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An Optimal Statistical Framework for Biomedical Data Analysis in Epileptic Seizures

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ABSTRACT: The tremendous development in all sciences in the late twentieth century, statistics progressed to take advantage of computer technologies in a way that makes science more intertwined with other sciences. It now uses statistics in commercial sciences, medical sciences, engineering, literature, and all other sciences without exception. The traditional methods of detection, based on manual analysis of epileptic seizures in electroencephalogram (EEG) data, have potential drawbacks and limitations, including pertinent issues such as time constraints in feature identification and susceptibility to potential errors, leading to inaccurate seizure detection. Therefore, developing an automated expert system to detect epileptic seizures can support a neurologist's effort to improve both the speed and the accuracy of detecting epileptic seizures.

In this study, we propose a novel technique for detecting epileptic seizures from EEG signals, which employs a second-order deference plots (SODP) with Adaptive Boosting Least Square-Support Vector Machine (AdaBoost-based LS-SVM) framework. The experimental modelling results demonstrate that the proposed AB-LS-SVM method, utilizing the SODP, is capable of achieving a satisfactory result (>98% classification accuracy). The results are compared with state-of-the-art methods tested with identical databases. The findings ascertain that the AB-LS-SVM, coupled with the SODP, can be explored as a promising diagnostic tool for its utility in seizure detection control units, and, therefore, may aid clinicians in medical diagnostics and interventions for epileptic disease and other medical expert systems where EEG data are analysed.

1. INTRODUCTION

The control center for the human nervous system is the human brain [1], [2]. The brain receives all signals from the body's sensory organs and mutates the information to be delivered to the muscles [1], [3]. The human brain comprises millions of nerve cells titled neurons. The cells generate electrical impulses and messages to produce thoughts, feelings, and movement; they control bodily functions[4]. Lately, brain signal analysis has become more sophisticated, with considerable researchers using distinct techniques such as the electroencephalogram (EEG), electrooculography (EOG) signals, and electromyography (EMG). The most fundamental studies were about investigating EEG signals through sleep stages, anaesthesia, alcoholism, and epilepsy.

Based on the recent report of the World Health Organization https://www.who.int/news-room/fact-sheets/detail/epilepsy [5]. Epilepsy is a chronic brain turmoil that impacts more than 50 million people globally, with almost 2.4 million people diagnosed with epilepsy yearly [5]. Therefore, epilepsy influences approximately 1% of the universal population. Epilepsy is distinct by recurrent episodes that cause involuntary movement of a specific part of the body, or the whole body, followed by

a loss of consciousness. Therefore, people who endure epileptic seizures, are at risk of premature death; up to three times higher than people who do not suffer seizures [5].

From the opinion of neurology, the major cause of most conditions of epilepsy is anonymous. However, some statuses could be a consequence of brain prejudice, tumours, and genetic factors. [6]. The majority of medical professionals nominate EEG – an electrophysiological monitoring procedure – to capture the electrical actions of the brain through placing electrodes in particular positions on a patient's scalp[3]. This technique can provide remarkable information to detect human brain activities and distinguish neurological ailments, such as encephalopathies, sleep disorders, epilepsies, brain deaths, and comas.

Biomedical researchers (biologists, physician-scientists, clinical trialists, and others) should have some knowledge of statistical standards to enable them to carry out a criticism of published literature in their area [7]. Statistics is one of the substantial sciences that plays an indispensable role in numerous research and studies[8], [9], [10]. In addition, statistics is deemed one of the ancient sciences, it arose with the primary human need to deal with values and elaborate on the conduct of daily life[10], [11], [12]. Recently, the requirement for utilizing statistical foundations in any project depending on the species of study that is carried out.

This research focuses on evolving an optimal model to analyse the bio-medical data (Epileptic Seizure) employing statistical approaches as a valuation of the improved classification models and project methods. This study reviews the fundamental scientific specifics related to biomedical datasets, beginning with the background of the brain signals.

Based on the knowledge of authors, no prior study has involved the second-order deference plots for diminution of EEG signal dimensionality coupled with Adaptive Boosting Least Squares-Support Vector Machine for the revelation of epileptic seizures in EEG signals.

2. MATERIALS AND METHODS

2.1 Methodology

Diverse devices have been improved to recognize and predict seizures in recordings of patients using motion sensors, heart-rate monitors, and electrodermal activity sensors. The generality of this equipment can reveal seizures activity in real-time; however, predicting seizure activity previously, which can ameliorate the lives of patients with epilepsy, demands a more precise and efficacious intelligence model to distinguish abnormalities in patients' recordings. In this project, the SODP coupled with the AB-LS-SVM is submitted to predict seizures in recordings of patients. Multiple clinical studies have been conducted applying standard EEG epileptic databases registered at the University of Bonn in Germany (Andrzejak et al., 2001). In previous studies, a maximum of seven various groups were formed. Nevertheless, in a recent study, an abundant combination of eight potential classification groups was created, as well as the group features from {A}vs{E}, {B}vs{E}, {C}vs{E}, {D}vs{E}, {AB}vs{E}, {AC}vs{E}, {CD}vs{E}, {ACD}vs{E}. The classes mentioned above were subsequently utilised to assess the newly presented AB-LS-SVM classification process. Consequently, in this research, an unprecedented contribution is built by constructing the AB-LS-SVM classification approach and employing the technique to detect epileptic seizures in patients. Fig. 1 illustrates the suggested AB-LS-SVM classification approach for epileptic EEG signal analysis, where the dimensionality of an EEG signal input is first diminished based on the covariance matrix method. The analysis demands the splitting of each single EEG channel into four distinct segments of lengths 1024, 1024, 1024, and 1025, respectively. To account for the non-stable nature of most EEG signals that are recorded in a real-world scenario, each segment is consequently divided into 32 clusters, and the covariance matrix is used to decrease the dimensionality of each of these clusters. To reveal prospective abnormalities in the prescribed EEG signal, the SODP is examined employing a statistical procedure, thus that five statistical features are extracted. To assort the extracted features into the 'seizure and the seizure-free' groups, as common in EEG signals, a novel classification model, identified as the Adaptive Boosting LS-SVM for time series applying the support vector machine algorithm, was designed and validated to fulfill its capacity to detect epileptic seizure.

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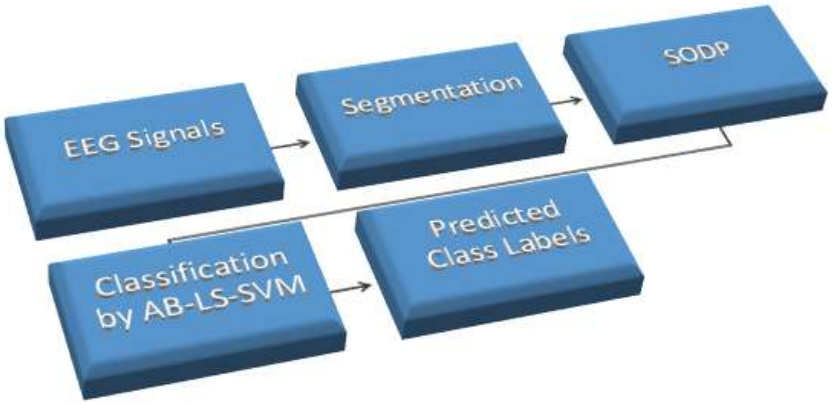


Figure 1 The proposed methodology developed for epileptic EEG signal classification of epileptic disease.

2.2 Datasets

The data employed in this study were compiled at the Epileptic Department of the University of Bonn, located in Germany. The EEG data, whose details have been equipped previously [13], are publicly reachable through a web link http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3 . To institute the specific database, the international 10–20 system was nominated to record EEG signals. All of the electrodes were applied to record Groups A and B, whereas the depthless electrodes were utilised to record Groups C and D, and the electrodes were used to record Group E. Fig. 2 illustrates the pre-surgical evaluation of epileptic patients, depending on the scheme of intracranial electrodes embedded. With all the EEG recordings, a 128-channel megaphone with a medium common reference was applied. Using a 12-bit resolution, the EEG recordings were perceived at 173.61 per second. 0.3–40 Hz a band pass filter was employed. EEG signals for all groups were gained by applying 100 single EEG channels of 23.6 s. Ten subjects were engaged to obtain EEG signals A–E. The datasets were acquired with open eyes in set A and closed eyes in set B, while sets C, D, and E were procured from five epileptic patients. The EEG signals of classes C and D were secured from five participants through seizure-free (Inter-ictal). While set E was adopted from all recording sites showing ictal activity. To pattern and assess the suggested AB-LS-SVM classification model, all of these classification groups (i.e., A, B, C, D, and E) have been employed in this research. Fig. 2 demonstrates the five classes of epileptic EEG signals (Raghu, Sriraam, Hegde, & Kubben, 2019).

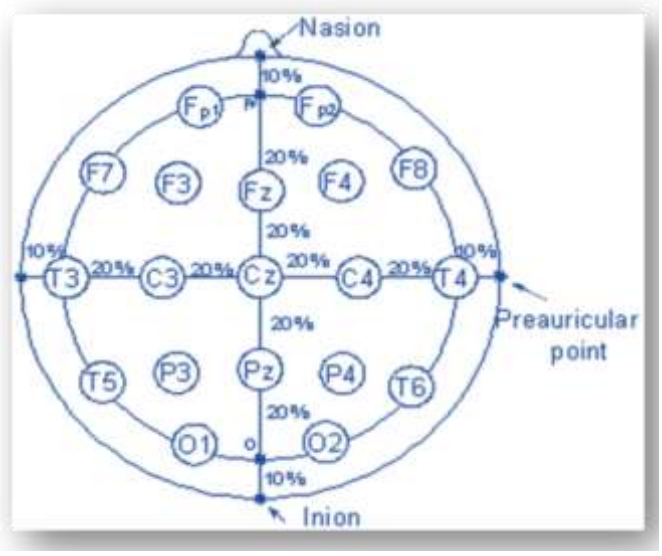


Figure 1 The 10/20 electrodes placement scheme for data obtained from Epileptic Department at University of Bonn located in Germany. www.aha.ru.

2.3 Second-order difference plot SODP

A graphical procedure arising from chaos theory that is applied to study the magnitude of variability in a time series is defined as the second-order difference plot SODP. A dependable automated system in the future could be a fusion of both the time domain and an effective frequency domain process. The procedure demonstrated here can be employed to provide an independent classification instrument, and can also be utilised as a complementary process to verify the frequency domain outcomes. The SODP of a time series *x(n)* of length *N* plots consecutive rates *X(n)* and *Y(n)* against each other, which are defined as[14], [15]:

$$X(n) = x(n+1) - x(n) \quad (1)$$

$$Y(n) = x(n+2) - x(n+1) \quad (2)$$

2.4 A Segmentation

An EEG signal could appear a non-stationary nature, which can also impact the accurate classification adequacy of the suggested classification model[16], [17], [18]. It is substantial to investigate the non-stationary nature of the EEG signal by splitting the EEG signal set into its respective segments in such a process that these signals can be deemed approximately stationary prior to utilising the practical classification model [8], [19], [20], [21]. In this project, each single EEG channel is fractionated into four segments of length 1024, 1024, 1024, and 1025, based on a particular period (≈ 5.9 s) for each segment. Additional importance is given to the non-stationary nature of the EEG signal, where each segment is subdivided into its sub-clusters. The covariance matrix is then used to minimize the cluster's dimensionality. To discover abnormalities in the EEG signal, the SODP is examined employing a statistical procedure, with five statistical features extracted. These five statistical features, which depend on the [mean, median, range, standard deviation, variation], are the fundamental characteristics ordinarily used to exemplify any EEG time series data. Fig. 3 clarifies the EEG signal segments.

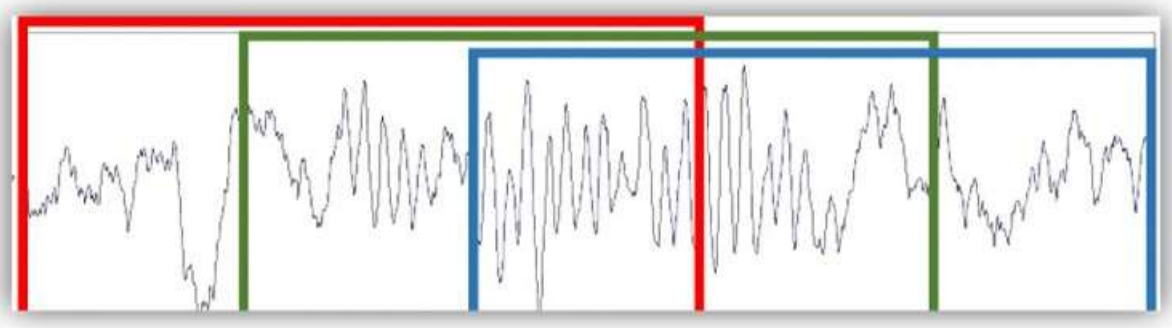


Figure 3 EEG signal segments

2.5 S Performance Evaluation

To assess the performance of the epilepsy classification and detection technique, applying the submitted AB-LS-SVM method, the following metrics are utilised[22], [23]:

2.5.1 Accuracy

The expression of accuracy is applied to evaluate the performance of the AB-LS-SVM process based on the following formula[24]

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \quad (3)$$

2.5.2 Sensitivity

Sensitivity is a statistical measure applied to compute the proportion of real positives[24]:

$$\text{Sensitivity} = TP/TP + FN \quad (4)$$

2.5.3 Specificity

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Specificity refers to the proportion of real negative predictions, defined as follows[24]:

$$\text{Specificity} = TN/(TN + FP) \quad (5)$$

2.5.4 Precision

The formula for precision in machine learning and statistics =TP / (TP + FP) (6)

2.5.5 F1-score

The F1-score is the harmonic mean of precision and recall, calculated with the formula[24]:

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \quad (7)$$

2.6 AdaBoost based LS-SVM technique (AB-LS-SVM classifier)

Lately, the necessity for a procedure qualified to predict seizures hours in advance reliably has boosted, to evolve the existing epileptic warning equipment to be triggered before the incipience of disabling clinical signs. Commonly, the quantity of non-epileptic segments in any actual-world EEG data is louder than that of the epileptic-based segments. To recognize the comparatively smaller magnitude of non-epileptic segments from the epileptic species segments, also to balance the EEG data (as a necessity for a machine learning algorithm), the recently suggested hybrid process, defined as AdaBoost based LS-SVM classifier[19] is presented.

3. RESULTS AND DISCUSSION

3.1 Experiment 1: normal vs epileptic classification (*AB* vs *CDE* and *AB* vs *CD*)

In this trial, diverse binary classification issues were discussed: normal {*A, B*} against non-seizure epileptic {*C, D*}, normal {*A, B*} against non-seizure and seizure epileptic {*C, D, E*}. Additionally, a 10-fold cross-validation process was employed to evaluate the performance of the suggested AB-LSSVM classifier model. Tables 1 and 2 elucidate the classification outcomes. Although some variance in the validation results, an average accuracy of 98% was achieved for AB vs CD. While for the case {A, B} vs {C, D, E} the technique determined an average accuracy of 98%, indicating the variation of the presented classification scheme adopted for epilepsy detection, applying the EEG signal.

Table 1. Classification accuracy for {*AB* vs *C, D, E*}

Fold	F1	F2	F3	F4	F5	F5	F7	F8	F9	F10	average
Accuracy	97%	99%	100%	96%	98%	99%	98%	100%	100%	98%	98%
Sensitivity	98%	96%	98%	97%	100%	97%	99%	98%	99%	100%	98%
Specificity	98%	96%	98%	97%	100%	97%	99%	98%	99%	100%	98%
Precision	98%	96%	98%	97%	100%	97%	99%	98%	99%	100%	98%
F_1	97%	95%	98%	95%	98%	97%	99%	99%	97%	98%	97%

Table 2. Classification accuracy for {*A, B*} vs {*C, D*}

Fold	F1	F2	F3	F4	F5	F5	F7	F8	F9	F10	average

Accuracy	100%	96%	100%	99%	98%	99%	98%	99%	100%	99%	98%
Sensitivity	98%	99%	97%	98%	100%	98%	100%	99%	97%	100%	98%
Specificity	98%	96%	98%	97%	100%	97%	99%	98%	99%	100%	98%
Precision	98%	96%	98%	97%	100%	97%	99%	98%	99%	100%	98%
F_1	97%	95%	98%	95%	98%	97%	99%	99%	97%	98%	97%

3.2 Comparison with different classification algorithms

To validate the solidity of efficiency in classifying EEG signals in epileptic patients, the performance of the objective model (i.e., AB-LS-SVM) was compared with that of well-known classifier system, such as the support vector machine.

Table 3 presents the 10-fold cross-validation results in comparison to various other competing procedures previously used in EEG signal classification problems. Obviously, the AB-LS-SVM classifier system exceeded the other classifiers. Whereas the SVM model (without the AdaBoost algorithm) achieved the second-highest accuracy level among all four-classifier systems[8], [25].

Table 3. Comparison of the objective method (i.e., AB-LS-SVM) with the other classifiers used as a validation tool.

Classifier Type	Fold	F1	F2	F3	F4	F5	F5	F7	F8	F9	F10	average
AB-LS-SVM	**Acc**	98%	98%	98%	99%	98%	99%	99%	99%	100%	99%	98%
	Sen	98%	97%	98%	99%	98%	99%	100%	99%	100%	97%	98%
SVM	**Acc**	97%	96%	97%	96%	96%	96%	96%	94%	97%	93%	95%
	Sen	97%	95%	94%	93%	98%	92%	95%	91%	96%	91%	94.2%

3.3 Discussion

3.3.1 Comparison with literature investigations

To yield a sturdy comparison, this project shows the results from the suggested processes together with various studies. Depending on the comparisons displayed in the study of [26], classified EEG signals into normal, inter-ictal, and ictal subjects based on the experiential mode decomposition technique, where the accuracy acquired was lower than the suggested AB-LS-SVM method.

Further relevance of the AB-LS-SVM procedure can be extracted from other research, such as[27], who applied a nonlinear feature model employing Hurst exponent (HE), Higuchi fractal dimension (HFD), largest Lyapunov exponent (LLE), and sample entropy (SE).

[28] classified group A vs group E by applying weighted permutation entropy merged with an SVM model, in the same study, just the classification accuracy (and not various other performance metrics used in the current study) was announced. Nevertheless, the outcomes obtained using the suggested AB-LS-SVM technique were significantly higher, demonstrating a notable advancement over earlier studies. The empirical wavelet transform (EWT)- based Hilbert marginal spectrum (HMS), derived by [29], classify epileptic seizure EEG signals, achieved a 98% classification accuracy with a 50% training rate.

By analysing the information shown in Table 3, it is obvious that the AB-LS-SVM process can be deemed an optimal procedure for this database (against the recent works).

3.3.2 **Limitation**

To the best of the author's knowledge, no prior studies have been conducted using our proposed model. In spite of this success, it might be possible to explore some limitations of the proposed model:

- An average accuracy of 98% was achieved for databases. The proposed method should be tested with larger clinical databases; we believe the proposed method may or may not yield perfect classification accuracy. The proposed model could be modified by testing other feature selection methods.
- Second, the proposed model could be computationally costly, especially when it is used in real time applications. However, this study will try to apply big data technology and use some parallel processing techniques to reduce time complexity of the prosed model by which the feature numbers would not be a problem

4. CONCLUSION

A functional epileptic detection procedure was presented, along with a robust statistical process for mitigating data dimensionality and extracting features, to determine a credible and versatile classification model for detecting epileptic conditions. To produce a dependable EEG classification model, an SODP was utilised to decrease the dimensionality of the EEG data applied in the suggested model. The AB-LS-SVM technique was designed to classify diverse groups of features in an effective epileptic detection process; the outcomes were compared with state-of-the-art procedures in identical databases. The results elucidated that the AB-LS-SVM classification process (coupled with SODP) was capable of achieving highly satisfactory outcomes, yielding more than 98% classification accuracy (on average) for various classification cases. Furthermore, the current findings reveal that the presented AB-LS-SVM model has a high possibility of being used for real-time detection of epileptic seizures, as it entails a minimal time complexity factor compared to other studies in the literature. Whereas the existing study has obviously led to a progressive technique for the detection of epilepsy. A separate study in the future could also employ the presented procedure to detect various other issues, such as signs of sleep spindles and K-complexes prevalent in EEG signals. The suggested AB-LS-SVM technique can be explored further to evolve a seizure warning system within a medical diagnostic platform that can eventually support practising neurologists to preferentially diagnose and treat neurological disorders based on EEG signals.

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AUTHOR CONTRIBUTIONS

Hanan Al-hadeethi: Conceptualization, Investigation, Data Curation, Formal Analysis, Methodology, Formal Analysis.

Ikhlas Al-hadeethi: Methodology, Formal Analysis, Writing—Review & Editing.

Auhood Al-Hossenat: Formal Analysis, Writing—Review & Editing.

Zuhair Ibrahim Alyasi: Supervision, Writing—Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are publicly available through a web link http://epileptologiebonn.de/cms/front_content.php?idcat=193&lang=3

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