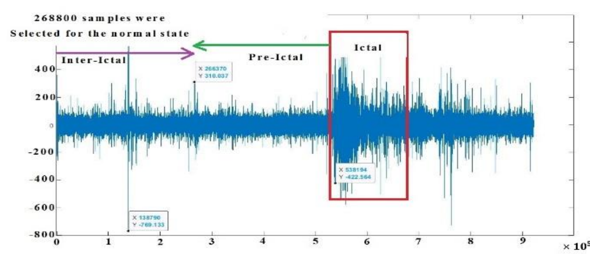


**Fig. 1.** Selection of data to apply to LSTM deep neural network

### *2.3 Data collection training and evaluation*

In the proposed method, all the algorithms mentioned in this research are trained in two different ways. The first method is the conventional method that has been used in previous research. In this method, the data related to each person is applied to the algorithms independently. Another method is the same proposed method of integrated participation. The same integration method uses the same data available to all participants in equal numbers to train the network. As in the conventional method, the ratio of test and train data in this method is 20% to 80%. In the same integration phase, data from six volunteers was randomly used for training and testing. The data collection ratio for test and train data of 20% to 80% was selected in this case.

### *2.4 Long short-term memory neural network*

The LSTM deep neural network is a feature structure of the Recurrent Neural Networks (RNN). This neural network is designed to solve the problem of long-term dependence on the RNN neural network. When applied to long-term data, the LSTM neural network has shown good performance. In recent research, the LSTM has been used to analyze and predict long data such as audio and video signals and time data. The structure of the LSTM neural network is shown in Fig. 2. In Fig. 2, it can be seen that the LSTM has internal features called gates, which control the information processing process. These gates also specify what data is important during processing and should be retained and what data should be deleted. As can be seen in Fig. 2, there are several different mathematical operations in the internal structure of the LSTM deep neural network. These operations help the LSTM network to store or delete information. The performance of the above operations will be examined to better understand the LSTM network. The cell state is one of the most important structures in the LSTM network. In this part, the information is improved during the processing sequence process. In other words, the cell state acts as an LSTM network memory. The gates update the information in the cell state section in the information processing process. These gates in the LSTM neural network decide what information should be entered into the cell state and what information should be stored or forgotten. The LSTM neural network's architecture contains three essential gates: forget, input, and output. In the forget gate, data from the current step's input and the previous step's hidden layer are processed through a sigmoid function, resulting in outputs between 0 and 1. A value close to 0 indicates a higher degree of data omission, while a value close to 1 signifies data retention. The role of the input gate is to update the cell state by adding or removing values. Here, the current input and the previously hidden layer data pass through a sigmoid function to determine which values are to be updated or discarded. This data is also processed by a tanh function, producing values between -1 and 1. The outputs from the sigmoid and tanh functions are then merged, with the sigmoid output dictating the extent of the tanh output to be preserved. The output gate evaluates the status of the hidden layer, which retains information from prior inputs. The current input and the prior hidden layer data are merged and sent through a sigmoid function, and the tanh function processes the new cell state value. The results produced by these functions are combined to determine the information the hidden layer will convey to the subsequent step. The new cell state and the updated hidden layer then advance to the next temporal step. Equations 3-8 provide insights into the relationships among the described gates, the preceding hidden layer, and the input.

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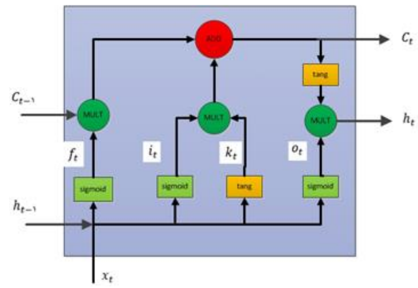


**Fig. 2.** The single-cell structure of the LSTM neural network

$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \quad \textbf{(3)}$$

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \quad \textbf{(4)}$$

$$k_t = tanh(W_{kx}x_t + W_{kh}h_{t-1} + b_k) \quad \textbf{(5)}$$

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \quad \textbf{(6)}$$

$$C_t = tanh(f_t(C_{t-1}) + (i_t \times k_t)) \quad \textbf{(7)}$$

$$h_t = o_t \times tanh(C_t) \quad \textbf{(8)}$$

## 3. Proposed method

One of the deep neural networks used to estimate epileptic seizures is the LSTM deep neural network. Most researchers use the algorithm shown in Figure 3A, known as the conventional system, to estimate epileptic seizures. The conventional system consists of several different parts including data, segmentation and LSTM deep neural network. Here, in addition to the conventional system algorithm, several new algorithms are presented to increase the accuracy of the epileptic seizures prediction system. In this research, the FFT and DCT functions and their parallel combination have been used before the LSTM deep neural network to increase the accuracy system, as shown in Figs. 3B, 3C and 3D, the results of which will be explained later. In the above algorithm, after the data of two Inter-Ictal and Pre-Ictal states have been divided and prepared, the FFT function is used to generate the frequency spectrum of brain signals; the LSTM deep neural network is then used to estimate epileptic seizures. Another function called the DCT is used before the LSTM neural network to increase the maximum accuracy of the algorithm (Fig. 3C). Both proposed algorithms provided acceptable system accuracy. By examining the results of the experiments, the algorithm with the DCT conversion function showed better system accuracy than the FFT method. Also, five voluntary data have been integrated to generalize the epileptic seizure prediction system and present a new algorithm (Fig. 4A). In this algorithm, the data of five volunteers are merged, and the merged data is applied to the LSTM neural network to estimate epileptic seizures. Also, the algorithms shown in Fig's. 4B, 4C, and 4D are used to increase the accuracy of the mentioned system. In the above algorithms, the FFT and DCT functions, as well as a combination of both, have been used before the LSTM

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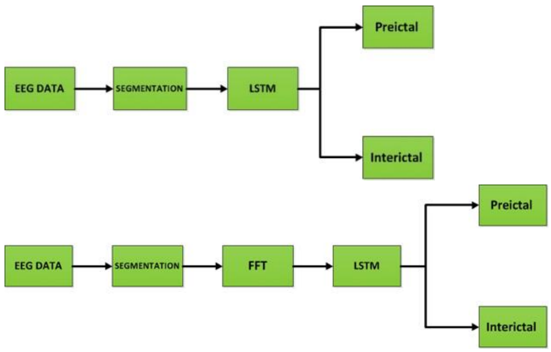
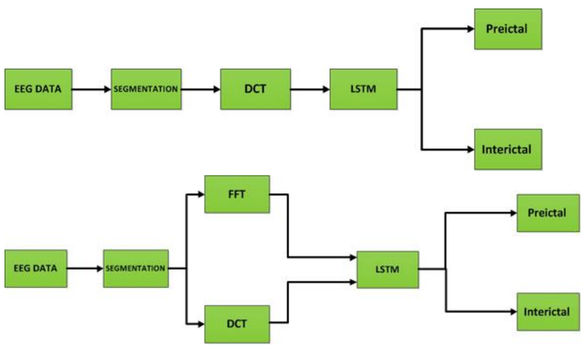
neural network. The above algorithms obtained acceptable results, which will be described below.

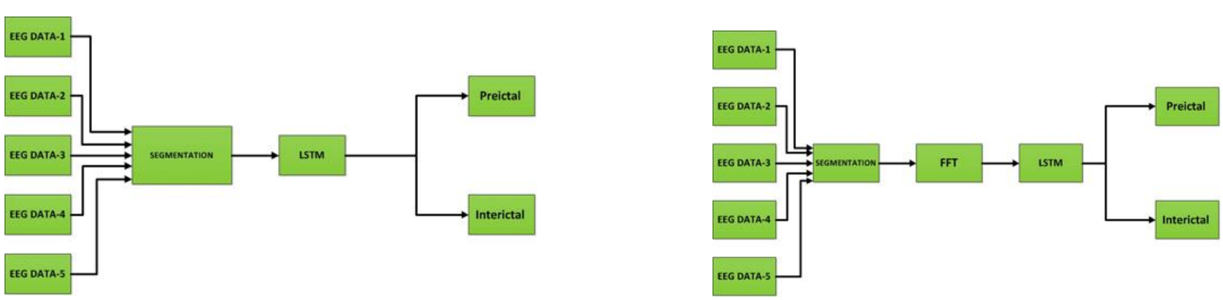



(A) (B)




(C) (D)

**Fig. 3.** Blok diagram of Conventional system (2A), Basic system 1 (3B), Basic system 2 (3C) and Basic system 3 (3D).




(A) (B)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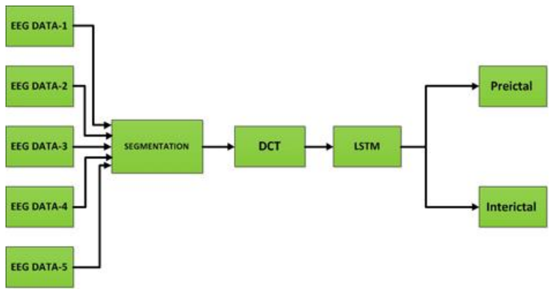
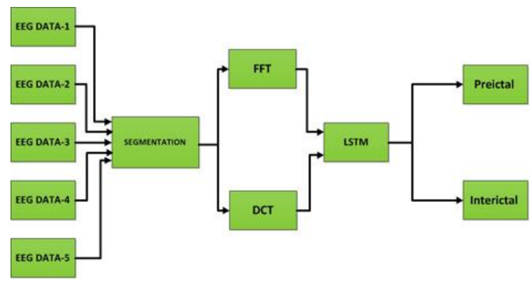



(C)




(D)

**Fig4.** Blok diagrams of Data integration system (4A), initial the FFT function (4B), initial the DCT function (4C) and initial the DCT and FFT functions (4D)

### *3.1 Proposed neural network architecture*

Fig. 5 shows the proposed LSTM deep neural network architecture. This structure consists of 23 cells at the entrance and 50 columns for 23 channels.

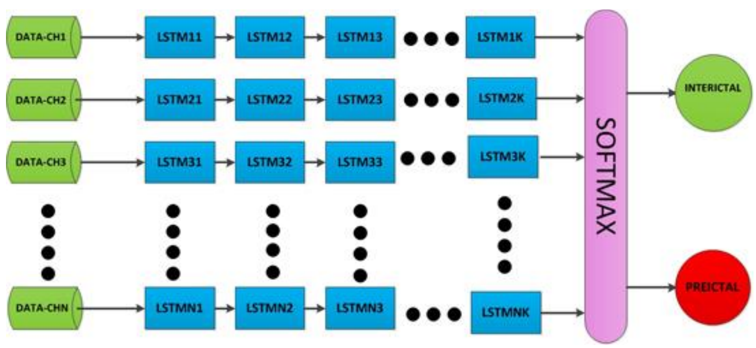



**Fig5.** The LSTM deep neural network architecture

## 4. Results

In this research, multiple tests were conducted using data sourced from the CHB-MIT platform to validate the features and effectiveness of the suggested algorithm and techniques. The outcomes of these experiments are detailed individually to underscore the efficacy of the introduced algorithms and approaches. The experiments performed are generally of two Inter-Ictal and Pre-Ictal classes. In the implementation of the proposed method, various experiments were performed by the algorithm shown in Fig. 3A on the data obtained from the CHB-MIT database, which was selected from the above data from volunteers 05-06, 05-13, 05-17, 05-22, 07-13, and 08-21. The results obtained from the above samples are shown in Fig's 6A-6F. In this study, the results of conventional algorithm tests are first shown for a comparison with the results of other proposed basic algorithms.

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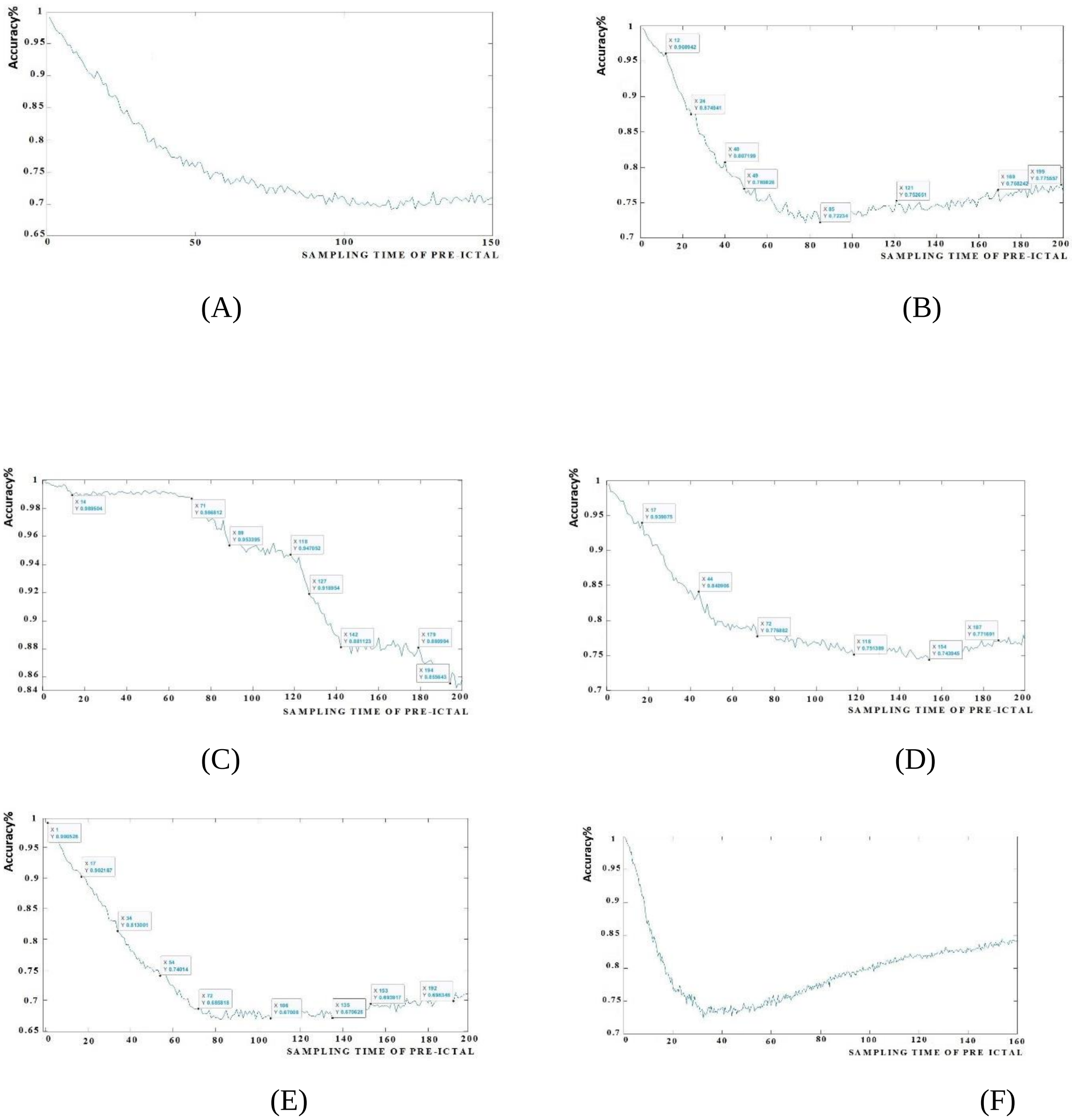


**Fig6.** Test results of the conventional LSTM neural network algorithm on data 0f volunteers 05-06 (6A), 05-13 (6B), 05-17 (6C), 05-22 (6D), 07-13 (6E) and 08-21 (6F).

As previously mentioned, for each of the above brain signal tests, a normal state of 268,800 samples was selected, and for the pre-ictal state, the number of samples was variable. The first 256 samples and then 512 samples were selected for the pre-ictal mode. In the third stage, 1024 samples were used, and in the last stage, 38,400 samples (i.e., 150 × 256) were used. At each stage, the accuracy of the experiments was recorded and stored, and finally, for the results of all tests performed, the accuracy changes of the proposed algorithm were plotted according to the number of selected samples for the Pre-Ictal mode. Of course, it is worth mentioning that more than 38,400 samples were selected for the Pre-Ictal mode for some volunteers. The horizontal axis shows the test stage in Fig's 6A-6F. As mentioned, the number of selected samples for the Pre-Ictal state is 256 × 1 in Step 1, 256 × 2 in the second stage, and 256 × 150 in the last stage.

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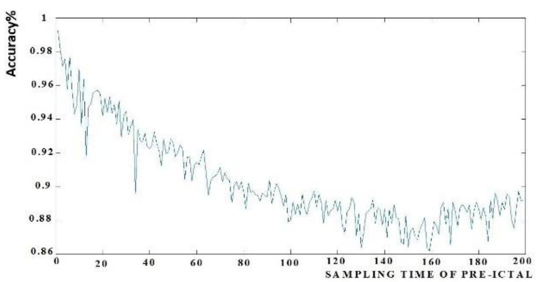
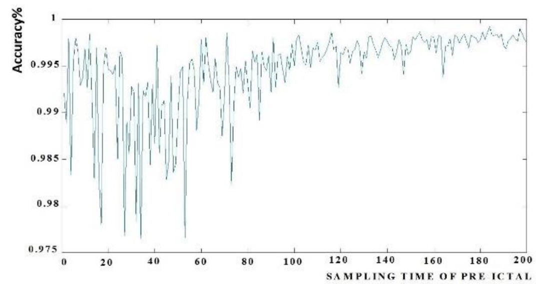
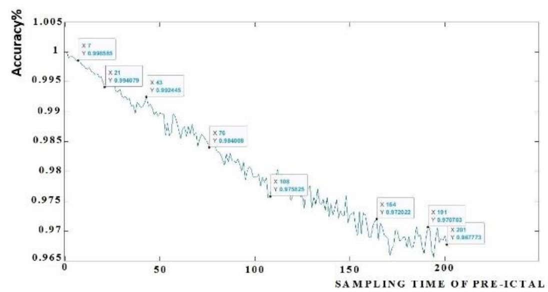
According to the results shown in Fig’s 6A-6F, the accuracy of the algorithm shows a significant decrease in proportion to the increase in the number of Pre-Ictal samples. Therefore, the algorithms shown in Fig’s 3B, 3C and 3D were used to increase the accuracy of the conventional system. From the data of six volunteers, the volunteer data numbered ID 08-21 was selected as a test sample. Here, the number of selected samples for Inter-Ictal and Pre-Ictal modes is the same as in the conventional system, and the data selection for the Pre-Ictal mode is similar to the conventional system. The results of these experiments are shown in Fig’s 7A, 7B and 7C, respectively. According to the results, in the algorithm with the DCT conversion function, the increase of system accuracy is greater than in the FFT function mode, and therefore, the DCT function was selected as a good initial feature. By using the FFT and DCT functions before the neural network, the accuracy of the algorithm increased dramatically, and numerical values of 99.1% and 90% were obtained, respectively. According to a comparison of Fig’s 6F and 7B, the accuracy of the above algorithm (Fig. 3C) shows an increase of 10% to 15%. However, in the algorithm shown in Fig. 3B, which is the initial function of the FFT, this value is 8% to 12%.




(A)




(B)




(C)

**Fig.7.** Test results of the proposed algorithm with the initial FFT function (7A), the initial DCT function (7B) and the initial FFT-DCT function (7C) on data 08-21

The uniqueness of the results makes the construction and design of epileptic seizure diagnosis and prediction equipment and the training and testing of the algorithm to be done independently for each person. On the other hand, training and testing the algorithm for each person independently is time-consuming and expensive. To solve this problem and achieve a comprehensive and general system that can be used on all people with seizures without the need

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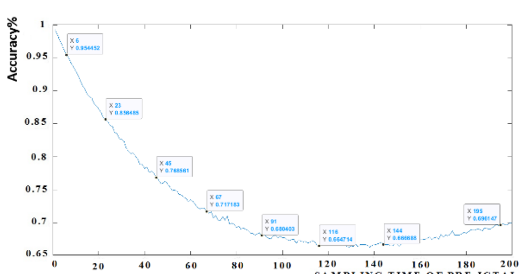
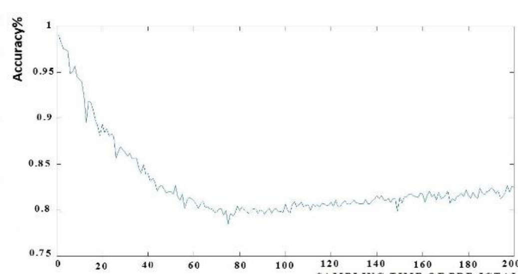
for retraining. Additional experiments were performed on the data obtained from the CHB-MIT database. In these experiments, data using the same integration method. Following the experiments, data from five volunteers with the number of samples mentioned in the previous experiments were selected to be applied to the algorithm shown in Fig. 4A. After the necessary data were prepared for Inter-Ictal and Pre-Ictal states, fits previous tests, an equal sample was selected from each volunteer for Inter-Ictal and Pre-Ictal states. In the first stage, 256 samples were selected from each volunteer for the Pre-Ictal state. In the second stage, 512 samples were selected from each volunteer. In the third stage, 1024 samples were selected. In the last stage, 256 × 200 samples were selected. Fig. 8A shows the results of the experiments performed in these steps. As can be seen, the accuracy of the algorithm decreases significantly when the sample data increases for the Pre-Ictal mode. Here, the proposed algorithms shown in Fig's 4B-4D were used to increase the accuracy of the above algorithm. The results of the proposed algorithms are shown in Fig's 8B-8D. The results of the proposed data merging algorithms show that the performance of the initial FFT function (depicted in Fig. 4B) in the data combination technique clearly surpasses that of alternative methods (Fig's 4C and 4D). Table 2 compares the results of the novel method with those of the conventional approach. According to this table, when the same participation techniques (uniform integration method) are used under similar conditions, the average precision rates for basic1, basic2, and the traditionally proposed methods are 90%, 99.1%, and 75%, respectively. However, these rates are somewhat lower than those achieved using a similar method the non-uniform integration strategy (non-uniform integration method). The average accuracy rates of the initial FFT function, the initial DCT function, and the traditionally proposed method were 83%, 80%, and 70%, respectively. Table 3 provides a more in-depth comparison of the newly recommended method with previous research attempts. According to Table 3, the new method demonstrates a distinct advantage in terms of accuracy when executed under the same conditions and when the same dataset is used. One significant limitation of the novel design methodologies is the computational burden introduced when creating foundational functions.




(A)

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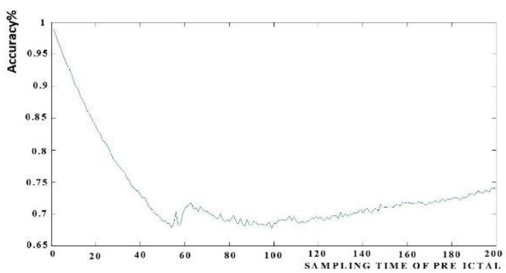


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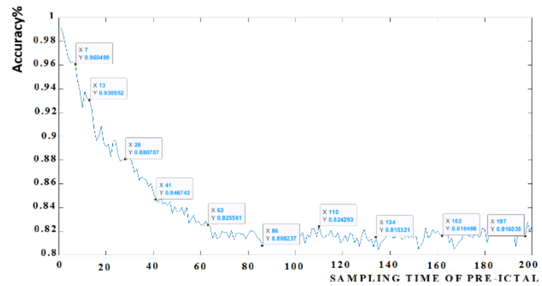


(D)

**Fig.8.** Results of the same data integration test of 5 voluntary using the proposed algorithm (8A), using the initial FFT function (8B), the initial function of DCT (8C) and the basic functions of the DCT and FFT (8D)

**Table 2.** The results of the tests performed integration method.

| | | Accuracy% | Accuracy% |
|---|---|---|---|
| case | method | uniform integration method | non-uniform integration method |
| 1 | conventional method | 75% | 70% |
| 2 | Basic1 proposed method | 90% | 83% |
| 3 | Basic2 proposed method | 99.1% | 80% |

**Table 3.** Comparison of results the proposed method and the other method

| Case | Authors | Dataset | Accuracy% | Sensitivity % | Specificity % |
|---|---|---|---|---|---|
| 1 | Xiaoyan Wei et al, 2018.[17] | Department of Neurology-Xinjiang Medical University | 90 | 88.9 | 93.78 |
| 2 | Syed Muhammad U. et al , 2021.[29] | The CHB-MIT | - | 93% | - |
| 3 | Meng .Z et al, 2018.[19] | The CHB-MIT | 95.6 | 94.2 | 96.9 |
| 4 | N. Ilakiyaselvan et al , 2020.[24] | The University of Bonn | 98.5±1.5 | 95±2 | - |
| 5 | Thara.D.K. et al, 2020.[31] | Department of Neurology-Xinjiang Medical University | 97.6% | - | - |
| 6 | M. U. ABBASI. et al, 2020. [22] | Department of Neurology-Xinjiang Medical University | 94% | - | - |
| 7 | Waqar .H. et al, 2020.[25] | The University of Bonn | 96.64% | - | - |
| 8 | Qizhong. Z. et al, 2021. [32] | The CHB-MIT | 90% | - | - |
| 9 | proposed method | The CHB-MIT | 98.1 | - | - |

## 5. Conclusions

As previously emphasized, the FFT and DCT methods are cornerstone algorithms, which are prominently showcased in Illustrations 3B and 3C. Based on a comparison of the results from tests on the foundational algorithms to those on the standard ones using data from participant number ID (08-21) (see Illustrations 6F, 7A, 7B and 7C), it is evident that the inclusion of these functions significantly boosts the accuracy of foundational algorithms compared to standard ones. Specifically, a comparison of Illustrations 6F and 7A shows an improvement in accuracy of about 8% to 12% when employing the FFT function. Similarly, a comparison of Illustrations 6F and 7B shows that an accuracy increase ranging from 10% to 15% was accomplished using the DCT function. A key focus of this study was the application of data fusion techniques for people experiencing epileptic episodes. As detailed in our methodologies, a defining feature of these fusion techniques is their ability to provide epilepsy detection and forecasting tools that are universally accessible. In other words, these tools are not custom-made for each individual, avoiding the added costs associated with developing and manufacturing tailored solutions. Our research delved into the data fusion strategy for individuals with epilepsy while adhering to this universal principle. Initially, the data fusion method was tailored for the standard algorithm, with Illustration 4A depicting the traditional approach that integrates data from five participants. The FFT and DCT were subsequently incorporated as preliminary steps to further refine the algorithm's accuracy within this data fusion framework before delving into the LSTM neural network, as represented in Diagrams 4B and 4C. To provide a comprehensive comparison and to develop the most accurate and sensitive algorithm, we introduced a holistic algorithm (Diagram 4D) that seamlessly combines both the FFT and DCT functions. An examination of the results from the fusion technique applied to both the proposed and standard algorithms clarifies that the precision of the advanced and foundational algorithms significantly outperforms the traditional algorithm. This underlines their potential for wide-ranging applications, including in clinical environments and as part of medical diagnostic tools. As demonstrated in Illustrations 8A-8D, the foundational algorithm, which integrates the FFT function in the data fusion process, consistently displays a marked improvement in system accuracy and performance compared to the other methodologies. It is crucial to note that traditional algorithms often skip this pivotal function, leading to a notable drop in both accuracy and sensitivity. We explored different testing and training schemes with the aforementioned algorithms to understand further the data associated with each methodology. One such scheme employs the conventional method in which the LSTM neural network is trained and tested individually for each participant, maintaining a testing-to-training ratio of 20% to 80%. A unified method was adopted in a subsequent approach tailored for both the proposed and standard algorithms. This method combines data from individuals with epileptic seizures. In this context, the LSTM neural network's testing and training for the combined data consistently follow a 20%-to-80% split.

**Research Highlights**

√ Epilepsy is a neurological disorder affecting approximately 1% of the global population.
√ Unanticipated epileptic seizures can interfere with people's daily activities.
√ The review of related studies shows that using a function before the neural network can improve the accuracy.

**What is new here?**

√ In this research, we process brain signals using FFT and discrete cosine transform (DCT) methods before inputting them into LSTM, aiming to improve the accuracy of automatic epileptic seizure prediction. It should be noted that in this research, the accuracy of 99% was achieved.

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## Authors' Contribution

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## Competing Interests

Authors declare all relevant interests that could be perceived as conflicting.

## Data Availability Statement

The data link is mentioned in the article.

## Ethical Statement

None to be stated.

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