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Effect of Monosodium Glutamate (MSG) On Tissue and Function of Liver and Kidney and Body Weight in Male Albino Mice

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Abstract:

Delivering a proper amount of anesthetic agent is a critical factor directly related to the health status of patients under surgery. Commercially available tools for measuring the level of anesthesia including Bispectral Index (BIS) were developed to monitor the depth of anesthesia (DoA), however, its combination of black box algorithm with hardware has limitations in algorithmic interoperability. In addition, many hospitals cannot afford it due to its high cost. This research aims to develop an intelligent model that can determine the DoA based on a signal from a single channel electroencephalograph (EEG). In order to split EEG signals, a sliding window is utilized in a segmentation technique. On each EEG segment, a hierarchical dispersion entropy, abbreviated as HDE, was calculated. The EEG signal is then retrieved with HDE characteristics after it has been split into four levels. Several other statistical metrics, such as Q-Q plots, regression coefficients, and correlation coefficients, are used in order to evaluate the suggested model that is based on HDE in terms of the BIS index. In addition, the suggested model is tested against the BIS index to determine how well it can predict the quality of the power signals. The findings indicate that the suggested model demonstrates an earlier reaction compared with the BIS index whenever the state of the patient transitions from deep to moderate anesthesia. The accuracy of the model that was proposed in this research came in at 95 percent.

Keywords: HDE, EEG, SQI, Monitor the Depth of Anaesthesia

Introduction:

Anesthesia is an essential component of today's surgical procedures. It is the primary challenge faced by anesthesiologists. That is determining to monitor the patient's depth of anesthesia (DOA) in the most effective manner [1]. Since anesthetics primarily influence patients' brains, electroencephalogram monitoring of DOA is particularly effective (EEG) [1]. Inadequate quantities of the drug may keep the patient's state at or near awareness, but high dosages of the anesthetic administered during the procedure may result in delayed recovery and coma [2]. The precise assessment of the anesthesia depth can therefore be used to direct the anesthesiologist in the appropriate administration of anesthetic drugs. In addition, it can guarantee the patients' safety and comfort during the procedure [3]. In the past, clinical signs such as breathing, sweating, heart rate, limb movements, blood pressure, and pulse have been utilized to perform the function of measuring the depth of anesthesia (DOA) [4]. Variations in these parameters may be caused, nevertheless, depending on the individual patient and the particular procedure being performed. Vasodilators and muscle relaxants can also be used to readily change clinical characteristics [5]. Therefore, there are considerable limits to using these clinical criteria to assess DOA.

Electroencephalogram (EEG) data to detect DOA has gained popularity in recent years. Recently, Bispectral Index (BIS) has been a frequent component of EEG-based monitoring devices for DOA [6]. The BIS algorithm divides the depth of anesthesia into a range from 0 to 100. However, there are significant drawbacks of BIS, such as its susceptibility to artifacts [7] and its delayed reaction time to changes in EEG [8]. In recent years, in order to address these concerns, a great number of models that can track the DoA have been developed. An EEG-based model was constructed to characterize different anesthetic states by Shih-Jui Chen et al. [9], for instance. The EEG data were broken down using empirical mode decomposition, which resulted in a collection of internal mode functions (IMFs). The Fast Fourier Transform (FFT) and the Hilbert Transform (HT) were combined and used in that study in order to investigate the frequency spectra of each IMF. From two groups of patients, probability distributions for all frequencies were created. Their findings demonstrated that the IMF frequencies reflected the DOA.

Benzy et al. [10] employed a wavelet transform in conjunction with a neural network model to evaluate the level of sedation experienced by the patient. A set of characteristics was then derived to track the DoA after looking at wavelet coefficients. In order to categorize anesthetic states, an ANN was used. Deep learning approaches have recently gained popularity for analyzing EEG data. Chowdhury et al. [11] proposal of a deep learning model to evaluate the DoA is one example. In all, 50 participants took part in the investigation. The suggested index of DoA was evaluated using two signals: photoplethysmogram and electrocardiogram (ECG). The suggested deep learning model was fed with each single-channel input in the form of an image. Nguyen et al. [12] created a novel Bayesian Depth of Anesthesia (BDoA) tool that analyzes five EEG signals to evaluate awareness and amount of anesthesia DoA using Bayesian techniques. The study's findings demonstrate that, in comparison to the BIS, the new indicator accurately assesses the patient's sleeping states. Multi-scale entropy is a novel technique created by Liu et al. [13] that applies entropy values to several time scales. Dataset for their study came from 26 patients. The findings showed that, in comparison to other models, the new model and the BIS index had a higher association. In order to monitor sedation, Guo and colleagues [14] used the wavelet transform method to analyze EEG data. The features acquired by the wavelet transform were then aggregated in order to determine the level of drowsiness.

Becauce the BIS have several limitations . It, for example, does not function with all anesthetic medicines, is not consistent between patients, and is delayed. The BIS and other devices have shown a long-time delay in reflecting a shift in awareness state. Previous studies tried to address these problems. However, the World Health Organization has not recognized any study so far. This motivated many researchers to search for new ways to address these problems.

In this study, we present an advanced model for monitoring the depth of anesthesia based on hierarchical decomposition and entropy. We chose the hierarchical dispersion entropy (HDE) algorithm. We relied on evaluating the model on some statistical properties in addition to evaluating the model in different signal qualities (weak and good), and the model proved its efficiency and success.

5. Materials and Methods:

a. Data of the Anesthetic:

The Database source Toowoomba St Vincent's Hospital located in Australia approved the study to proceed in accordance with ethical standards. In total, there were 37 adults who participated in this research project as patients. In addition to the BIS index and EEG signals, the obtained EEG data also included a monitoring error log and a real-time log. Table (1) shows the demographic information, type presented, type analysis, sample frequency, the channel selected, and additional information about the Dataset.

Table (1) Information on the dataset

Demographic information	Gender (15 females and 22 males) Age (22-35 years) Weight (55-150)
Type Presented	Midazolam (mg)= (2-5) Alfentanil (mg)=(500, 750, 1000) Propofol (mg)=90-200)(Parecoxib (mg)=(40) Fentany1(mg)=(100-150)
Type analysis	offline analysis
Sample frequency	128 HZ

b. Signal Quality Indicator:

The SQI, or Signal Quality Indicator, is a measurement of the quality of the signal that is calculated by taking into account information on artifacts, impedance, and other parameters. The BIS monitor provides a signal quality score in addition to providing a real-time EEG signal, BIS values, EMG, and burst and suppression ratio [15]. Additionally, the BIS monitor displays BIS values. If the SQI number is less than 15, it indicates that the BIS values cannot be displayed on the screen at the same time as other variables and parameters. On the other hand, if the SQI number is greater than 15, it indicates that the BIS values are more accurate and dependable [15]. The BIS device displays false values as a result of the signal's low quality. We go through a few of the causes of poor EEG signal quality (low signal) below:1) Due to patient movements, the connection between sensors and the skin of the patient is unstable. 2)Incorrect operation, environmental or equipment-related noise. 3)When the patient transitioned from an awake condition to an anesthetized state.

In order to accurately evaluate how well the suggested model performs under a variety of anesthetic settings, the EEG sample that is used needs to strike a balance between the anesthetic states and the awake states. For the performance evaluation, we chose samples with high enough SQI index values, excellent baseline BIS values, and raw EEG data. 18 people in all are chosen for this investigation as consequence. Those individuals had ID numbers of two through eight, eleven, thirteen, eighteen, twenty, twenty-one, twenty-two, four-twenty, twenty-five, twenty-nine, and thirty. We also evaluated how well the suggested technique performed in situations with poor signal quality. This implies that the BIS index cannot show accurate numbers on the screen when SQI is less than fifteen. For the purpose of this inquiry, individuals fourteen, twelve, seventeen, and thirty-two have been selected as examples of poor signal quality. An illustration of EEG data with good signal quality and low signal quality can be found in the section of discussion in Figure 8.

c. The Proposed Method:

In the course of this research, a reliable model for tracking DoA based on (HDE). The methodology that has been suggested to evaluate the DoA is shown in Figure 1. Denoising is performed on the raw EEG data using a refined version of the nonlocal mean method. A sliding window method was used to separate the EEG signals that have been de-noised into EEG segments. The signal from the EEG is broken down into four distinct levels. The HDE is derived from each individual EEG segment. The extracted characteristics were put to the test, and a comprehensive investigation was carried out in order to determine which features were the most effective in representing EEG signals. The suggested model is assessed in comparison to the BIS by the utilization of regression, the correlation coefficient, and the Q-Q plot. When a patient's state transitions from light anesthesia to deep anesthesia, the acquired features demonstrated a strong correlation between the suggested model and the BIS. This indicates that the proposed model is better suitable for the real-time DoA assessment than the BIS.

d. De-noising of the EEG Signal:

The captured EEG signals were filtered to remove noises such as an electrocardiogram (ECG), EMG noises (muscle stimulation), and noise generated from devices utilized in the operating room, such as the interference of wires energy and poor fixation of the EEG electrodes. In this investigation, the EEG signals were filtered using an enhanced version of a nonlocal mean technique (NLM). Together, the modified NLM approach and the wavelet transform (WT) method were used to analyze the data. In order to break down the aesthetic EEG signals into varying amounts of Wavelet coefficients, the WT was utilized. The Wavelet coefficients were then subjected to an application of the NLM. In order to reconstruct the noiseless EEG signals, the filtered Wavelet coefficients must first undergo processing. For further information regarding this methodology, kindly refer to our earlier research work [16, 17].

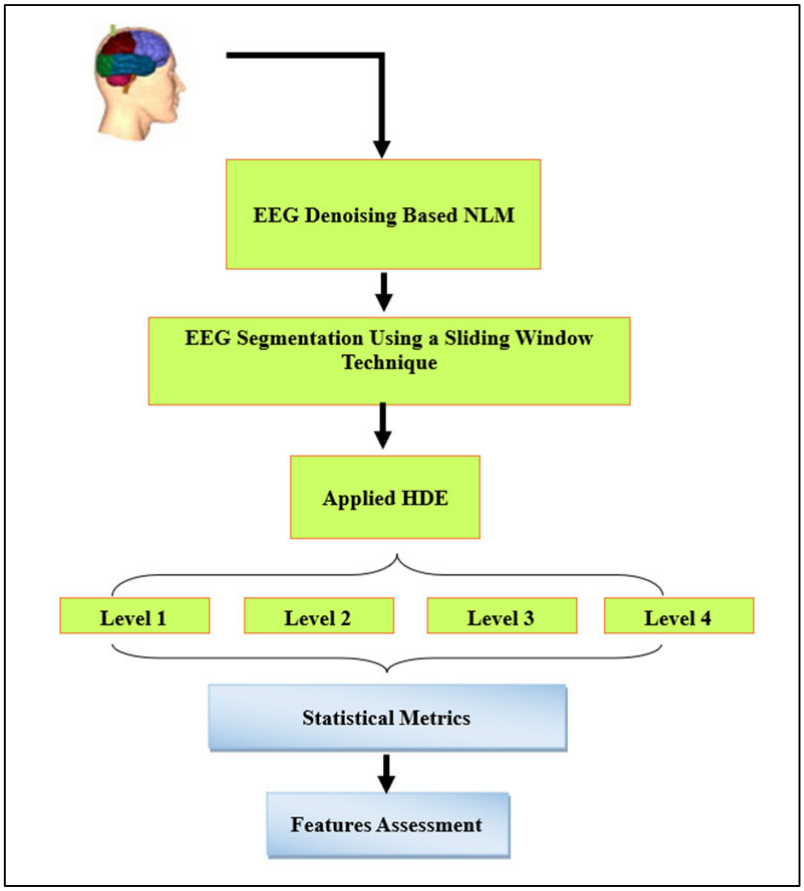

Figure 1. The Proposed Framework of DoA Monitoring

e. Segmentation:

A sliding window method is applied to the process of segmenting EEG signals in order to calculate HDE. Figure 2 demonstrates the segmentation technique. For the purpose of this investigation, a window length of 56 seconds was chosen, with an overlap of 55 seconds. Best on our prior studies [36], The calculations using a window size of 56 seconds with an overlap of 55 seconds produced satisfactory findings for the Department of the Air assessment. Assume X is the EEG signal of n datapoints, E = {e1, e2, e3, … …, ek} . The EEG signal, denoted by E, was then segmented into Z-overlapping windows. Z = $\{w1, w2, \dots, wz\}$, where wz = {e1, e2, … . , en}. As a consequence of this, the EEG signal is divided up into Z segments, and each window of these segments has 6720 data points. Notice, we determined the values of the parameters (window size and overlap) above in proportion to the way the BIS device works in recording data points, as it depends on recording data from one minute at a time and interfering with the length of the EEG signal.

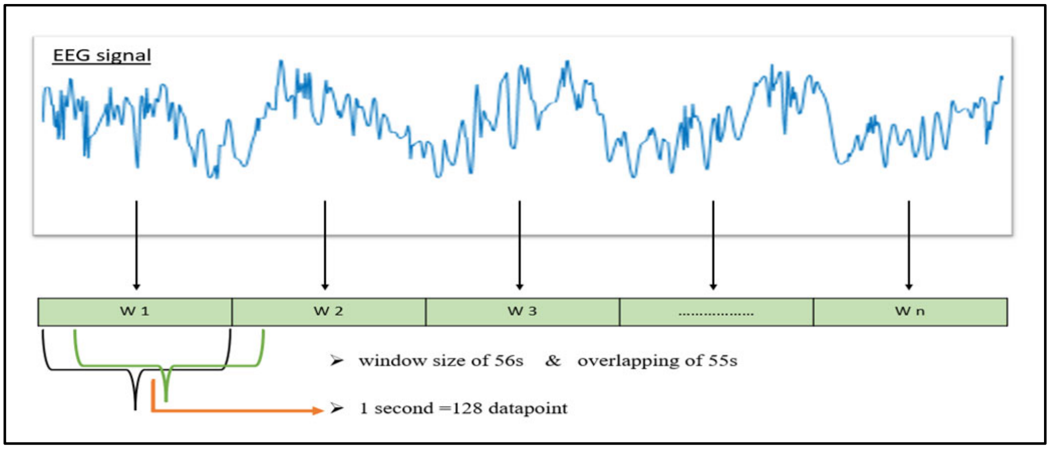

Figure 2. Slide Window Technique

f. Analysis of EEG Signals Based on Hierarchical Dispersion Entropy (HDE):

After Previous studies have found that multiscale analysis algorithms evaluate only low-frequency signal components [18,19]. As a result, a hierarchical DE (HDE) technique was developed, which combines hierarchical decomposition with DE to improve establish the consistency of complicated signals and more fully measure the signal content. Figure 3. Show the diagram of the Hierarchical Dispersion Entropy (HDE) algorithm. Suppose we have the following signal for which we will compute HDE s_1 L= (l_1, l_2, ..., l_n) of length M (M = 2m, m is a positive integer) The steps will be:

First Step: steps for hierarchical analysis of vibration signals. The hierarchical analysis is illustrated in the diagram below (figure 3).

The second step: is to calculate the dispersion entropy of several hierarchical nodes.

$$\mathbf{DisEn}(\mathbf{X}, ɱ, č, \mathbf{d}) = \sum_{\pi=1}^{č^{ɱ}} \mathbf{p}\left(\pi_{v_0,v_1\ldots v_{ɱ-1}}\right) . \mathbf{ln}\left(\mathbf{p}\left(\pi_{v_0,v_1\ldots v_{ɱ-1}}\right)\right) \quad (1)$$

To obtain the HDE, the DE of the hierarchical component at node D and layer k is calculated:

$$\mathbf{HDE}\ (L,k,D, ɱ, č,\tau) = \mathbf{DE}\ (L_{k,D}, ɱ, č,\tau) \quad (2)$$

g. HDE Method Parameter Selection (Parameter Selection) :

In this particular piece of research, the computation of HDE involved the thoughtful selection of four parameters: embedding dimension, class number, time delay, and hierarchical stratification. There will be three hierarchical layers, and the inline dimension will be three. The time delay will be one, and there will be three total, and the class number or c group number is set to 5. It is explained why we specifically chose these values in our previous two studies [18],[19] for more details.

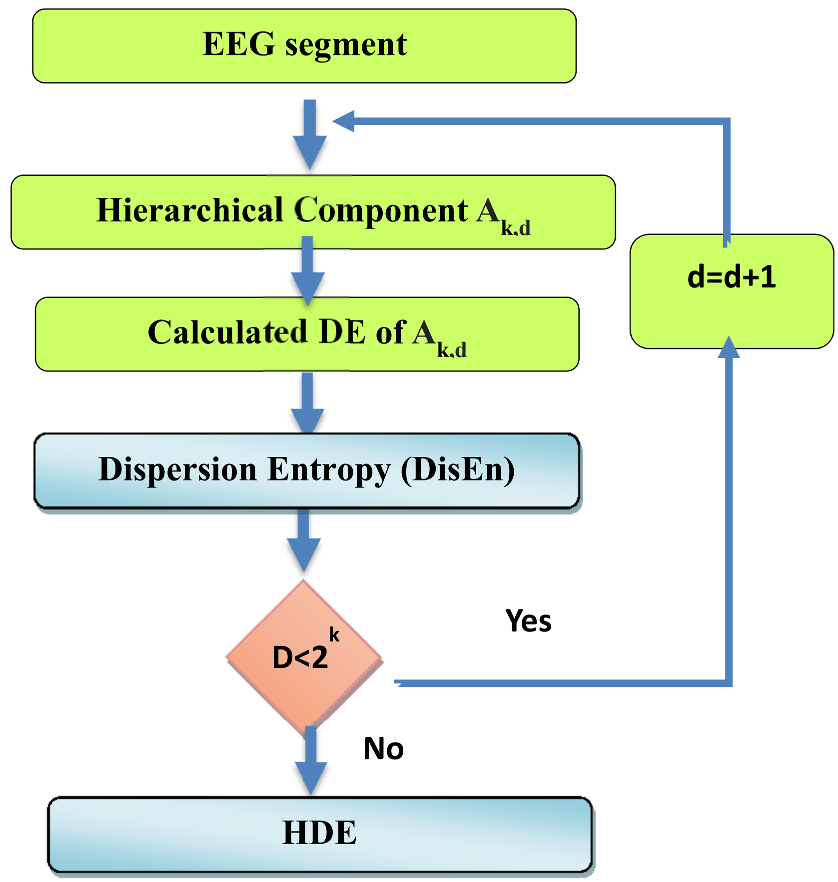

Figure 3. Hierarchical Dispersion Entropy (Hde)

6. Results:

In this section, the main findings were discussed using several statistical metrics. accuracy, sensitivity, specificity, Q-Q, regression, and correlation coefficients. were used to evaluate the performance of the proposed model. The EEG data from two EEG channels (Ch1, and Ch2) were tested separately, and our findings showed that Ch 2 gave satisfactory results. The proposed model was tested with other types of entropy, and the model was also tested in the case of poor signal quality, and the new model proved its efficiency.

2.1 DoA Assessment Based on EEG Channels:

The results of the simulation in this study made use of (EEG) recordings that were obtained from two channels. The Pearson correlation coefficient was used to determine the magnitude of the linear relationship that exists between EEG channels and the BIS. As can be shown in Figure 4, the characteristics derived from channel 2 had a much stronger correlation with the BIS index than those obtained from Channel 1. As a direct consequence of this, the elements described in Channel 2 were incorporated into the structure of the suggested model.

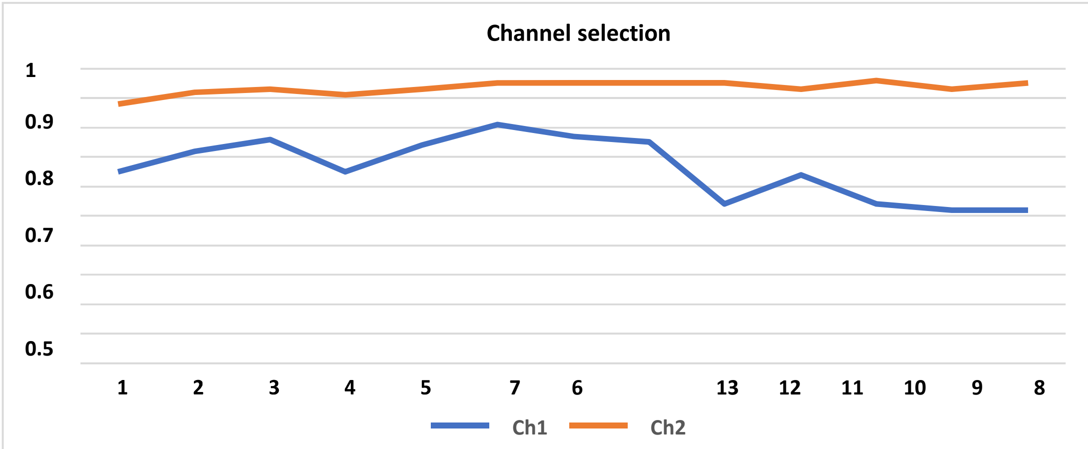

Figure 4. Channel selection based on the correlation coefficient

2.2 Performance Evaluations Based on Regression Model

The strength of an association between the autonomous variable and the dependent variable is assessed statistically. The measurement of designation is another name for it. It is between 0 and 1. There is a significant correlation between the two variables and vice versa if the coefficient of determination is near one. To evaluate how closely the suggested model resembles the BIS. All twenty-two individuals were factored into the regression analysis. Figure 5 depicted the regression line between the suggested model and the BIS. For each person involved in this investigation. The twenty-two patients' average coefficient determination was 0.96.5. These obtained findings demonstrated that the proposed simulation and BIS index had similar behavior.

$$corr = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n\sum x^2 - \sum x^2}\ \sqrt{n\sum y^2 - \sum y^2}} \qquad (3)$$

2.3 Performance Evaluation using Quantile-Quantile (Q-Q) plot

The validity of two samples is assessed using the Q-Q plot depending on whether they share the same distribution, tail behavior, and distribution shape. The reference line is plotted at 45 degrees. If the two sets were drawn from the same population with the same distribution, then the points should roughly lie along this reference line. The further apart these two data sets are from this reference line, the stronger the evidence is that they came from different populations with different distributions. As can be seen in Figure 6, the Q-Q plot of the recommended model and the BIS index have the same distribution and behave in the same manner.

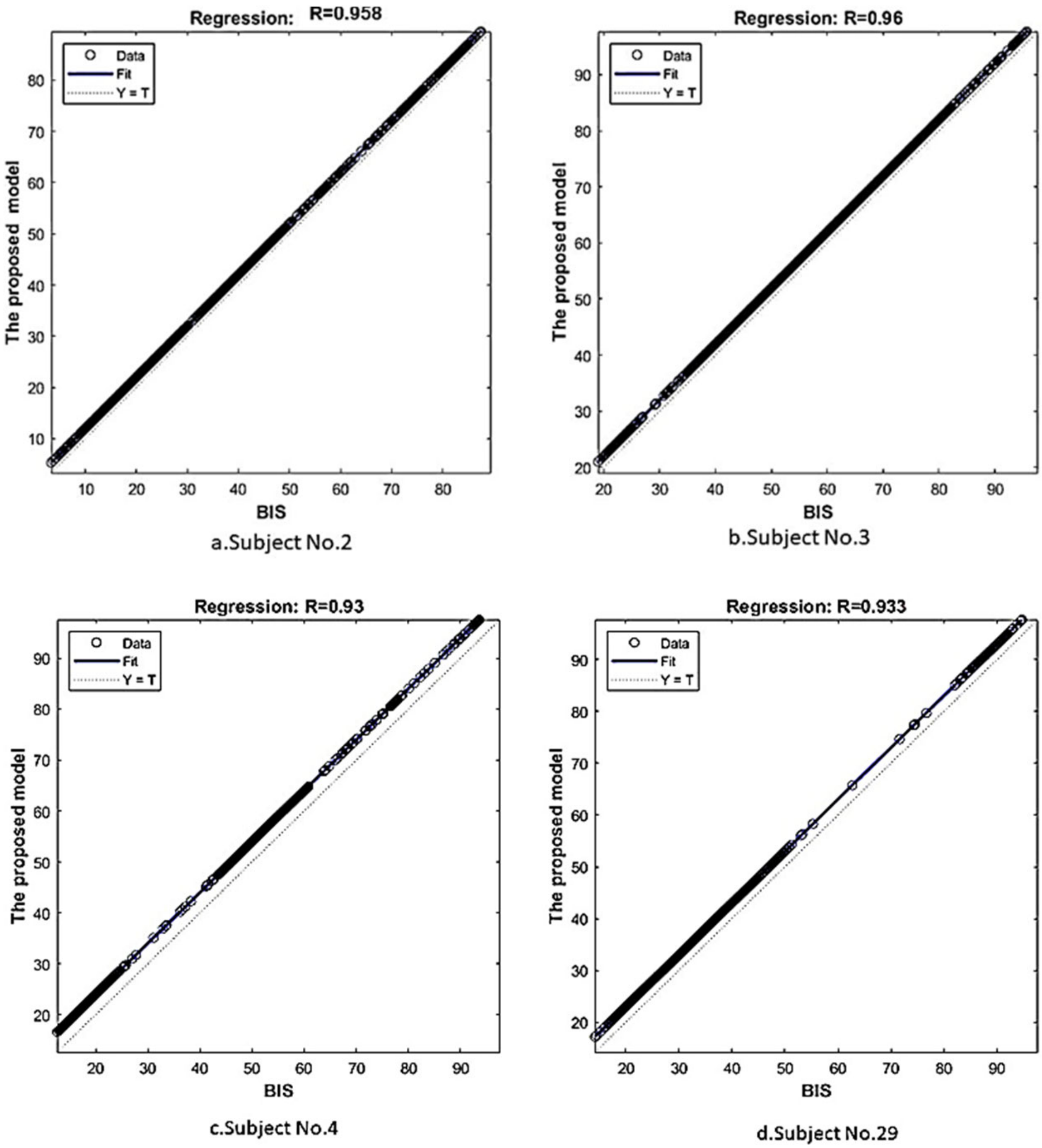

Figure 5. The BIS index's regression line and proposed model are shown.

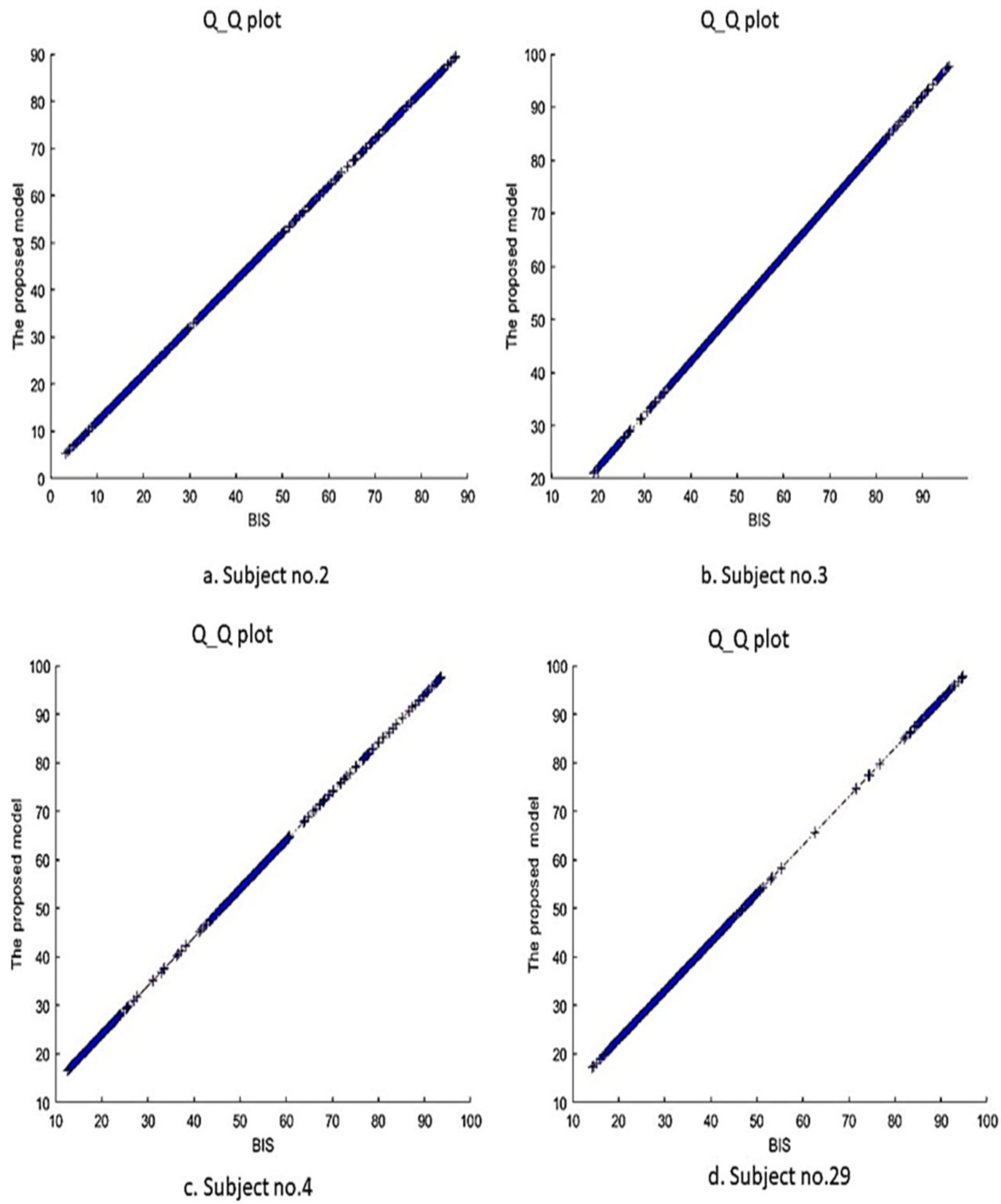

Figure 6. Q_Q figure showing the relationship between the BIS index and the proposed model.

2.4 Evaluation of Performance in Accordance with The Pearson Correlation Coefficient

The strength of the suggested model's linear association with the BIS index was determined using the Pearson correlation coefficient. Its result falls between (1-,1), where one denotes the robust negative correlation among a suggested style and the BIS, one denotes a strong positive correlation, and 0 denotes a lack of relationship between the two. We can see from the data in Fig. 7 that the suggested model generated behavior that was comparable to the BIS. For the twenty-two individuals, the correlation coefficient values were computed. 95.5 percent on average was the correlation coefficient average. The results demonstrated that this model produced an excellent quality performance through all topics**.**

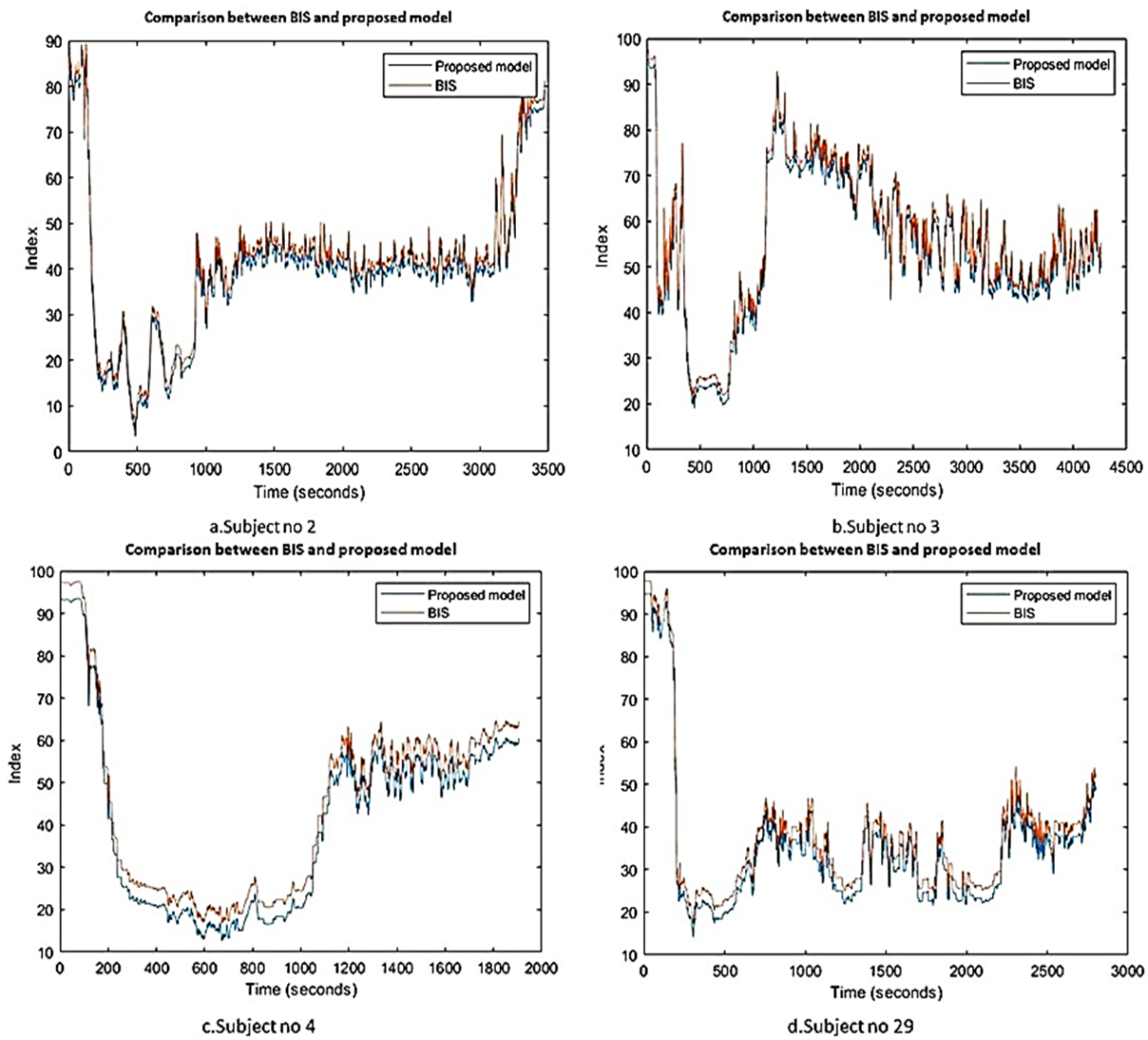

Figure 7. A comparison of the suggested index with the BIS index.

7. Discussion:

• In this study, the performance of the suggested model was evaluated using a power signal quality indicator. Four patients with the IDs 11, 12, 14, and 32 had their EEG recordings collected since the BIS did not accurately represent their DOA. The results for the four subjects ID.11, ID.12, ID.14, and ID.32 are reported in Figure 8. The findings for subject ID 14 show that the BIS index did not adequately represent its values from 500 to 900 s, when the suggested model correctly estimated the DoA. Also shows from the 800s to the 1100s illustrate another instance where the BIS was unable to demonstrate the DoA. In this situation, the suggested model successfully predicts the DoA. On the other hand, the model that was suggested provided an illustration that was more accurate and consistent regarding the transitions from one anesthetic condition to another. Between 550 and 750 seconds and 800 and 1100 seconds, respectively, the BIS was unable to accurately portray the patient's state for subjects ID 11 and ID 12, respectively.

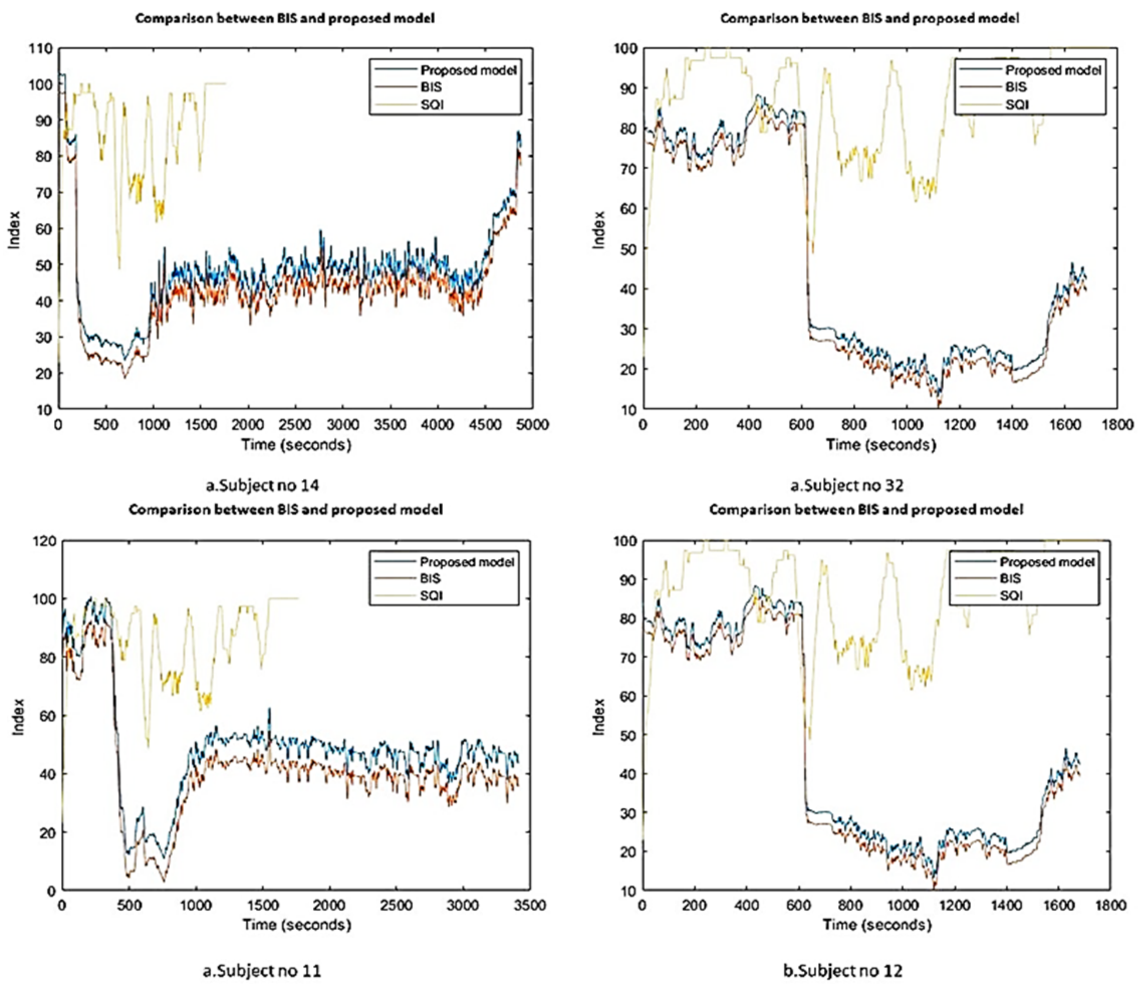

Figure 8. Comparison between BIS and proposed model in good and poor signal quality.

- The HDE was evaluated alongside a number of other entropy characteristics, such as sample entropy (MSE), multiscale fuzzy entropy (MFE), and hierarchical fuzzy entropy (HFE), and hierarchical entropy (HE). All of these entropy features were considered in the evaluation. Table 2 presents the results of the average regression as well as the AUROC for the HDE with the MSE, MFE, HFE, and HE. The MSE, MFE, HFE, and HE all achieved lower levels of accuracy than the HDE, which achieved 96 and 95 percent respectively. It was clear that the HDE performed better in the DoA compared to the MSE, the MFE, the HFE, and the HE.

Table 2 Comparative analyses of HDE, with various entropy features

Methods	ACC	AUROC
M.S.E	88.20%	87.10%
H.E	85.60%	84.70%
M.F.E	83.40%	84.60%
H.F.E	78.60%	77.30%
H.D.E	96.40%	95.250%

8. Conclusion:

In this study, A solid model was put out in this work to use HDE to monitor the (DoA). Multiple measures were used to evaluate the suggested model. The suggested model offers two contributions. First off, because it only used one channel of EEG as an input to calculate the BIS value, the suggested model works well as a (DoA) monitor at minimal cost and with ease. Compared to earlier techniques, this characteristic made it easy to compute BIS using a reasonably straightforward process. Second, deeper comprehension of EEG processes during anesthesia may be achieved by using the retrieved characteristics depending on the HDE, which had been employed to observe the (DoA). The performance evaluation's data may not have been adequate to allow for a generalization of the characteristics that were derived between EEGs and the BIS index. To assess the suggested model utilizing EEG recordings gathered from various procedures at various institutions, more investigation is required.

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