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RESEARCH ARTICLE - ELECTRICAL ENGINEERING

Formulation of a Novel Classification Indices for Classification of Human Hearing Abilities According to Cortical Auditory Event Potential signals

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Abstract

The classification of brain response signals as per human hearing ability is a complex undertaking. This study presents a novel formulated index for accurately predicting and classifying human hearing abilities based on the auditory brain responses. Moreover, we presented five classification algorithms to classify hearing abilities [normal hearing and sensorineural hearing loss (SNHL)] based on different auditory stimuli. The brain response signals used were the electroencephalography (EEG) evoked by two auditory stimuli (tones and consonant vowels stimulus). The study was carried out on Malaysian (Malay) citizens with and without normal hearing abilities. A new ranking process for the subjects' EEG data and as well as ranking the nonlinear features will be used to obtain the maximum classification accuracy. The study formulated classification indices (CVHI, PTHI &HAI); these classification indices classify human hearing abilities based on the brain auditory responses using features in its numerical values. The K-nearest neighbor and support vector machine classifiers were quite accurate in classifying auditory brain responses for brain hearing abilities. The proposed indices are valuable tools for classifying brain responses, especially in the context of human hearing abilities.

Keywords ElectroEncephaloGram (EEG) · Cortical auditory evoked potentials (CAEPs) · Regression · Empirical mode decomposition (EMD) · Classification · Cross-validation

1 Introduction

Cortical auditory evoked potentials (CAEPs) represents the combined neural activities in the auditory cortex that respond to the onset, change, or offset of sounds [1]. Electroencephalography (EEG), which is a noninvasive tool, measures the electrical activity of the brain [2]. EEG records the electrical voltage fluctuations along the scalp. It has far-reaching implications in clinical practice, encompassing epileptic diagnosis, patient coma monitoring, and brain damage assessments [3]. EEG signals play an important role in both diagnosing neurological diseases and understanding psychophysiological processes [4].

Signal classifications were based on the extraction of several features. A feature is anything that can be determined as being either present or absent in an item [5], while feature extraction is a more general form of this supposition; it attempts to find new data that can be used to reconstruct the original dataset belonging to a class [5]. Feature extraction can be used as a preprocessor for applications, such as visualization, classification, detection, and verification [6].

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Extracting informative and discriminative features from EEG signals is often of crucial importance toward representing and classifying the patterns of brain activations [7].

These features will be used as inputs to the classifier. Their selection is crucial, since they define the level of the difficulty of the classification process. Sometimes, features are selected using prior knowledge of classified signals, but there is no exact method that can confirm the suitability of a method for solving classification accuracy problems [8].

Research on the classification of brain EEG signals for different types of EEG signal cases has been reported in the past few years. [9–13] discussed various entropies used for an automated diagnosis of epilepsy using EEG signals. It resulted in a good review of multiple classifiers for the diagnosis of epilepsy. Other cases included the sleep EEG activity during hypopnoea episodes [14], the early detection and classification of Dementia [15], and many other EEG signals cases [4,16–19].

Many systems used the auditory evoked potentials (AEP) signal classifications process in their applications. AEP signal classifications are used in brain–computer interface applications (BCI) [20], brain hearing problems [21], and others [22].

AEP signal classifications are regarded as a clear indicator in brain–computer interface (BCI) application. However, in BCI systems, the AEP signal classifications serves as an alternative to visual evoked potentials (VEP) signals classification, where the extraction of suitable features from the AEP signals, combined with a classification process, leads to the stimulus and nonstimulus activities being identified alongside other hearing control activities [20,23]. Gao et al. [20] reviewed the challenges in AEP signals processing of BCI systems.

Extraction feature and classification performance of AEP signals are critical because AEP signals are generally weak and difficult to detect. Therefore, the proper type of stimuli, effectiveness of the classifiers, and AEP signals features (selection, extraction and ranking) is needed to realize practical applications and obtain the ultimate perfect decision in applications that uses AEP signals for the classification process.

On the other hand, the AEP signal classification helps in investigations involving the detection of brain hearing ability level identification, concordant brain abilities, and abnormalities pertaining to brain activities. In fact, AEP signal classification is essential and a very important tool in diagnosing, evaluating, and detecting neurological difficulties related to the hearing process. AEP signal classification produce an efficient clinical application and the development of superior aural rehabilitation techniques [21,24,25]. Sriraam [21] reported a feature extraction method from AEP signals with the classification process in order to distinguish between stimulus and nonstimulus activities.

The classification of biomedical signals using an index is rarely reported in previous studies, especially in cases using EEG signals. Up till now, some studies formulated biomedical indices in different biomedical issues that exclude the EEG signals. DHANJOO N. GHISTA, in 2009, developed a new concept of a nondimensional Physiological Index (NDPI) [26]. It is made up of several parameters characterizing organ function/dysfunction, a physiological system function and disorder, and an anatomical structure's property and pathology in the format of a medical assessment test; the NDPI combines these parameters into one nondimensional number.

Acharya [27] proposed an index to detect Sudden Cardiac Death. In this index, they classified ECG signals into normal and SCD cases. However, they did not clearly explain how they obtain these values, they reported using the trial-and-error method. We detailed our formulation of a classification index vis-à-vis the EEG signal.

This classification study helps solve this critical issue by proposing novel indices that directly uses EEG features in the classification of the brain responses, especially for human hearing abilities [normal hearing and moderate sensorineural hearing loss (SNHL)]. These classification indices could be used to efficiently investigate hearing abilities from a difficult-to-obtain hearing response subjects or patients (e.g., infants, children, and difficult-to-test patients). This could be done by using a simple feature linear binomial. As per these indices, the classification process could be simple, easy, and quite accurate. We look for the optimal combination of classifiers and feature sets to optimize performance.

The study assumes that the nonlinear feature extraction method, with two ranking processes (subjects ranking and features ranking methods), would result in increased classification accuracy. We start with the decomposition method, followed by the feature extraction methods, subject data and feature ranking methods, and finally the classification methods.

The paper is organized in the following order. Section 1 introduces the subject. Section 2 will explain the methodology involved in this work. Section 3 will describe the EEG data analysis for the experiment, while Sects. 4 and 5 will detail and discuss the results. Section 6 concludes the entire work.

2 Methodology

In this study, we collected, cleaned, decomposed, extracted features, and classified the EEG AEP signals.

2.1 Participant/Subjects

The study was carried out on two groups of participants. All participants involved in this study were tested by the Otorhinolaryngology (ENT) department in University Malaya Medical Centre (UMMC) using the routine pure tone audiometry measurement. The groups are described as follows:

1- Ten adult right-handed Malay males (mean age = 23.5 year, SD = 2.52). The ENT department in UMMC confirmed that all the subjects possess the normal range of pure tone audiometry response. All subjects reported normal audio-logical presentation in both ears (air conduction thresholds 20 dB hearing level (HL) from 125 to 4000 Hz bilaterally, 40 dB HL at 6000 and 8000 Hz, and pure tone average (PTA; average from 500 to 4000 Hz) of 15 dB HL. However, the test considered more than 10 subjects. Some subjects' recording suffers from artifacts, noises, recording calibration, and device setting problems.
2- Ten adult right-handed Malay male patients suffering hearing loss (HL) (fluent Malay-speakers), who are 35–50 years old experiencing bilateral sensorineural hearing loss (SNHL) for more than 6 months with no history of using hearing aids (mean age = 41.7 year, SD = 4.643). All patients selected for this work experienced a bilateral sensorineural hearing loss (SNHL) based on the average of their 1000–4000 Hz pure tone air conduction threshold (PTA: 50–74 dB HL, moderate HL). However, the test had considered more than 10 patients. Some subjects' recording suffers from artifacts, noises, recording calibration and device setting problems. The study selected the recording signals for patients that had the most successful, free of artifacts, and noiseless signals. The patients were recruited from the population in Kuala Lumpur, Malaysia. A bilateral sensorineural hearing loss patients recruited in this study were healthy and normal, with no history of otological, psychological, or neurological complications and without speech (fluent Malay-speakers). The experimental protocols were approved by the Medical Ethics Committee of the University Malaya Medical Center (IRB Reference Number: 1045.22). Each participant submitted a written consent form prior to the experiments. A simple mini-mental state examination (MMSE) test was also conducted prior to the experiment to ensure that the subject's mental abilities, memory capabilities, and attention and language proficiency met the required standards [28].

All participants showed 100% awareness, with healthy normal abilities and responses. However, the test had accounted for more than the required number of subjects and patients. Certain recordings suffered from artifacts, noises, recording calibration, and device setting problems. The study selected the recording signals that had the most successful, free of artifacts, and noiseless signals.

2.2 Stimuli

The study consisted of two disparate types of auditory stimuli; pure tone frequency burst (1 kHz vs. 4 kHz) and speech consonant—vowel (CV) (/ba/ vs. /da/), presented at $\sim$ 85−90 dB sound pressure level (SPL). The tone stimulus lasted for 200 ms, generated by a software program in MATLAB R2013b from (mathwork.com), with (fall time = 10 ms, plateau time = 190 ms) represented at two different frequencies; 1000 Hz and 4000 Hz tone stimuli [29].

The /ba/ and /da/ tokens were characterized by their contrasting voiced/voiceless articulatory features of speech, where /ba/ has a higher formant frequency and onset frequency of the formant transitions compared to /da/ [14,30]. The speech stimulus was recorded at 44,100 Hz sampling rate from the natural speech produced by a female Malay speaker. The CVs were edited into 200 ms in duration by removing the vibration of the vocal cords portion, the final part of the steady-state vowel, and windowing of the offset. The stimuli were presented with a pseudo-randomized oddball sequence of 80% standard and 20% deviant presentations, with an inter-stimulus interval (ISI) of 800 ± 500 ms, and delivered via Sennheiser HD 428 closed circumaural headphones to both ears. The oddball paradigm is an experimental design procedure, where sequences of a repetitive auditory stimuli are frequently interrupted by a deviant stimulus. Deviant stimuli are hidden in a rare occurrence issue among a series of more common standard stimuli. The oddball paradigm could successfully evoke robust and reliable phenomena that have been used as markers of hearing functions. Moreover, this oddball task, like any other complex paradigm, evokes activation in a network of brain regions representing various cognitive components of the task, such as the hearing process [31].

In this study, the Pure Tone stimulus had a standard stimulus of (1 kHz) and a deviant stimulus of (4 kHz). Also, the CV stimulus had a standard stimulus of (da) and a deviant stimulus of (ba). The stimuli presented were calibrated at ear level using a KEMAR ear-and-cheek simulator (G.R.A.S. Sound and Vibration, 43AG) and a type 1 integrating sound level meter (Norsonic, nor140) [32].

The Tone and CV stimuli contrast were delivered separately and tested in two trials. Each trial consisted of 350 stimuli, i.e., 70 deviant stimuli and 280 standard stimuli. Thus, there were 140 deviant stimuli and 560 standard stimuli presented over two trials. The order in which the stimuli were presented ensured that there were 3–5 standard stimuli between each deviant one. There was no counterbalance for this study; that is, the (1000 Hz/da) stimulus was always the standard, while the (4000 Hz/ba) stimulus was always deviant.

2.3 ERP Recording

The subjects were seated in a comfortable armchair inside a soundproofed chamber. They were instructed to minimize, and if possible eliminate, any eye blinking or muscle movements. The recording was done in various sessions at $\sim$ 35 min each. To ensure the continuation of passive listening conditions, written short stories were presented throughout the experiment. The recording was done at 500 Hz sampling rate using the wireless Enobio EEG/ERP acquisition system [33].

Data were recorded from eight Ag/AgCl electrodes mounted on Neoprene EEG cap, and located over the following scalp sites: three electrodes were located on the midline of the head; Fz, Cz, Pz, and a fourth electrode was located on left-hand side of the scalp, C3 (according to the modified International 10–20 System) [34]. Electroencephalography (EEG) activity from each electrode was recorded with the common mode sense (CMS) active electrode, while the driven right leg (DRL) passive electrode was referred to the linked mastoid. The recording device Enobio EEG/ERP provided an on-line filter, consisting of a bandpass filter, with passband (2–40 Hz) second-order Butterworth FIR.

2.4 ERP Waveform and Component Analysis

After ERP data collection, the responses evoked by the standard and deviant stimuli for both stimulus types (Pure Tone and CV) first went through preprocessing to correlate the baseline drift and filtered off-line at 2–30 Hz using second-order Butterworth FIR bandpass filter. These evoked responses were averaged for each trial separately, then averaged again over another time with other trials within a session. Some recording sessions contained more than two trials, while some sessions resulted in bad trials (corrupted by artifacts and noises). The averaged trials were taken from successful runs that were free from artifacts, noises, and clearly evoked the auditory ERP signals. This averaging process was separately done for each used electrode. However, the standard average responses excluded responses to the stimulus occurring immediately after the deviant stimulus and vice versa for the deviant average response. The raw averaged EEG AEP signals were de-noised by the empirical mode decomposition (EMD) technique [35]. The EMD technique provided a simple, fast, and efficient artifact cleaning tool [36]. EMD de-noising could eliminate noises even if combined with the original data. However, there are many cleaning methods that could be used to de-noise raw signals [36].

The criteria used to determine ERP response presence or absence were (1) using visual inspection where the ERP is present if individual ERP peaks were larger than the level of the prestimulus baseline; (2) using ERP analysis included baseline-to-peak amplitude and latency comparison with a typical standard ERP waveform described in [37–39], where N1 & N2 were defined as the most negative peak occurring 80–150 ms and 180–250 ms after the onset of stimulus, respectively. P1, P2, & P3 were also defined as the most positive peaks between 55–80 ms, 145–180 ms, and 220–380 ms, respectively.

2.5 Segmentation of CAEP Signals

The averaged CAEP signals were segmented individually into time segments per the CAEP latencies components, where the P1 (latency window 20–100 ms), N1 (latency window 60–160 ms), P2 (latency window 140–240 ms), N2 (latency window 160–300 ms), and P3 (latency window 240–420 ms) [37,40,41]. The latencies were visually obtained using automated latency detection algorithms. This was done separately for each stimulus responses.

2.6 Features Extraction

To extract the features from the averaged CAEP data, nonlinear feature extraction methods were used in this work, such as Kolmogorov–Sinai entropy (KolmogEnt.), Sample Entropy (SampleEnt.), and Approximate Entropy (ApproxEnt.). This was because brain neurons are controlled by nonlinear phenomena, such as the threshold and saturation processes. Therefore, its behavior can be regarded as nonlinear, while nonlinear dynamic analysis can be regarded as an integral approach in detecting mental tasks as it provides more information compared to that reported by traditional linear methods [15]. Approximate Entropy (ApproxEnt.) evaluate the instability of variation in the signal, while Sample Entropy (SampleEnt.) measures the regularity of physiological signals. Furthermore, Kolmogorov–Sinai entropy (KolmogEnt.) evaluates the uncertainty of signals with respect to time. It is also a measure of the rate of information generation, which can be used in signal processing to distinguish useful signals from intrusive noises [4,9,42].

Kolmogorov–Sinai entropy (KolmogEnt.): Evaluates the uncertainty of any signal with respect to time. It can be computed from the embedded time series signal [43].

$$\text{KolmogEnt.} = \lim_{r\to 0}\lim_{m\to\infty}\frac{1}{\tau}\frac{\text{Cm}(r,\text{Nm})}{\text{Cm}+1(r,\text{Nm}+1)} \quad (1)$$

where Cm (r,Nm) is the correlation function, providing the probability of two points being closer to each other than r.

Approximate Entropy (ApproxEnt.) is used to evaluate the instability of variation in the signal [44]. It detects the changes in the underlying episodic behavior and compares the similarity of the samples via pattern length (m) and similarity coefficient (r).

$$\text{ApproxEnt.} = \ln\left(\frac{\text{Cm}(r)}{\text{Cm}+1(r)}\right) \quad (2)$$

where $\text{Cm}(r)$ is the pattern mean of length m, and $\text{Cm}+1(\text{r})$ is the pattern mean of length $m+1$.

Sample Entropy (SampleEnt.) [45] measures the regularity of a physiological signals, and is independent of pattern length.

$$\text{SampleEnt.} = -\log\left(\frac{A}{B}\right) \quad (3)$$

where A contains the total number of vector pairs of length $\text{m}+1$, and B contains the total number of vector pairs of length m.

2.7 Feature Ranking

The analysis of variance (ANOVA) statistical test was used to rank features in two phases [46]:

1- The ranking subject's or SNHL patient's averaged CAEP data. The test determines the F-value and p-value (probability-value) for each subject separately. The subjects and patients were ranked from less significant to most significant based on their respective F-value and p-value.

2- Ranking features. Similarly, the test determines the F-value and p-value for each feature separately, then rank the features in an ascending order (based on F-value and p-value) [9]. Also, there were other ranking methods, such as Receiver Operating Characteristic Curve (ROC) [47], Bhattacharyya distance [48,49], fuzzy max-relevance, min redundancy (mRMR) [50], and Wilcoxon signed-rank test [51], all of which could be used to rank features.

2.8 Formulation of Classification Indices for Classifying the Human Hearing Abilities

To accurately decide on a system that uses classification in its process, a very accurate classifier is needed. However, it is not as straightforward as it seems. It is more convenient for researchers to use a single integrated index that is significantly different in the two classes (accuracy 100%). This concept of integrated index was conceived and advanced by Acharya et al. [27]. Based on that fact, we formulated integrated indices, which could be defined as the Consonant Vowels Hearing Index (CVHI), Pure Tone Hearing Index, and Hearing Abilities Index (HAI). The (CVHI) index was formulated using nonlinear features constructed from the auditory brain responses evoked by the CV stimulus. This consolidated index was formulated to produce values that are significantly different in normal hearing subjects and from the SNHL patients. This (CVHI) classification index can distinguish between normal hearing and the SNHL abilities. Moreover, using a similar approach to formulate the (CVHI), we formulated the (PTHI) classification index. The (PTHI) index was formulated using the nonlinear features constructed from the auditory brain responses evoked by Pure Tone stimulus. This consolidated index was formulated to produce values that are significantly different in normal hearing subjects and SNHL patients.

The Hearing Abilities Index (HAI) are formulated by combining the nonlinear features constructed from the auditory brain responses evoked by Pure Tone stimulus and CV stimulus in such a way that the consolidated index values were significantly different in the two distinct classes (normal hearing class and SNHL class).

2.9 Classification

A classifier is a technique that utilizes various independent variable values called features as inputs to predict the corresponding class to which the independent variable belongs(s) to. For EEG signal analysis, the features could be any extracted signal information, such as frequency or power, while the class can be the type of task or stimulus during recording. A classifier needs to learn parameters from training signal. The learned classifier is an algorithm that combines features and classes. Learning will enable the classifier to predict new unused cases in the training data. The performance of the classifier is tested on different sets of instances. SVM, K-nearest neighbor (KNN), Classification Trees (Bagged decision tree), linear discriminate analysis (LDA), and Naïve Byes (NB) were the classifiers used in this work [52–54]. SVM used a kernel trick to transform the data points into a higher dimensional space, which was then separated by a hyperplane at maximal margins. The K-nearest neighbor determine the testing samples' class using the majority class of the k-nearest training samples. Linear discriminate analysis (LDA) is a generalization of Fisher's linear discriminant, which is a method used in statistics, pattern recognition, and machine learning to determine a linear combination of features that characterizes or separates two or more classes of objects or events. The classification tree is used to predict the membership of cases or objects in the classes of a categorical dependent variable from their measurements on one or more predictor variables. The Naïve Bayes is a simple and efficient statistical method based on Bayes' theorem classification trees (Bagged decision tree) [52,54]. A feature extraction method was applied onto the EEG signals in the time domain, which were Sample Entropy, Approximate Entropy & Kolmogorov Entropy. These features were nonlinear [27].

The classifier's performance was determined using performance parameters (Accuracy, Sensitivity, Specificity and Precision) [16], defined as:

$$\text{Accuracy} = \frac{\text{Number of correctly classified observation}}{\text{Number of total observation}} \tag{4}$$

$$\text{Sensitivity(True Positive Rate)} = \text{TPR} = \frac{\text{TP}}{P} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{5}$$

$$\text{Specificity (SPC)(True Negative Rate)} = \text{SPC} = \frac{\text{TN}}{N} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \tag{6}$$

where TP denotes true positive, TN denotes true negative, FP denotes false positive, and FN denotes false negative.

3 Results

In this study, the experiments were conducted and the results collected. Only the Cz electrode data were selected for further process and analysis, as it was most significant toward cortical auditory evoked potential (CAEP) waveform in response to auditory stimuli. Furthermore, this electrode demonstrates the highest signal-to-noise ratio as opposed to other electrodes [55].

3.1 Data Cleaning and Averaging

All the EEG recorded data were de-noised using the EMD technique and subsequently averaged (see Sect. 2). Figure 1 shows the averaged raw EEG signal and those cleaned by the EMD EEG signal for (Cz, 4000 Hz stimulus) from normal hearing subjects.

3.2 Data Decomposition

As per CAEP components latencies, the averaged CAEP signals were segmented individually into time segments, such as P1 (latency window 20–100 ms), N1 (latency window 60–160 ms), P2 (latency window 140–240 ms), N2 (latency window 160–300 ms), and P3 (latency window 240–420 ms).

3.3 Feature Extraction and Ranking

The feature extraction method used on the decomposed components of EEG signals in the time domain were Sample Entropy and Approximate Entropy & Kolmogorov Entropy. A new ranking process for the ranking subjects was used by the recorded EEG data based on the ANOVA way. The ANOVA F-value was used to rank all the subjects and features. The p-value and ANOVA F-value evaluated the highest discrimination capability of these features. Subjects were ranked in an ascending order (as per the F-value and p-value), allowing us to obtain the most effective subjects (EEG data). Features were also ranked from the most significant to the least significant feature (based on F-value and p-value). Features with ($P > 0.05$) were excluded from any further processes. The F-value helps characterize the features' performance. Features with the highest F-values were ranked the highest, as they provide a significant difference between the tone and CV classes. Thus, it is assumed that the summation of various features and ranking can help improve the rate of classification.

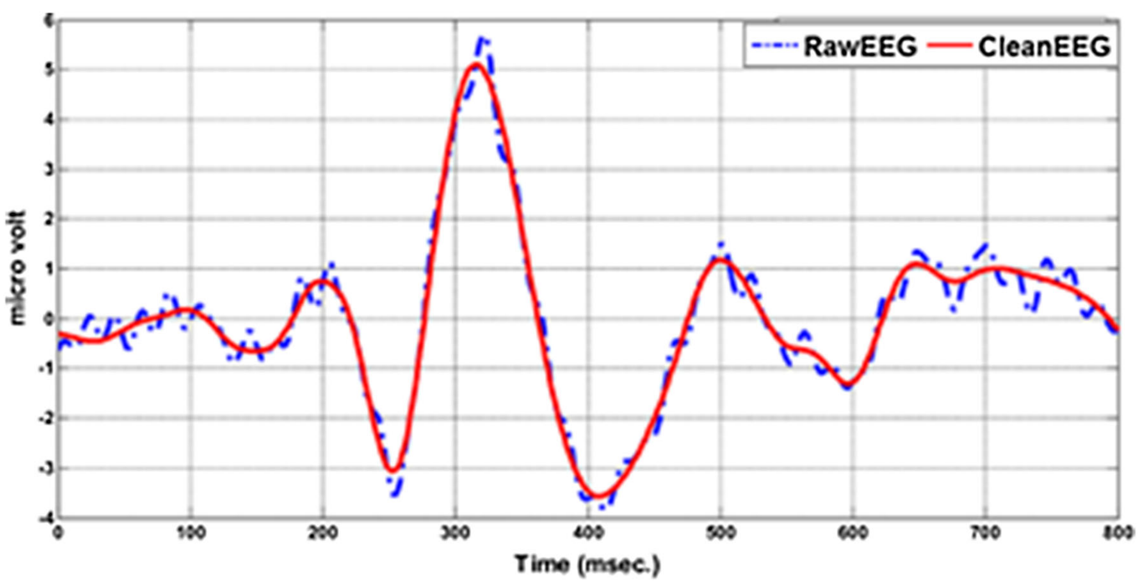

Fig. 1 A sample of the average ERP waveforms

Table 1 The default setting parameters

Classifier	Classification parameters
KNN	For 2-class ($K = 1$), Iteration 1000, Threshold for stopping $= 1 \times 10^{-7}$
SVM	'kernel_function' rbf'—Gaussian Radial Basis with scaling factor, sigma, of 1. Separating hyperplane are: SMO, Iterations allowed is 15,000, Tolerance $= 1 \times 10^{-3}$, Kernel cache is 5000, C is set as 1, and the polynomial kernel is 3. Gamma parameter (γ) using values from 0.01 to 0.1 (10 steps)
TREE	Subtrees = 0; label = vector, Kfold = 4, Threshold for stopping $= 1 \times 10^{-7}$, Tolerance = 1e − 3.
LDA	For Disk rim Type 'linear'; Delta = 0; Gamma = 0, Kfold = 4. Iteration 1000, Tolerance $= 11 \times 10^{-3}$.
NB	Normal (Gaussian) distribution, Threshold parameter is 0.001, Iteration 1000

3.4 Classification Performance

To distinguish the respective EEG CAEP signals, both stimuli were contrasted to determine if there was a significant difference in the CAEP of both stimuli. Five classification methods were used to learn, classify, and distinguish the CAEP signals for both stimuli contrasts. K-nearest neighbor (KNN), classification trees (Bagged decision tree), support vector machine (SVM), linear discriminate analysis (LDA), and Naïve Bayes (NB) were used to compare the accuracy of the performance of each classification system in classifying CAEP signals. However, each used classification algorithms utilized the default setting parameters. The default setting parameters are listed in Table 1.

A cross-validation method was used to determine the trained and tested sets. The cross-validation process could be done via multiple approaches (i.e., K-fold cross-validation, Holdout validation ... etc). This study used K-fold cross-validation, with $k = 4$. This will use 75% of the data in the classification matrix to develop an automated system and obtain features used to train the classifier, while 25% were used to test the classifier performances. Training and testing were conducted four times, and the classification accuracy is averaged over four trials. Cross-validation was used to define a dataset to "test" the model in the training phase (i.e., the validation dataset) to limit problems of overfitting. The fitting process optimizes the model parameters to make the model fit the training data as well as possible [56].

3.4.1 Classification of Hearing Abilities Due to Auditory Brain Responses Evoked by CV Stimulus

The feature matrix formed and generated by the successful features extracted from the nonlinear feature methods was (120 samples × 5 intervals) elements. This matrix contains two types of stimuli (da & ba) and three features (KolmogEnt., SampleEnt., and ApproxEnt.), with the number of participated subjects (10 for both groups one for the normal hearing subjects and 10 for the SNHL patients) multiplied by five times of CAEP's responses intervals, which were (P1, N1, P2, N2 & P3) intervals. Therefore, the classification matrix consists of (120 samples × 5 intervals) elements using the fourfold cross-validation. The training matrix was 90 × 5, while the test matrix was 30 × 5. The latter was used to evaluate classification performance, as classification accuracy provides a good indicator for brain hearing abilities. The sets of decomposed EEG CAEP data with its features (as in Sect. 3.3) were classified using SVM with RBF kernel, linear discriminant analysis (LDA), KNN with $k = 1$, Classification Trees (Bagged decision tree), and Naïve Bayes (NB) classifiers for both cross-validation methods. Thus, we used Eqs. (4, 5, and 6) to obtain the classification performance parameters for all used classifiers. The performance parameters (Accuracy, Sensitivity and Specificity) for the fourfold cross-validation method were obtained. Table 2 lists the performance parameters for classification of the (NH & SNHL patients) groups due to their auditory brain responses evoked by CV stimulus.

3.4.2 Classification of Hearing Abilities Due to Auditory Brain Responses Evoked by Pure Tone Stimulus

As per the explanations in Sect. (3.4.1), the feature matrix formed and generated using the successful features extracted from the nonlinear feature methods was (120 samples × 5 intervals) elements. This matrix contains two types of stimuli (1 kHz and 4 kHz), three features (KolmogEnt., SampleEnt., and ApproxEnt.), with the number of participated subjects (10 for both groups, one for normal hearing subjects, and 10 for SNHL patients) multiplied by five times the CAEP's responses intervals, which were (P1, N1, P2, N2 & P3) intervals. Therefore, the classification matrix consists of (120 samples × 5 intervals) elements using fourfold cross-validation. The training matrix was 90 × 5, while the test matrix was 30 × 5. The latter was used to evaluate classification performance, as classification accuracy provides a good indicator for brain hearing abilities. The sets of decomposed EEG CAEP data with its features (as per Sect. 3.3) were classified using SVM with RBF kernel, Linear Discriminant Analysis (LDA), KNN with k = 1, Classification

Table 2 The performance parameter of classifiers due to auditory brain responses evoked by CV stimulus

Classifier	Performances parameters	Sample	Classified as	
			NH	SNHL
KNN		Normal hearing	53	7
		SNHL	7	53
	Accuracy		$106/120 = 0.8833$	
	Sensitivity		$53/60 = 0.8833$	
	Specificity		$53/60 = 0.8833$	
SVM		Normal hearing	56	4
		SNHL	6	54
	Accuracy		$110/120 = 0.9166$	
	Sensitivity		$54/60 = 0.9000$	
	Specificity		$56/60 = 0.9333$	
TREE		Normal hearing	52	8
		SNHL	8	52
	Accuracy		$104/120 = 0.8666$	
	Sensitivity		$52/60 = 0.8666$	
	Specificity		$52/60 = 0.8666$	
LDA		Normal hearing	51	9
		SNHL	10	50
	Accuracy		$101/120 = 0.8416$	
	Sensitivity		$50/60 = 0.8333$	
	Specificity		$51/60 = 0.8500$	
NB		Normal hearing	49	11
		SNHL	12	48
	Accuracy		$97/120 = 0.8083$	
	Sensitivity		$48/60 = 0.8000$	
	Specificity		$49/60 = 0.8166$	

Trees (Bagged decision tree), and Naïve Bayes (NB) classifiers for both cross-validation methods. Thus, we used Eqs. (4, 5, and 6) to obtain the classification performance parameters for all used classifiers. The performance parameters (Accuracy, Sensitivity & Specificity) for the fourfold cross-validation method were then obtained. Table 3 lists the performance parameters for the classification of the (NH & SNHL patients) groups due to their auditory brain responses evoked by Pure Tone stimulus.

3.4.3 Classification of Hearing Abilities Due to Auditory Brain Responses Evoked by CV Stimulus and Pure Tone Stimulus

Using the auditory brain responses evoked by both type of auditory stimulus to classify hearing abilities for both tested groups (normal hearing or SNHL), a feature matrix generated from the successful feature extraction method has (240 samples $\times$ 5 intervals) elements. The matrix contains four types of stimuli (1 kHz, 4 kHz, da and ba), three features (KolmogEnt., SampleEnt., and ApproxEnt.), and a few participated subjects (10 for both groups one for normal hearing subjects and 10 for SNHL patients) multiplied by five times CAEP's responses intervals, which were (P1, N1, P2, N2 & P3) intervals. Therefore, a classification matrix consists of (240 samples $\times$ 5 intervals) elements using fourfold cross-validation. The training matrix was 180×5, while the test matrix was 60×5. The latter was used to evaluate classification accuracy, as it is an excellent indicator of the human brain responses to different auditory stimulus. By using Eqs. (4, 5, and 6), the performance parameters for both tested groups were then obtained. Table 4 lists the performance parameters for the classification of the (NH & SNHL patients) groups due to their auditory brain responses evoked by both auditory stimulus.

3.5 Formulation of Hearing Abilities Classification Indices

The descriptions procedure of the integration or formulation of the classification indices can be seen in Fig. 2.

Table 3 The performance parameter of classifiers due to auditory brain responses evoked by Pure Tone stimulus

Classifier	Performances parameters	Sample	Classified as	
			NH	SNHL
KNN		Normal hearing	53	7
		SNHL	8	52
	Accuracy		$105/120 = 0.8750$	
	Sensitivity		$52/60 = 0.8666$	
	Specificity		$53/60 = 0.8833$	
SVM		Normal hearing	54	6
		SNHL	7	53
	Accuracy		$107/120 = 0.8916$	
	Sensitivity		$53/60 = 0.8833$	
	Specificity		$54/60 = 0.9000$	
TREE		Normal hearing	52	8
		SNHL	9	51
	Accuracy		$103/120 = 0.8583$	
	Sensitivity		$51/60 = 0.8500$	
	Specificity		$52/60 = 0.8666$	
LDA		Normal hearing	50	10
		SNHL	11	49
	Accuracy		$99/120 = 0.8250$	
	Sensitivity		$49/60 = 0.8166$	
	Specificity		$50/60 = 0.8333$	
NB		Normal hearing	47	13
		SNHL	14	46
	Accuracy		$93/120 = 0.7750$	
	Sensitivity		$46/60 = 0.7666$	
	Specificity		$47/60 = 0.7833$	

3.5.1 Consonant Vowels Hearing Index (CVHI)

The CVHI Index is developed by ranking the nonlinear features extracted from the auditory brain responses evoked by CV stimulus. These features were then used to develop an optimally distinguishing index. Therefore, the mathematical formulation of this Integrated CVHI Index is:

$$\begin{aligned}\text{CVHI} = 28.670 + 22.921 \times \text{SampleEnt} - 289.017 \\ \times \text{ApproxEnt.} + 121.680 \times \text{KolmogEnt.} \end{aligned} \tag{7}$$

Equation (7) is derived using linear regression analysis, which was performed for the data listed in Table (A1) using the "least squares" method to fit a linear equation for a set of classified data to maximize the discrimination between the two classes, where first, the nonlinear features were ranked from the least significant, which is the SampleEnt. as the first variable in the equation, then ApproxEnt. as the second variable and the highest significant variable was KolmogEnt. In the case of the third one, it was done for the CV stimulus. Second, all feature values were sorted in a descending order (from largest to smallest) for each stimulus (da & ba) individually. The ranked and arranged data are tabulated in Table (A1). The ranges of the CVHI for brain hearing abilities response to CV stimulus are shown in Table 5. Figure 3 shows the plot of CVHI for the two classes of human brain hearing abilities response. This CVHI can be improved by taking better features and more data in each class.

3.5.2 Pure Tone Hearing Index (PTHI)

Like the approach reported in Sect. 3.5, the PTHI Index is developed using the ranking nonlinear features extracted from auditory brain responses evoked by Pure Tone stimulus. Then, these features were used to develop the optimally distinguishing index. Therefore, the mathematical formulation of this Integrated PTHI Index is given by:

$$\begin{aligned}\text{PTHI} = 31.097 - 134.545 \times \text{SampleEnt} - 86.260 \\ \times \text{ApproxEnt.} + 112.883 \times \text{KolmogEnt.} \end{aligned} \tag{8}$$

Equation (8) is derived using linear regression analysis, which is done for the data listed in Table (A2) using the "least squares" method to fit a linear equation for a set of

Table 4 The performance parameter of classifiers due to auditory brain responses evoked by both auditory stimulus

Classifier	Performances parameters	Sample	Classified as	
			NH	SNHL
KNN		Normal hearing	106	14
		SNHL	15	105
	Accuracy		$211/240 = 0.8791$	
	Sensitivity		$105/120 = 0.8750$	
	Specificity		$106/120 = 0.8833$	
SVM		Normal hearing	109	11
		SNHL	13	107
	Accuracy		$216/240 = 0.9000$	
	Sensitivity		$107/120 = 0.89166$	
	Specificity		$109/120 = 0.9083$	
TREE		Normal hearing	104	16
		SNHL	16	104
	Accuracy		$208/240 = 0.8666$	
	Sensitivity		$104/120 = 0.8666$	
	Specificity		$104/120 = 0.8666$	
LDA		Normal hearing	102	18
		SNHL	19	101
	Accuracy		$203/240 = 0.8458$	
	Sensitivity		$101/120 = 0.8416$	
	Specificity		$102/120 = 0.8500$	
NB		Normal hearing	100	20
		SNHL	21	99
	Accuracy		$199/240 = 0.8291$	
	Sensitivity		$99/120 = 0.8250$	
	Specificity		$100/120 = 0.8333$	

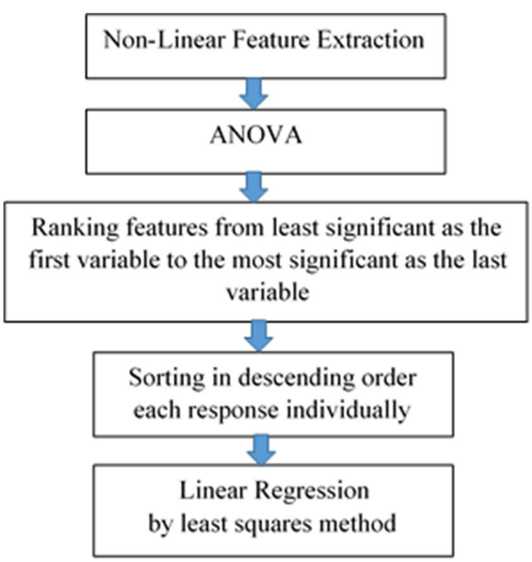

Fig. 2 The formulation procedure for the classification indices

Table 5 Range of CVHI Index for hearing abilities of Brain as per CV stimulus

Brain response to	Normal hearing	SNHL
Average	12.4466	27.1534
SD	5.9112	4.8560

classified data to maximize the discrimination between the two classes, where first, the nonlinear features were ranked from the least significant, which is the SampleEnt. as the first variable in the equation, then ApproxEnt. as the second variable, and the highest significant variable was KolmogEnt. as the third, which was done for the Pure Tone stimulus. Second, all features' values were sorted in a descending order (from largest to smallest) for each stimulus (1 Hz and Hz) individually. The ranked and arranged data are listed in Table (A2). The ranges of the PTHI for brain hearing abilities response to Pure Tone stimulus are shown in Table 6. Figure 4 shows the plot of PTHI for the two classes of human brain hearing abilities response, which can be improved by taking better features and more data in each class.

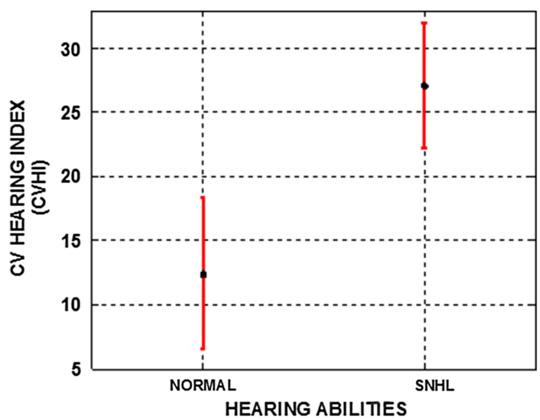

Fig. 3 Variation of CVHI Index for hearing abilities of Brain as per CV stimulus

Table 6 Range of PTHI Index for hearing abilities of Brain as per Pure Tone stimulus

Brain response to	Normal hearing	SNHL
Average	13.0861	26.5139
SD	5.9183	4.8631

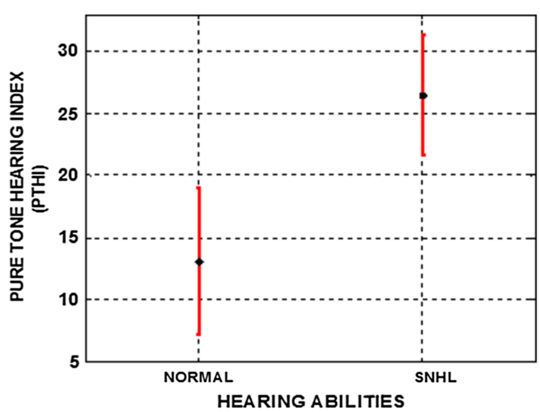

Fig. 4 Variation of PTHI Index for hearing abilities of Brain as per Pure Tone stimulus

3.5.3 Hearing Abilities Index (HAI)

The HAI Index is developed using the ranking nonlinear features extracted from auditory brain responses evoked by both auditory stimulus. Then, these features were used to develop the optimally distinguishing index. Therefore, the mathematical formulation of this Integrated HAI Index is:

$$\begin{aligned} \text{HAI} = 54.151 - 105.223 \times \text{SampleEnt} - 410.350 \\ \times \text{ApproxEnt.} + 285.160 \times \text{KolmogEnt.} \end{aligned} \quad (9)$$

Equation (9) is derived using the linear regression analysis performed for the data listed in Table (A3) using the "least squares" method to fit a linear equation for a set of classified data to maximize the discrimination between the two classes.

Table 7 Range of HAI Index for Brain hearing abilities as per both auditory stimulus

Brain response to	Normal hearing	SNHL
Average	26.1538	57.0185
SD	12.1206	13.9093

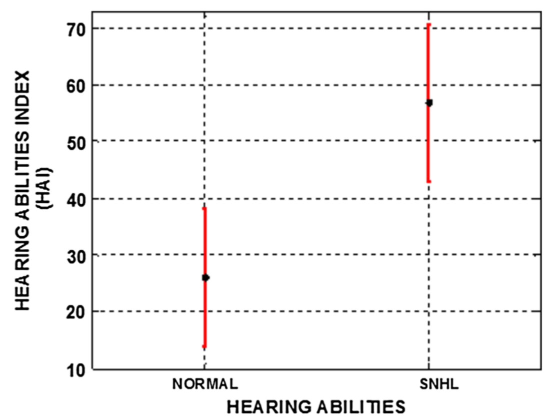

Fig. 5 Variation of HAI Index for Brain hearing abilities as per both auditory stimulus

The ranked and arranged data are listed in Table (A3). The ranges of the HAI for brain hearing abilities response evoked by both auditory stimulus (the Pure Tone and CV stimulus) are shown in Table 7. Figure 5 shows the plot of HAI for the two classes of hearing abilities per both auditory stimulus. This HAI can be improved by taking better features and more data in each class.

4 Discussion

The most important aspect of this study is the formulation of a novel classification indices using EEG CAEP signals. These indices (CVHI, PTHI & HAI) significantly identified the CAEP signals evoked from the normal hearing and SNHL brain's responses due to the different auditory stimulus (Pure Tones and CV stimuli), making it useful to predict hearing abilities using a simple linear binomial.

In other words, the hearing classification indices efficiently identified the brain hearing abilities (normal hearing and SNHL) extracted from the CAEP responses evoked by an auditory stimulus. The classification indices can easily classify or recognize the human brain responses evoked from the normal hearing brain or SNHL brains. CVHI used only the auditory brain responses evoked by CV stimulus for formulating its simple linear equation, while the PTHL used only the auditory brain responses evoked by Pure Tone stimulus for formulating its simple linear equation. However, the HAI classification index used both the auditory brain responses evoked by two auditory stimuli (Pure Tone stimulus and CV stimulus) for formulating its simple linear equation.

These classification indices could be used efficiently to investigate the hearing abilities from a difficult-to-obtain hearing response subjects (e.g., infants, children, and difficult-to-test patients) using only a simple linear binomial.

In fact, one of the major purposes of this study was to compare the performances of the classification algorithms in classifying Hearing abilities (normal nearing and SNHL) due to the auditory brain response (AEP EEG signal) evoked by an auditory stimulus (Pure Tones stimulus and CV stimulus). Moreover, the study also compared classification algorithms for the classification of brain hearing abilities with the integrated novel classification indices (CVH1, PTHI & HAI). CAEPs recordings were obtained from all the participants for both Pure Tones and CVs stimuli. The classification process using classification indices was conducted in the time domain in a very short processing time, which makes our novel classification (approaches or) indices (CVH1, PTHI & HAI) efficiently function in real time classification applications.

We selected the best distinguishing nonlinear CAEP features and combine them into an integrated novel classification indices. The index (CVHI) [Eq. (8)] could optimally separate the auditory brain response classes due to brain hearing abilities (see Fig. 2). However, when comparing CVHI that is (100%) accurate, different classifiers were used in this study to classify the auditory hearing brain responses due to the auditory stimulus (CV stimuli) reporting an accuracy of 90.32% as its maximum (see Table 2) [9,15]. Similarly, the index (PTHI) presented in Eq. (9) could optimally separate the auditory brain response classes due to brain hearing abilities (see Fig. 3). However, when comparing the PTHI that reports an accuracy of (100%), the different classifiers used in this study to classify the auditory hearing brain responses due to the auditory stimulus (CV stimuli) reported an accuracy of 89.16% as its maximum (see Table 3) (see Table 2) [9,15].

The index (HAI) presented by Eq. (10) could optimally separate the auditory brain response hearing abilities classes. However, comparing the HAI that reported an accuracy of (100%), the different classifiers used in this study to classify the auditory brain responses due to different auditory stimulus (Pure Tone & CV stimuli) reported an accuracy of 90% (see Table 4) [9,15].

Indeed, the formulation of the CVHI classification index was better than other classification indices. The multiple R, which is the correlation between actual and predicted values of the dependent variable for the CVHI was (0.870627637), while the multiple R for the PTHI was (0.821811945), and for HAI, it was (0.836751088) for the same input set. This indicated that CV stimulus evoked more homogenous brain responses, which resulted in a more efficient classification index [57]. Moreover, CV stimulus brain responses reported high accuracies in the used classification algorithms.

The results showed that the time domain segmentation method and the nonlinear feature entropies methods resulted in a high classification performance. This was because brain neurons are controlled by nonlinear phenomena, such as the threshold and saturation processes. Therefore, its behavior can be regarded as nonlinear, and nonlinear dynamic analysis can be regarded as an integral approach in detecting mental tasks because it provides more information compared to that reported by traditional linear methods [15]. Approximate Entropy (ApproxEnt.) evaluate the instability of variation in the signal, while Sample Entropy (SampleEnt.) measures the regularity of physiological signals, and Kolmogorov–Sinai entropy (KolmogEnt.) evaluates the uncertainty of any signal with respect to time. As per Sect. (4.3), many features were extracted from the decomposition process.

4.1 Classification Accuracy

The SVM and KNN classifiers were highly accurate in classifying human hearing abilities due to auditory brain responses, which means that the classifiers work in the time domain with the nonlinear feature extraction methods perfectly. However, the algorithm proposed in this work, using SVM as classifiers, resulted in a better accuracy than the system using Trees (Bagged decision tree), KNN, BN, and LDA classifiers. This is because the features extracted with nonlinear feature extraction methods are more accurate, and the fact that the structure of the classification algorithm depends on the RBF kernel threshold level design. The boundary conditions (or regions) resulting from the threshold level works in the same manner of the classification indices, but with wide ranges (forbidden regions) of prediction areas [58].

Similarly, the features used in the other work combined with a SVM classification algorithm would lead to decreased accuracy [8,53]. The NB classifier reported the lowest classification accuracy obtained in this study. The lowest classification accuracy reported by the Naive Bayes classifiers is highly scalable, requiring several parameters that are linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation used for many other types of classifiers [59].

In fact, the nonlinear feature extraction methods (KolmogEnt., SampleEnt., and ApproxEnt), cross-validation methods, and the ANOVA ranking and selection method for the time segmentation method are efficient tools/procedure for obtaining a high classification performance and classifying auditory evoked potential response (CAEP) [9].

Many experimental studies used classification algorithms to classify Human brain EEG signals reported being able to predict the outcome of simple response from brain signals recorded from different ethnic groups [60]. This study compared the classification of brain auditory responses evoked by an auditory stimulus. Tables 2, 3 and 4 and the predicted novel classification indices report an accurate and high classification performance in the time domain using the nonlinear features. These indices and the classification approach described in this study could be recommended for use in BCI systems and other system that uses brain signal classification applications. We outlined several limitations faced by the work, such as the sample size being small. Further analysis involving large databases should be performed in any future works. In fact, the limitation of the sample size could affect the accuracy of classification for all used classifiers. Also, the limitation of the sample size makes it somewhat hard to formulate or predict classification indices.

5 Conclusion

Until recently, the classification of a brain response signal is challenging. The novel classification indices formulated or predicted in this study for classifying the auditory brain responses (CAEP) as per hearing abilities (normal hearing or SNHL) resulted in a very accurate classification performance (100%). Moreover, this study formulated a novel classification indices (CVHI, PTHI & HAI) for classifying human hearing abilities as per the auditory brain responses (CAEP). These indices used highly ranked nonlinear features to formulate a simple linear binomial equations or formulas. These linear binomial equations enable the researchers and any applications that used classification of brain signals to easily and effectively estimate or predict the exact hearing abilities of the tested brains.

Furthermore, the study found that the SVM classification algorithm has the highest classification accuracy among other classification algorithms used in this study for classifying human hearing abilities as per the auditory brain responses (CAEP). This was concluded by establishing classification methods for brain response signals EEG (auditory event-related potentials) to classify the hearing abilities in the human brain (normal hearing and SNHL).

Unlike other methods, this method has the advantage of ranking both recorded EEG data and extracted features. These features are based on time analyses of the EEG recorded signals. There were also no signal processing methods that could classify the evoked brain EEG signal stimulated by auditory stimuli (Tone and CV stimulus) that is (100%) accurate. Thus, we attempted to classify the brain's Hearing abilities as per the auditory brain response. Finally, the study concluded that the time segmentation method with nonlinear features, such as KolmogEnt., ApprosEnt., and SampleEnt. results in a high classification performance for almost all utilized classifiers in cases of auditory evoked responses. Both the SVM and KNN classifiers reported high accuracies in the time domain. This study also detailed several limitations faced by the work, such as the sample size being too small. Further analyses involving larger databases should be performed in any future works.

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Author contributions Ibrahim Amer Ibrahim and Dr. Hua-Nong Ting conceived and designed the experiments; Ibrahim Amer Ibrahim, Prof. Dr. Mahmoud Moghavvemi and Dr. Hua-Nong Ting performed the experiments; Ibrahim Amer Ibrahim, Prof. Dr. Mahmoud Moghavvemi and Dr. Hua-Nong Ting contributed reagents/materials/analysis tools; Ibrahim Amer Ibrahim and Dr. Hua-Nong Ting wrote the paper.

Compliance with Ethical Standards

Conflicts of interest The authors declare no conflict of interest.

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