Detection of Post-stroke Epilepsy Using EEG Signal Analysis and Logistic Regression

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Abstract

Background: Epilepsy is a common neurological disease caused by abnormal discharges from hyperexcitable neurons in the brain. Electroencephalography (EEG) is one of the main tools used for epilepsy diagnosis. However, there is still no reliable framework for the clinical detection of post-stroke epilepsy.

Methods: A total of 1,323 EEG records from 831 stroke patients at Taipei Veterans General Hospital (TVGH) were collected from 2012 to 2017. After removing signal noise, common spatial patterns (CSP) were used as spatial filter and enhanced the signal features of our raw EEG. Morlet wavelet transform was then used in specific frequency bands for spectrum analysis. Finally, statistical features were extracted and fed to machine learning models for detection of post-stroke epilepsy.

Results: Results showed that the Logistic Regression model with four features (coherence, entropy, kurtosis, and skewness) significantly outperforms related machine-learning-based epilepsy detection approaches, achieving an F1 score of 65.3%, sensitivity of 27.2% and specificity of 83.0%.

Conclusions: A system for the detection of post-stroke epilepsy shows promising results, but further studies are needed for post-stroke clinical care.

Keywords: Electroencephalography, machine learning, post-stroke epilepsy, spectrum analysis

Background

Epilepsy is a neurological disease that affects more than 60 million people worldwide (roughly 1% of the global population) [1]. Epilepsy results from excessive electrical discharges in a group of brain cells, and can be regarded as a chronic noncommunicable disease of the brain that affects quality of life. EEG is one of the main tools used for the noninvasive and painless diagnosis of epilepsy through the attachment of electrodes to the scalp to record electrical activity in the brain. In the past, diagnosticians had to manually identify epilepsy-indicating patterns in the EEG output, a time-consuming and labor-intensive process. Machine learning algorithms are used to assist physicians in interpreting EEG efficiently [2] and detecting potential seizures automatically [3] for clinical diagnosis decision support.

Common brain insults related to epilepsy include traumatic brain injury and stroke. A recent study has shown that approximately 9.3% of stroke victims subsequently experience epileptic seizure [4]. However, EEG is not routinely used in stroke patients, despite providing real-time and dynamic information for very early-stage diagnosis.

Epileptiform discharges in patients with acute stroke do not suggest post stroke epilepsy in acute stroke patients because they might only reflect irritating features following acute insult. There has recently been some limited progress in this regard [5]. One recent study showed that early EEG abnormalities are independent predictors of post-stroke epilepsy [6].

Although machine learning analysis of EEG is helpful for epilepsy diagnosis, these abnormalities were not sensitive or specific to post-stroke epilepsy and these findings still cannot be applied for the clinical detection of post-stroke epilepsy. Therefore, our research objective is experimentally applied machine learning models to improve detection of post-stroke epilepsy. We attempt to find usable machine learning models to aid clinical diagnosis and make it possible to predict overall epilepsy development in a wider population.

Related Work

EEG signal analysis based statistical features for epilepsy detection can be commonly divided into four categories as follows: 1) Features related to the waveform, such as maximum & minimum, root mean square value, standard deviation, kurtosis and skewness [7]. 2) Features related to frequency, including percentile, median frequency [8]. 3) Features related to power, including wave energy and relative energy [9] [10]. A recent study also found that the combination of kurtosis, skewness and relative energy by frequency band provides the best performance [11]. 4) Features related to information domain, including Approximate Entropy (ApEn), Sample Entropy (SampEn), Phase Entropy 1 (S1), and Phase Entropy 2 (S2) [12].

Many machine learning classifiers have been widely used to differentiate seizure and non-seizure signals in EEG files. A Support Vector Machine (SVM) method was used with a patient-specific approach in time-sensitive clinical procedures [13]. Common Spatial Patterns (CSP) have been used to extract features from time-domain signals and train SVM [14]. Discrete Wavelet Transform was used for signal decomposition and SVM classification [15]. Other classical classifiers, such as K-Nearest-Neighbors (KNN), have also been developed and trained with Discrete Wavelet Transform to not only detect seizures, but also to classify EEG signals as normal, background or epileptic [16]. The KNN algorithm was further developed by selecting neighbors with multiple distances [17]. Shoka et al. compared the performance of different epileptic seizure detection techniques using machine learning classifiers [18], including SVM, KNN, decision tree, ensemble learning and logistic regression. Decision tree and ensemble learning were found to provide greater accuracy, while SVM and logistic regression have greater sensitivity. Saminu et al. conducted a thorough investigation of epilepsy detection systems from pre-processing to classification [19], providing a clear view of the framework or processes involved in EEG signal detection and classification.

Recently, logistic regression has emerged as one of the most commonly used classifiers for epilepsy detection based on EEG signals. Lifting-based discrete wavelet transform is used in preprocessing to extract EEG signals and coefficients which are then fed into Logistic Regression (LR) and a multilayer perceptron neural network (MLPNN) [20]. To compare LR and MLPNN classifiers, multiple signal classification, autoregressive and periodogram methods were used to obtain the power spectral densities of the EEG signals. This also showed that neural rhythms provide better seizure identification than LR. However, LR modeling has continued to improve and, using non-linear Independent Component Analysis as a dimensionality reduction technique, LR can accurately detect epileptic cases with 95.88% accuracy, 95.71% specificity and 96.04% sensitivity [21]. Though relatively few studies have examined the use of LR modeling in automatic seizure detection, the application and practicality of the LR should not be underestimated.

Methods and materials

EEG Data Acquisition

There were three types of stroke: Infarction, Intracerebral hemorrhage and Subarachnoid hemorrhage. The EEG dataset was retrospectively obtained from the Taipei Veterans General Hospital (TVGH) in Taiwan using a total of 1323 EEG sessions from 831 stroke patients from 2012 to 2017. The age (mean, median and interquartile ranges) for the population were 75.88, 80 and 23, respectively. In total, 198 patients had EEG measurements at least two times. In more detail, patients were divided into two groups: 197 patients (393 EEG sessions) suffered from post-stroke epilepsy, while 634 patients (930 sessions) did not have epilepsy during the stroke follow-up period. The former of repeated sampling was 85/182 (46.7%) patients with at most 9 times for EEG measurements. At average, 2.6 EEG measurement for 85 patients and 1.7 EEG for the overall. The latter of repeated sampling was 113/649 (17.4%) patients with at most 6 times. At average, 2.01 EEG measurements in 113 patients and 1.2 EEG for the overall.

EEG was performed using the international 10-20 system, and recorded with a sequence of “rest, photic stimulation, rest”. Photic stimulation was performed using different frequency bands with a sequence of 13 Hz, 5 Hz, 7 Hz, 9 Hz, 11Hz, 13 Hz, 15 Hz, 17 Hz and 19 Hz with a duration of 10 seconds. Overall, 21 channels were used, including Fp1, Fp2, F3, F4, Fz, F7, F8, C3, C4, Cz, T3, T4, T5, T6, P3, P4, Pz, O1, O2 , A1 and A2. Each measurement of time interval was different. At average, the time from stroke to EEG was 34.9 days. The EEG recording duration was 1074.3 at average, approximately 17 minutes.

System Design

Figure 1 shows the four-step process used in the present study for post-stroke epilepsy detection by EEG: pre-processing, spectrum analysis, feature extraction and classification.

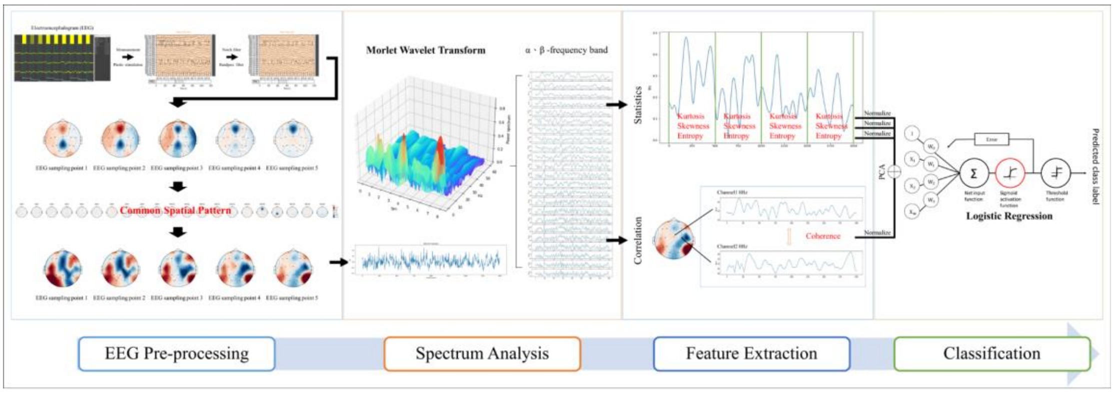

Fig. 1 EEG-based post-stroke epilepsy detection. First, we use EEG pre-processing to remove signal noises and strengthened features. Spectrum analysis is then used to separate brainwaves in terms of different frequency bands. Feature extraction is used to reduce dimensionality without losing relevant information. At the last stage, the

extracted features are fed into a logistic regression model for epilepsy detection on stroke patients.

Pre-processing

8-second epochs of EEG for further analysis were retrieved from raw EEG in the state of rest and photic stimulation. The sampling rate of the raw EEG ranged from 250 to 1000 Hz. Therefore, resampling of raw EEG to 250 Hz was performed.

A band-pass filter was used with cutoff frequencies from 1 to 60 Hz to minimize ambient noise. We used CSP as spatial filter and enhanced the signal features of our raw EEG. The basic principle of CSP is to use matrix diagonalization to find a set of optimal spatial filters for projection, so as to maximize the variance value difference of different types of signals, and to obtain eigenvectors with a higher degree of discrimination. The value is sorted by descending power to find the whitening eigenvalue matrix, so it also has the effect of a spatial filter.

CSP can be used for three-dimensional data. For example, time-domain EEG data has three dimensions: sample, electrode, and time. This method is often used on binary classification tasks such as imaginary motion classification based on EEG data, but can also be applied to multivariate tasks. In terms of binary classification, the co-spatial model first obtains the variance matrices C1 and C2 of the two types of data and averages them respectively to obtain the average variance matrix.

Next is to find the eigenvalues and arrange them in descending order. The eigenvectors of average variance matrix are sorted according to the size of the eigenvalues. Use the eigenvalue and eigenvector to obtain the whitening eigenvalue matrix. This matrix can calculate the new variance matrix C1_new, C2_new. When one class has the largest eigenvalue, the other class is the smallest. Finally, a spatial filter is constructed through the existing whitening matrix and eigenvector, and the matrix is obtained by projecting the original EEG signal.

Spectrum Analysis

This research compared the effects of time-domain and frequency-domain analysis. The data indicate that spectrum analysis provides more suitable features on this dataset. EEG has its physiological significance in different frequency bands, delta waves (δ, 0.5-4Hz) is prone to occur in Deep sleep conditions, and theta waves (θ, 4-8Hz) are prone to occur in Drowsy conditions, alpha waves (α, 8-13Hz) are prone to appear in Relaxed and Eye close conditions, beta waves (β, 13-30Hz) are prone to appear in Excited and Eye open conditions. Therefore, feature extraction can be performed on time-domain or frequency-domain signals. The time domain signal to frequency domain signal method includes Fourier transform, FFT, STFT and Wavelet Transform [22]. Since the application of EEG signal analysis in post-stroke epilepsy is a new topic, the frequency range of our research experiment is large. After our experimental comparison and the characteristics of wavelet transform (time-frequency window that can be modulated), we focus on the introduction of wavelet transform.

Compared to Fast Fourier Transform and Short-time Fourier Transform, Wavelet Transform allows for multiresolution analysis and generates smoother features, thus allowing for the analysis of nonlinear and nonstationary signals containing multiscale features. It also shows better results in our dataset. Wavelet coefficients are obtained using Morlet Wavelet Transform. The Morlet wavelet is obtained from roughly sinusoidal signals tapered by a Gaussian window, providing both good temporal and spectral precision [23].

Experimental data during either resting state and photic stimulation is captured when patients are awake. Consequently, after applying spectrum analysis, we mainly observe the wavelet in two frequency bands $\{\alpha, \beta\}$. After the experimental comparison, it was observed in this data set that if δ, θ, α, β are mixed and matched, the combination of α and β is also the best.

Feature Extraction

Feature extraction is an important step in machine learning analysis and is used here to transform the time domain EEG signals into more observable frequency domain signals. This is a process of dimensionality reduction without losing relevant information, simplifying the accurate description of the data set.

Coherence (C) analysis is widely used to study brain activity and was used here to extract partial and spatial EEG signals and to evaluate the linear correlation between particular spectrum channels. Kurtosis (K) describes the peak or flatness of a frequency distribution. Skewness (S) is a measure of symmetry. The value of skewness indicates whether the shape is left-sided or right-sided. Entropy (E) is associated with disorder, and increases with the number of samples, but falls with uneven distribution results. Kurtosis, Skewness and Entropy are calculated by the following equations:

$$K = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^2} - 3 \tag{3}$$

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^{3/2}} \tag{4}$$

$$E = -\sum_{i=1}^{n} p(x_i)\log(p(x_i)) \tag{5}$$

where x_i is the i^{th} input data, n is sample size and $\bar{x}$ indicates the mean value of all samples.

Before features are fed to the classifier, normalization and principal components analysis (PCA) are implemented. Normalization basically brings multiple signals into a predefined range to reduce deviation, accelerate learning and improve accuracy, but potentially removes physiologically significant events from the original data. PCA helps compute the first few principal components for dimension reduction and to accelerate learning. Using these principal components as eigenvectors, this technique simultaneously maximizes the variance of the projected data and minimizes information loss.

Classification

Following the process of data preprocessing, wavelet transform, feature extraction, normalization and PCA, the extracted features are fed into a logistic regression model for epilepsy detection.

Logistic regression is a type of model used for analyzing dichotomous outcomes, such as win/lose or survive/die. Since the model predicts the best separation if something is true or false, this model performs well when the data separation is apparent.

In our work, the dichotomous variable represents the presence or absence of post-stroke epilepsy. In the linear model, the relationship between outcome and the weight is defined as:

$$logit\ (p) = ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n \qquad (6)$$

where β_0 is the intercept and β_1, β_2..., β_n denotes the coefficients corresponding to the inputs x_1, x_2..., x_n. However, logistic regression can be regarded as a special case of the generalized linear model. It does not require Gaussian distributed independent variables. Rather than predicting changes in the response variable itself, it calculates changes in the logarithm of odds of the response variable [20]. We need to convert the weighted sum to a probability of a particular outcome. The output probability value should lie between 0 and 1 instead of being a numeric value. The logistic function model squeezes the output of a linear equation and is mathematically expressed as:

$$P(x) = \frac{1}{1 + e^{-logit(p(x))}} \qquad (7)$$

The outcome is no longer linearly related to explanatory variables. By increasing the value of input feature x_i, the odds actually change by a factor of $\exp(\beta_i)$. Based on the computed odds, it shows the relationship between the categorical dependent variable and other independent variables. Beyond serving as a classification model, logistic regression also provides probabilities. Furthermore, this well-established algorithm has already been developed to deal with multi-class classification problems.

System Evaluation

Evaluation metrics are used to measure the quality of machine learning algorithms, allowing for iterative improvement until a desirable result is obtained. There are a variety of metrics to help analyze model performance. The choice of metric is based on the model purpose and type. Here, we select F1 score, accuracy and specificity as performance indicators.

F1 score is useful for models requiring both good accuracy and recall for a classification problem. Scored between 0 and 1, F1 is the harmonic mean of precision and recall values, computed by "(8)". When selecting parameters, this metric gives the same importance to each class, so underrepresented data will not be ignored. As the data acquired from TVGH is imbalanced, we assess the macro F1-score to evaluate model performance. Sensitivity reports the number of items correctly identified as positive out of total true positives. Specificity predicts actual negatives of a condition. Mathematically, sensitivity and specificity can respectively be expressed by Eqs. (9)

and (10).

$$F1 = 2 * \frac{precision * recall}{precision + recall} \tag{8}$$

$$Sensitivity = \frac{true\ \ positive}{true\ \ positive + false\ \ negative} \tag{9}$$

$$\text{Specificity} = \frac{true\ \ negative}{false\ \ positive + true\ \ negative} \tag{10}$$

Sensitivity and specificity are pivotal factors especially in diagnosis testing with the following outcomes: 1) True positive: epileptic subject is correctly identified as epileptic; 2) False positive: healthy subject is incorrectly identified as epileptic; 3) True negative: health subject is correctly identified as not epileptic; 4) False negative: epileptic subject is incorrectly identified as healthy. Sensitivity reflects the model's ability to correctly identify epileptic subjects, while specificity correctly identifies healthy subjects. Good evaluation metrics for sensitivity and specificity will help guide clinical decisions and improve the timeliness of treatment.

Settings

Extensive experiments were conducted to investigate the effectiveness of various models for epilepsy detection in patients with stroke. We used nested cross-validation to divide the data into training, testing and validation datasets. The procedure included a double loop where the outer loop is used to average k scores and evaluate the training quality on the inner loop, and the inner loop tunes the hyperparameters to obtain an optimal result. The outer loop generated five different test sets which are further split into five inner folds. Nested cross-validation provided a nearly unbiased estimate of the true error [28].

In this study, the sample rate is 250. The final frequency resolution [fmin:fstep:fmax] is composed of 8Hz、1Hz、30Hz. We calculated the Morlet Wavelet by giving the central frequency and created a Morlet Wavelet by specifying a central frequency. Then we used the Morlet Wavelet to convolve the input temporal data. Frequency ration (number of cycles) is 7.

Results

Epilepsy detection with different combination of features

Extracted features including coherence (C), kurtosis (K), skewness (S) and entropy (E) were grouped into three combinations to determine which test produced the best performance. We used the EEG after preprocessing steps such as event detection, resampling, filtering, etc. The 21 electrodes are combined for coherence operation, and the frequency domain is 8~30 Hz (α, β wave), getting a total of 4830 coherence features.

The captured eight-second brainwave data was used as a time segment to analyze the α and β wave patterns. Statistical analysis was performed to obtain 21×23×4×3, having a total of 5,796 spectral signal statistical features. Before exploiting the machine learning model, we used PCA to select the data used for model training. The number of components of PCA is selected during the interactive verification process. The component of 150 gave the best result.

We applied three different groups of features to nine machine learning models. Among nine models, four features of coherence, kurtosis, skewness, and entropy together gave the best F1-score in SVM, KNN, LR, RF and AdaBoost models. Take LR and SVM as example in Table 1 and Table 2. According to the existing experimental data, we believe that Coherence has the greatest contribution, and adding the other three characteristics has extra positive impact. To analyze whether there is an epilepsy, observing the correlation changes between electrodes has a more significant effect, but the statistical data of a single channel is also helpful for the machine learning model. Table 3 shows the results for various feature combinations on the average of nine models. Grouping four features of coherence, kurtosis, skewness, and entropy together gave the best F1-score and specificity, while grouping three features of kurtosis, skewness, entropy without coherence had the highest sensitivity.

Table 1. Epilepsy detection using LR with different combination of features

Features	F1	Sensitivity	Specificity
C	65.1%	26.2%	**83.4%**
K+S+E	62.2%	**32.6%**	73.9%
C+K+S+E	**65.3%**	27.2%	83.0%

Table 2. Epilepsy detection using SVM with different combination of features

Features	F1	Sensitivity	Specificity
C	64.3%	25.0%	82.6%
K+S+E	62.8%	**29.7%**	76.7%
C+K+S+E	**64.5%**	25.6%	**82.7%**

Table 3. Average results of epilepsy detection with different combination of features

Features	F1	Sensitivity	Specificity
C	62.2%	27.1%	77.6%
K+S+E	61.5%	**28.1%**	75.6%
C+K+S+E	**62.3%**	25.7%	**78.7%**

Epilepsy detection with different machine learning models

Nine machine learning models, including SVM [24], KNN [25], LR [26], Decision Tree (DT) [27], Random Forest (RF) [28], Extra Tree (ET) [29], Gradient Boost Decision Tree (GBDT) [30], Extreme Gradient Boosting (XGBoost) [31] and Adaptive Boosting (AdaBoost) [32] were used in this work, with epilepsy detection results summarized in Table 2. LR model achieves the best F1 score of 65.3%, with a specificity of 83.0%, but a slightly lower sensitivity of 27.2%. F1 is suitable for the performance evaluation of machine learning models with unbalanced data. In comparison of F1-scores of nine models, the results showed that LR and SVM had better results. Further comparing LR and SVM, we obtained 100 sets of F1 data sets with the mean F1 of LR is 0.6532 and SVM is 0.6451. LR has better confidence level than SVM with p-value 2.93e-55 ($P < 0.001$).

Table 2. Epilepsy detection with different machine learning models

Classifier	F1	Sensitivity	Specificity
SVM	64.5%	25.6%	82.7%
KNN	63.6%	23.6%	82.4%
LR	**65.3%**	27.2%	**83.0%**
DT	60.2%	26.6%	74.2%
RF	62.0%	26.4%	77.4%
ET	60.3%	**30.6%**	71.9%
GBDT	61.7%	22.3%	79.9%
XGBoost	60.7%	23.5%	77.1%
AdaBoost	62.7%	25.6%	79.3%

Comparison between the proposed methodology and previous results

Zheng et al. [14] used CSP to extract features from time-domain signals and train SVM. Kurtosis and Skewness were used to extract features from the time domain signal, extracting relative frequency band energy features after wavelet transform using multilayer perceptron [11]. Roy et al. [1] focused on multi-class seizure type classification instead of seizure detection. Correlation coefficients and eigenvalues were extracted as features from the frequency domain using KNN. Table 3 shows that our proposed model outperforms these three approaches when applied to post-stroke epilepsy data. Model distinguishes interictal epileptiform from focal slowing caused by stroke, and identifies epilepsy in stroke patients.

Table 3. Comparison with related works

Methods	F1	Sensitivity	Specificity
Zheng et al. [14]	60.0%	**30.8%**	71.5%
Sally et al. [11]	58.4%	29.6%	69.1%
Roy et al. [1]	60.6%	26.8%	75.0%
Our model	**65.3%**	27.2%	**83.0%**

Discussion

This study proposes an algorithm to detect post-stroke epilepsy by EEG abnormalities in post-stroke patients. We found that the Logistic Regression machine learning algorithm provides the best results for epilepsy detection in post-stroke patients, with an F1 score of 65.3%.

In the short-time 8-second EEG interpretation, this method achieves results of low sensitivity and moderate specificity. In fact, we can understand that the EEG signal of 8 seconds does not necessarily show the characteristics of post-stroke epilepsy. In contrast, an 8-second brain wave can be better identified by the ML method without the characteristics of post-stroke epilepsy.

According to the above, we applied this system to the longer EEG data in our experiments, performed an examination every 8 seconds, and recorded the results of each examination to determine whether the longer EEG signal has post-stroke epilepsy. The EEG signal analysis of 1 minute and 54 seconds can obtain F1-score of 71.9%, Sensitivity of 44.8% and Specificity of 83.1%. Even though sensitivity is relatively low, it helps identify potential epilepsy in stroke patients. Moderate specificity is less vulnerable to misjudge. We believe that it has the advantages of short-time identification and aiding clinical diagnosis. If the accuracy can continue to be improved, it will become a rapid screening system or assist physician detection.

Three additional pre-processing techniques were used to transform raw data into comprehensible and useful data. A band-stop filter attenuates a specific range of frequencies to a very low level, thus eliminating the effect of electrical noise. Notch filter has a very small stop range and is used to determine the negligible impact of 60 Hz AC noise on F1 score. We assumed that the data was not subject to serious 60Hz interference. However, to prevent interference from new data sources collected under different circumstances or other special cases, notch filter is still implemented before the band-pass filter.

Event-related desynchronization (ERD) and event-related synchronization (ERS) are non-phase locked and frequency-band reactivities. ERD reflects a decrease of oscillatory activity related to an internally or externally paced event. In contrast, ERS indicates an increase in rhythmic activity. ERD/ERS can be used to study the dynamics of cortical activation patterns [38], thus smoothing signal variability in spatial mapping. Since cognitive and motor processing cause dynamic patterns in EEG, experiments were conducted to determine that pre-processing without ERD/ERS process and with CSP improves performance in most models, thus ERD/ ERS was excluded from pre-processing.

This research, however, is subject to several limitations. This study emphasized the importance hypothesis for the EEG electrodes regarding post-stroke. At first, we divided the areas that may be affected by stroke into seven areas. The reason is that the electrodes in the areas damaged by the stroke may have higher sensitivity. Since stroke is a local abnormality, it can be reasonably assumed that epilepsy is localized. According to the doctor's suggestion, the 10-20 system electrodes can be divided into seven major stroke areas, which are Fp. Area (Fp1, Fp2), F Area (F3, F4, Fz), F&T Area (F7, F8), F&P Area (C3, C4, Cz), T Area (T3, T4, T5, T6), P Area (P3, P4, Pz) and O area (O1, O2). However, the results of the partition training model were not good, so this method was not used. We speculated that there are too few data on post-stroke epilepsy in each area after the partition. Consequently, the learning effect is not promising and local strokes may also cause widespread abnormalities, such that deep brainstem strokes affect consciousness. Despite the fact, the feasibility cannot be ruled out. If continuously collecting more data in the future, we expect to achieve better predictions by the partition training model. Furthermore, if further research is carried out with stroke labels indicating to which brain region the data belongs, more experiments can be conducted based on the assumption that epileptogenic is a partial injury. Then, the best model of each brain region may outperform the 10-20 system. For future studies, stroke patients should be classified by seizure type. The data indicating the time difference between the stroke and seizure should also be further discussed.

Conclusions

Detection of post-stroke epilepsy is difficult by visual interpretation of EEG. In this study, we introduce a machine-learning system to detect post-stroke epilepsy. This research uses Event Detecting, Resampling, Filtering, Epochs, Spatial Filtering

Complete data cleaning. Convert 21-time domain EEG channels to frequency domain through Morlet Wavelet Transform to observe α (8-13Hz) and β (13-30Hz), and extract kurtosis, skewness, and entropy on the waveform in units of every two seconds feature, obtain 21x23x4x3, a total of 5796 feature points, and take the fourth feature of coherence between channels, which is 23 frequency bands in 210 associations, a total of 4830 feature points, and complete feature extraction. Then the four features were normalized and merged, and the LR model was trained by the PCA method after dimensionality reduction. This system can significantly improve the f1 score of epilepsy after stroke. The preliminary results break the new ground, but further research is needed to achieve the goal of clinical applications.

Declarations

Ethics approval and consent to participate

This study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board of TAIPEI VETERANS GENERAL HOSPITAL (protocol code TPEVGH IRB No. 2018-10-007AC with approval Nov. 3, 2018). Informed consent was obtained from all subjects involved in the study. Written informed consent has been obtained from the patients.

Consent for publication

Not applicable.

Availability of data and materials

All data were collected from the patients who had been admitted to the hospital, Because of the hospital’s regulations, the data cannot be made publicly available. The data request should be contacted Dr. Chien-Chen Chou via ccchou5@vghtpe.gov.tw

Competing interests

The authors declare no competing financial interests.

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Authors’ contributions

Conceptualization, C.-C. C. and P.-L. L.; methodology, T.-C. H. and L.-H. L.; software, T.-C. H.; validation, C.-C. C. and T.-C. H.; formal analysis, T.-C. H. and Y.-X. H.; investigation, C.-C. C.; resources, Y.-Y L. and I-H. L.; data curation, C.-C. C, Y.-Y L.

and I-H. L.; writing— original draft preparation, Y.-X. H.; writing—review and editing, L.-H. L.; visualization, T.-C. H. and L.-H. L.; supervision, L.-H. L.; project administration, P.-L. L. and K.-K. S.; funding acquisition, K.-K. S. All authors have read and agreed to the published version of the manuscript.

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References

1. S. Roy, U. Asif, J. Tang, and S. Harrer. Machine learning for seizure type classification: setting the benchmark. arXiv: 1902.01012, 2019.
2. Paul Y. Various epileptic seizure detection techniques using biomedical signals: a review. Brain Inform. 2018 Jul 10;5(2):6. doi: 10.1186/s40708-018-0084-z. PMID: 29987692; PMCID: PMC6170938.
3. Johannes P. et al. Automated Long-Term EEG Review: Fast and Precise Analysis in Critical Care. Front Neurol. 2018; 9: 454.
4. Alexander E. MErler, MD et al. Population-Based Assessment of the Long-Term Risk of Seizures in Survivors of Stroke. Stroke. 2018;49:1319–1324.
5. Zou, S., Chen, Y. Research progress on the prediction of post-stroke epilepsy. Acta Epileptologica. https://doi.org/10.1186/s42494-020-00031-z.

6. Bentes C, Martins H, Peralta AR, Morgado C, Casimiro C, Franco AC, Fonseca AC, Geraldes R, Canhão P, Pinho E Melo T, Paiva T, Ferro JM. Early EEG predicts poststroke epilepsy. Epilepsia Open. 2018 Mar 7;3(2):203-212.
7. S.Priyanka et al. Feature selection and classification of Epilepsy from EEG signal. 2404-2406. 10.1109/ICECDS.2017.8389880.
8. Polat H. et al. Epileptic seizure detection from EEG signals by using wavelet and Hilbert transform. 2016; doi: 10.1109/MEMSTECH.2016.7507522.
9. Bogaarts JG, et al. Optimal training dataset composition for SVM based age independent, automated epileptic seizures detection. J Med Bio-logical Eng Comput. 2016;54:1285–1293. doi: 10.1007/s11517-016-1468-y.
10. Guo L. et al. Classification of EEG signals using relative wavelet energy and artificial neural networks. Proceedings of the 1st ACM/SIGEVO Summit on Genetic and Evolutionary Computation. 2009; doi: 10.1145/1543834.1543860.
11. Sally Al-Omar et al. Classification of EEG Signals to Detect Epilepsy Problems. IEEE. 2013; doi: 10.1109/ICABME.2013.6648833.
12. U. Rajendra Acharya et al. Automated diagnosis of epileptic EEG using entropies. Biomed Signal Process Control. 2012;7(4):401–408. doi: 10.1016/j.bspc.2011.07.007.
13. A. Shoeb, H. Edwards, J. Connolly, B. Bourgeois, T. Treves and J. Guttag. Patient-specific seizure onset detection. Conf Proc IEEE Eng Med Biol Soc. 2004; doi: 10.1109/IEMBS.2004.1403183.
14. G. Zheng et al. Seizure prediction model based on method of common spatial patterns and support vector machine. 2012 IEEE International Conference on Information Science and Technology. 2012; doi: 10.1109/ICIST.2012.6221603.

15. P. Deshmukh, R. Ingle, V. Kehri and R. N. Awale. Epileptic seizure detection using discrete wavelet transform based support vector machine. 2017 International Conference on Communication and Signal Processing (ICCSP). 2017; doi: 10.1109/ICCSP.2017.8286736.
16. A. V. R. Holla and P. Aparna. A nearest neighbor based approach for classifying epileptiform EEG using nonlinear DWT features. 2012 International Conference on Signal Processing and Communications, SPCOM 2012. doi: 10.1109/SPCOM.2012.6290014.
17. J. Na, Z. Wang, S. Lv and Z. Xu. An Extended K Nearest Neighbors-Based Classifier for Epilepsy Diagnosis. IEEE Access. 2021; doi: 10.1109/ACCESS.2021.3081767.
18. A. A. E. Shoka, M. M. Dessouky, A. S. El-Sherbeny and A. El-Sayed. Fast Seizure Detection from EEG Using Machine Learning. 2019 7th International Japan-Africa Conference on Electronics, Communications, and Computations. 2019; doi: 10.1109/JAC-ECC48896.2019.9051070.
19. Saminu S, Xu G, Shuai Z, Abd El Kader I, Jabire AH, Ahmed YK, Karaye IA, Ahmad IS. A Recent Investigation on Detection and Classification of Epileptic Seizure Techniques Using EEG Signal. Brain Sciences. 2021;11(5):668.
20. Subasi A, Erçelebi E. Classification of EEG signals using neural network and logistic regression. Comput Methods Programs Biomed. 2005;78(2):87-99.
21. H. Rajaguru and S. K. Prabhakar. Non linear ICA and logistic regression for classification of epilepsy from EEG signals. 2017 International conference of Electronics, Communication and Aerospace Technology. 2017; doi: 10.1109/ICECA.2017.8203602.

22. Alexandros T. Tzallas et al. Epileptic Seizure Detection in EEGs Using Time–Frequency Analysis. IEEE Transactions on Information Technology in Biomedicine. 2009; doi: 10.1109/TITB.2009.2017939.
23. Cohen MX. A better way to define and describe Morlet wavelets for time-frequency analysis. Neuroimage. 2019;199:81-86.
24. Evgeniou Theodoros, Pontil Massimiliano. Support Vector Machines: Theory and Applications. Conference of Machine Learning and Its Applications, Advanced lectures. 2001; doi:10.1007/3-540-44673-7_12.
25. Cuningham, P. & Delany, S.J. k-nearest neighbour classifiers. Mult Classif Syst, 2007.
26. D.W. Hosmer, S. Lemeshow. Applied Logistic Regression. Wi- ley, New York; 1989.
27. S. R. Safavian and D. Landgrebe. A survey of decision tree classifier methodology. IEEE Trans. Syst., Man, Cybern., vol. 21, pp. 660-674, 1991.
28. L. Breiman. Random forests. Machine learning, vol. 45, pp. 5-32, 2001.
29. P. Geurts, D. Ernst and L. Wehenkel. Extremely randomized trees. Mach. Learn., vol. 63, no. 1, pp. 3-42, 2006.
30. Jerome H. Friedman. Greedy function approximation: A gradient boosting machine. The Annals of Statistics. 2001; doi: 10.1214/aos/1013203451.
31. T. Chen and C. Guestrin. XGBoost: A Scalable Tree Boosting System. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 785-794, 2016. https://doi.org/10.1145/2939672.2939785.
32. Y. Freund and R. Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. European Conference on Computational Learning Theory. https://doi.org/10.1007/3-540-59119-2_166.