Gerontology & Geriatrics: Research

Open Access

Austin Publishing Group

Review Article

Advancing Epilepsy Diagnosis: Insights from EEG Signal Analysis with SVM and CNN

Liqiang Zhang[1#]; Ting Wang[1*#]; Yu Xia[1]; Chenglong Cai[1]; Conghao Lin[1]; Weiran Zhu[2]; Yixin Zhang[1]; Zhangqi Feng[3]; Nongyue He[1]

[1]School of Biological Science and Medical Engineering, Southeast University, Nanjing, 210096, China

[2]Nanjing University of Science and Technology, Nanjing, 210094, China

[3]SceneRay Co., Ltd., Suzhou, 215123, China

***Corresponding author:** Ting Wang, School of Biological Science and Medical Engineering, Southeast University, Nanjing, 210096, China.
Email: tingwang@seu.edu.cn

[#]These authors contributed equally to this work.

Received: December 16, 2024; **Accepted:** January 03, 2025; **Published:** January 09, 2025

Abstract

Epilepsy is a common neurological disorder in elderly populations, often linked to age-related conditions such as stroke and neurodegeneration. Traditional EEG signal analysis for epilepsy diagnosis is time-consuming, subjective, and unsuitable for clinical use, emphasizing the necessity for automated approaches. This study evaluates the performance of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) in classifying EEG signals for epileptic seizure detection, utilizing the Bonn University EEG dataset. Time- and frequency-domain features were extracted, and 10-fold cross-validation was employed to validate the results. The findings reveal that SVM achieved 100% accuracy in distinguishing simple EEG states, such as healthy versus seizure conditions. Meanwhile, CNN outperformed SVM in processing more complex signals, achieving an average accuracy of over 98%. The results highlight the potential of integrating traditional machine learning with deep learning methods to enhance diagnostic accuracy and efficiency. These findings lay a strong foundation for developing advanced EEG-based diagnostic tools tailored to elderly epilepsy patients, facilitating more timely and effective clinical interventions.

Keyword: Seizures; Electroencephalogram; Machine learning; Pattern recognition

Introduction

Epilepsy is one of the long-term, non-infectious neurological conditions that characterized by periodic seizures and temporary dysfunction caused by abnormal discharges of neurons in the brain. Seizures will arise movement issues, issues controlling urine or bowel movements, unconsciousness, or other cognitive impairment. Until now epilepsy can be examined or predicted using Electroencephalography (EEG) data [1,2].

Seizures are often investigated using a 20-minute pre-seizure recording. However, in the event of uncommon seizure identification, long-term EEG recordings are required, which takes time. The visual analysis of EEG to identify seizures is not the same as human expertise. For this reason, computerized epileptic seizure diagnosis is crucial in the clinical context. The process of extracting hidden patterns from EEG signals in order to identify seizures is known as pattern recognition [5,8]. Numerous feature extraction techniques, during EEG signal analysis, researchers typically perform feature selection before applying classification methods. EEG signals encompass various features, including time-domain, frequency-domain, peak, and time-frequency domain characteristics, which carry extensive information. Determining the most suitable features for different classification algorithms, such as support vector machines, Bayesian neural networks, decision trees, and random forests, represents a significant and challenging research focus. EEG signals carry extensive information about the human body, particularly in patients with mental illnesses. These signals can, to some extent, indicate the timing of seizures. In recent years, EEG analysis has been widely applied in disease detection, including conditions such as obsessive-compulsive disorder, Alzheimer's disease, and epilepsy, with the latter being the most commonly detected and predicted disorder, and scholars have developed many automatic detection algorithms for EEG signal analysis, which are used to identify different epileptic states by converting the EEG information into different outputs, Epileptic seizures can be categorized into three phases: pre-seizure, inter-seizure, and seizure. The EEG signals during these phases exhibit significant differences, which can be effectively identified using distinct EEG signal characteristics. The main purpose of EEG signal-based detection algorithms is to make the detection process more accurate and faster, different machine learning algorithms have been applied in recent years, where semi-supervised learning and detection algorithms are combined to classify the epileptic status using EEG signals. Deep learning algorithms are also widely used for automatic classification of epilepsy, using the self-learning properties of deep learning algorithms to automatically classify epileptic and normal patients by features, deep learning has also achieved good results in this area, these algorithms employ time-frequency maps and integrate them with deep learning for algorithmic analysis, demonstrating high accuracy and precision. This suggests that combining imaging techniques with deep learning could be a promising approach to enhance the accuracy of EEG signal-based epilepsy detection algorithms in the future. Subasi (2007) proposed a classification scheme for epileptic EEG signals using Discrete

Citation: Zhang L, Wang T, Xia Y, Cai C, Lin C, et al. Advancing Epilepsy Diagnosis: Insights from EEG Signal Analysis with SVM and CNN. Gerontol Geriatr Res. 2025; 11(1): 1108.

Wavelet Transform DWT, which first divides the EEG signals into several different frequency subbands, and by the different eigenvalues that can be obtained in the coefficients of the DWT, the appropriate eigenvalues are selected for classification, and this method achieves 94.5% accuracy, 94% specificity and 95% sensitivity.

Recently, some scholars have started to apply Support Vector Machine (SVM) algorithm to EEG signals, before that, SVM has been applied to image and video recognition in a large number of fields, and after the EEG signals processed by SVM have obtained excellent results, SVM is more and more used for epileptic seizure prediction, because SVM has been widely used in other fields researchers are very familiar with the algorithm, so applying SVM to new fields is reasonable and has a certain degree of sensitivity. Since SVM have been widely used in other fields and researchers are familiar with the algorithms, applying SVM to new fields is reasonable and has some advantages. The SVM is a widely used machine learning algorithm for epilepsy diagnosis and prediction. It efficiently processes EEG signal data to distinguish between seizure and non-seizure states. By extracting time-domain, frequency-domain, and time-frequency-domain features from EEG signals, SVM achieves high accuracy in various classification tasks. EEG signals, characterized by complex high-dimensional features, are well-suited for SVM processing. By selecting appropriate kernel functions, SVM can handle both linear and nonlinear patterns in EEG signals effectively. Studies indicate that SVM-based EEG signal classification algorithms typically achieve accuracies exceeding 90%, particularly in detecting epileptic seizure states. However, the large volume of EEG data presents challenges, including the high cost of data labeling and the difficulty of selecting the most discriminative features for analysis.

Nicolaou (2012) used aligned entropy features together with SVM as a classifier to achieve 99.77% accuracy for ABCD-E in the Bonn dataset, and 93.55% accuracy for classes A-E. Gandhi, Panigrahi, and Anand (2010) also used SVM as a classifier. The feature extraction is done by first using wavelet transform to obtain features such as entropy, standard deviation etc. from the EEG signals and ABCD-E can also achieve 95.44% accuracy. The vast majority of the work on EEG signals for disease recognition can be done using Support Vector Machines (SVM) and Deep Learning, which are common classifiers used to differentiate between EEG signals of epileptic patients and normal people, where Support Vector Machines in support vector machine achieves a good accuracy for all A-E classes, but it is significantly less accurate than deep learning when dealing with other diseases (e.g., B-E, B-C, C-E).

Classification and quantity of features will affect accurate classification of patterns. To increase the classification accuracy of seizure detection, we combine several feature extraction and classification strategies and apply the pattern recognition methods described. It was suggested that the classifier has the greatest impact on the recognition results, followed by the selection of feature values, and the appropriate feature values paired with the classifier can greatly improve the recognition accuracy. The aim of this study is to evaluate the pattern recognition accuracy of deep learning and classical machine learning on the same set of wire data and to find out the best pattern recognition technique for accurate diagnosis of epileptic seizures. In which in the recognition distinction between groups A-E, both machine learning patterns achieved the best results reached 100% accuracy, while in the other groups of comparative recognition, deep learning is greater than the traditional machine learning in terms of recognition accuracy.

Related Work

The interaction ideas and techniques that are closely related to integrated embodiment are presented in this section. These include shared agency, technological embodiment, and human-computer integration.

Dataset Description

The training dataset used in this study is a publicly available dataset from the University of Bonn, frequently referenced in numerous published papers for epilepsy detection and prediction studies. Data acquisition was conducted by Andrzejak et al. in 2001 using the standard 10-20 system of brain electrodes. After acquisition, the dataset was categorized into four groups: EEG signals from individuals without epilepsy with eyes open (A), individuals without epilepsy with eyes closed (B), individuals with epilepsy during interictal states (C), and individuals with epilepsy during seizure states (E). The data were recorded at a sampling frequency of 173.61 Hz, with each segment having a duration of 23.6 seconds.

We aim to evaluate the performance of traditional machine learning and deep learning methods in seizure detection for epilepsy, focusing on both time efficiency and accuracy. However, the current dataset is insufficient for training deep learning models effectively. To address this, we propose augmenting the dataset to achieve a size suitable for deep learning training.

We used a sliding window model for data augmentation, in (T. Zhang et al, 2017), the authors used a sliding window with a window size of 512 and a step size of 480, while we use a sliding window with a window size of 512 and a step size of 64 (87.5% overlap).

The signals are first divided into a training dataset and a test dataset, which account for 90% and 10% of the total dataset, respectively, and then expanded using a sliding window, so that each signal in the training set with a length of 4097 is partitioned into 57 new signals, each of which can be considered independent. In this way new signals are created for each category, totaling 5130 signal instances, which are used to train the CNN model afterwards.

EEG Data Segmentation

The EEG dataset we used is from the open wire EEG dataset from the University of Bonn, Germany, which consists of five sets of EEGs in different states A-E, the data's were recorded for 23.6 seconds and 100 different channels were recorded, A-E are the EEG data in different states, where A,B were recorded in five non-epileptic

Table 1: Description of the Bonn data set.

	Healthy people		Epileptic		
	Z	O	N	F	S
Status	Eyes open	Eyes close	interictal period	interictal period	seizure
Data type	Cephalic layer	Cephalic layer	intracranial	intracranial	intracranial
Electrode position	Scalp	Scalp	Hippocampal structures	focal area	focal area

Table 2: Accuracy of traditional machine learning methods for epilepsy recognition for different combinations of datasets.

Case	Accuracy	Sensitivity	Specificity	Precision	Recall	F-measure
A-C	87.500000	100.000000	83.680000	84.000000	100.000000	0.893600
A-D	90.000000	100.000000	72.450000	86.666667	100.000000	0.928580
A-E	100.000000	100.000000	100.000000	100.000000	100.000000	1.000000
B-C	95.000000	95.450000	100.000000	100.000000	95.450000	0.954500
B-D	92.500000	100.000000	100.000000	100.000000	100.000000	0.938700
B-E	100.000000	100.000000	100.000000	100.000000	100.000000	1.000000

individuals in the eyes open and closed states, and the dataset C was recorded in epileptic patients during the pre-seizure period, the activity of the hippocampus, data set D is the epileptic data of the focal area during the pre-seizure period, and data set D is the epileptic focal area during the seizure period, all the recorded data went through a 128-channel amplifier with a sampling rate of 173.61 Hz, and the final data obtained were 4097 samples, and by segmenting the data to divide the 4097 samples into sizes of 512 data segments, finally we can get eight groups of data segments, we extract the statistical eigenvalues of the data by using discrete wavelet transform to obtain the statistical features of each data segment, and use the technique of pattern recognition for epileptic EEG segmentation.

Design Exemplar

In that part, we use both classic machine learning approaches and deep learning-based neural networks to detect the identical collection of epileptic EEG data. Subsection 3.1 describes a series of feature extraction using raw EEG signals in the traditional machine learning approach; DWT decomposition is used to obtain the feature values, and then SVM is used for classification; and subsection 3.2 presents the structural model of cnn and how to construct the classifier.

Traditional Classification of Machine Learning Methods

We utilize DWT to extract features because, from the perspective of the accuracy of the retrieved features, it is a better and more efficient procedure than typical machine learning approaches, which require us to have a process of processing the data to get the feature values. DWT is a multiscale signal analysis approach whose fundamental idea is to employ wavelet basis functions to divide the signal into several sub-bands of different frequencies, after which the signal may be analyzed and processed. It is a multilayer decomposition, in contrast to regular orthogonal transformation. In the figure2, the signal is decomposed across three layers. In the first layer, it is split into a high-frequency component (D1) and a low-frequency component (A1), each with a length equal to half of the total signal length. In the second layer, the low-frequency component (A1) is further decomposed into a high-frequency part (D2) and a low-frequency part (A2), each with a length equal to half of A1. This process continues iteratively in subsequent layers. However, the total length of the decomposition results remains N. The signal is broken down into high-frequency part D3 and low-frequency part A3, each having length N/8, using continuous decomposition. remains N.

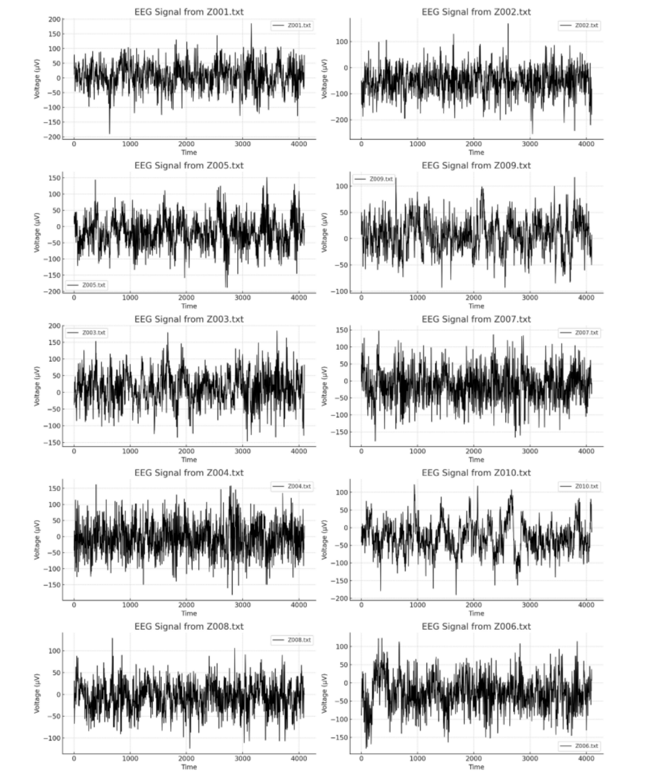

Figure 1: EEG data fragment from the University of Bonn.

The approximate signal can be broken down into numerous low-resolution components by repeatedly undergoing a continuous decomposition procedure. Although the decomposition process can theoretically go on forever, in reality, the number of decomposition layers that is right for a given signal is typically determined by the signal's properties or other relevant factors.

In this study, the signal 'x' was decomposed into four levels of detail coefficients (D1, D2, D3, and D4) and approximation coefficients (A4) using the equation x=D1+D2+D3+D4+A4x = D1 + D2 + D3 + D4 + A4x=D1+D2+D3+D4+A4. Since epileptic seizure features are primarily concentrated in wavelets of levels 3 and 4, we focused on extracting and analyzing the wavelet coefficients from these specific levels.

a. Statistical Features: Statistical attributes, including mean, median, mode, standard deviation, minimum, maximum, skewness, and kurtosis, were extracted from the segmented EEG signals. Among these, mean, skewness, and kurtosis were highlighted due to their relevance to the analysis.

b. Non-linear features:

Hjorth parameters are a set of statistics used to characterize the time domain of a signal, including Activity, Mobility and Complexity. They can be used to analyses EEG signals, Electrocardiogram (ECG) signals, etc. Hurst components provide a way to measure fractals.

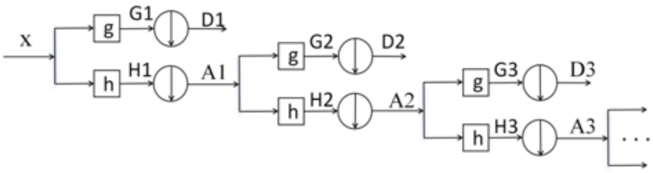

Figure 2: Process of DWT signal decomposition method.

Datasets		MAV+SD+AVP	MAV+SD	MAV+SAVP	AVP+SD	MAV	SD	AVP
A-E	Accuracy(%)	99.87	100	99.87	99.87	99.87	100	99.87
	Sensitivity(%)	100	100	100	100	100	100	100
	Specificity(%)	99.75	100	99.75	99.75	99.75	100	99.75
B-E	Accuracy(%)	97.87	97.87	97.87	98.25	98.25	97.62	97.87
	Sensitivity(%)	100	100	100	99.48	99.48	100	100
	Specificity(%)	95.92	95.92	95.92	97.07	97.07	95.46	95.92
C-E	Accuracy(%)	95.5	97.25	95.5	95.25	95.25	97.25	95.5
	Sensitivity(%)	96.42	97.25	96.42	95.25	95.25	97.48	96.42
	Specificity(%)	94.6	97.25	94.6	95.25	95.25	97.01	94.6
D-E	Accuracy(%)	93.87	94.5	93.87	95.62	95.62	94.75	93.87
	Sensitivity(%)	93.54	93.41	93.54	94.4	94.4	94.3	93.54
	Specificity(%)	94.2	95.6	94.2	96.91	96.91	95.2	94.2

Figure 3: Classification results of CNN classifiers on the dataset.

After obtaining the desired feature values, we use SVM to classify the extracted features which are used as inputs to SVM. After obtaining the desired feature values, we use SVM to classify the extracted features and use them as input to SVM. Here we obtain similar conclusions to those reached by Nicolaou and Georgiou (2012) using SVM as a classifier, where more than 99% accuracy can be achieved in the case of A-E in the University of Bonn dataset. The maximum accuracy for other diseases such as B-E, C-E, D-E, ABCD-E is around 95%.

Classification of Deep Learning Methods

Deep learning models automatically learn the structure of the EEG signals from the dataset and classify them autonomously, contrary to the traditional machine learning approach of SVM mentioned above, which requires the extraction of feature values, then the selection of a subset of the extracted features, and finally the use of a classifier to perform the classification. The convolutional layer is the most critical component of the CNN model, responsible for extracting local features from the input data. It performs convolutional operations by computing the dot product between the convolutional kernel and the input data as the kernel slides across the data, resulting in values for the feature map. This localized computation effectively captures spatial patterns in the input data, and the use of multiple convolution kernels allows for the extraction of diverse features. In this way, the CNN learns the hierarchy of discriminative information by analyzing the signal.

The deep learning-based EEG signal detection system for epilepsy comprises three components, as illustrated in the figure. The first component involves segmenting the signal into sub-signals using a fixed-size sliding window technique to increase the data volume. The second part of the article focuses on signal transformation. The signal is prepared for model training by converting it from the time domain to the frequency domain. For segmented signals, the Short-Time Fourier Transform (STFT) is used to perform this conversion before the data is input into the model. The third part involves constructing the CNN model. The CNN architecture includes an input layer, convolutional layer, activation function layer, pooling layer, fully connected layer, and output layer. Using the constructed CNN model, we train the epileptic EEG signal data. CNN offer a significant advantage over traditional classifiers when analyzing high-dimensional data. In the convolutional layer, CNN utilize a parameter-sharing scheme to control and reduce the number of parameters.

As illustrated in Figure 2. X, the input layer receives raw data, such as images and EEG signals, and converts them into multidimensional arrays suitable for network processing. The convolutional layer then extracts local features from the data using convolutional kernels. Specifically, six feature maps are derived from the input layer through 5x5 kernels that capture spatial structure information. Next, the activation function layer, typically employing ReLU, introduces nonlinearity to enable the network to learn complex patterns. Following this, the pooling layer down samples the feature maps using max pooling or average pooling, reducing dimensionality and computational complexity while retaining critical features and improving translational invariance. Finally, the fully connected layer consolidates the extracted features for classification or regression, and the output layer, often using Softmax or Sigmoid functions, provides predictions. For classification tasks, this includes outputs like seizure state detection or non-seizure identification.

Result

After selecting different data models, we then perform different combinations of classifications from which we can see more clearly to distinguish epileptic EEG signals from non-epileptic EEG signals. These species combinations have been widely used in other studies such as (Sharmila et al, 2016). All experiments utilized 10-fold cross-validation, a model evaluation method where the dataset is randomly partitioned into 10 equal-sized subsets (folds). In each iteration, one subset is used as the validation set, while the remaining 9 subsets serve as the training set. Model training and validation are performed independently for each fold. After 10 iterations, the average of all validation results is calculated as the final evaluation metric for the model. This approach effectively minimizes assessment bias caused by a single dataset split, maximizes data utilization, and is particularly

Data sets	C-NN	SVM
	Accuracy（%）	Accuracy（%）
A-E	100	100
B-E	98.5	99.3
C-E	97.2	99.65
D-E	95.65	94.3
AB-E	98.73	99.18
AC-E	99.3	99.5
AD-E	96.6	97.1

Figure 4: Comparison of classification results between SVM and CNN classifiers.

suitable for scenarios with limited sample sizes. Additionally, the stratified 10-fold cross-validation method ensures balanced category distribution, making it ideal for handling class imbalance issues in classification tasks.

In this paper, three commonly used performance metrics are used for experimental analysis, i.e., accuracy, sensitivity and specificity. They are defined as follows:

Accuracy = (IN+TP)/(TP+IN+FP+FN)

Sensitivity = TP/(TP+FN)

Specificity = TN/(TN+ FP)

In the formula presented above True Positive (TP): A correct prediction where the model identifies a seizure, and a seizure actually occurs. False Negative (FN): An incorrect prediction where the model fails to detect a seizure, even though a seizure actually occurs. False Positive (FP): An incorrect prediction where the model detects a seizure, but no seizure actually occurs. For real-time monitoring in medical devices, minimizing FN is critical to avoid underreporting and ensure patient safety. Conversely, for mass screening purposes, reducing FP is essential to minimize the disruptions caused by false alarms.

Results from Traditional Machine Learning

The accuracy for epilepsy detection using SVM classifier ranges from 87.5% to 100% The accuracy of this system for the combination of A-C, A-D and A-E datasets is 87.5%, 90.0% and 100% respectively. In addition, SVM has the highest accuracy for A-E, B-E datasets and the results are shown in Fig3. The program was written in the MATLAB package R2023b environment running on a machine with 1.6 GHz HP CPU processor and 16GB RAM.

We have found that for all combinations of statistical features, the accuracy obtained using the SVM classifier is 100% for both normal eyes open and seizure EEG datasets. Moreover, it has been observed that the accuracy specificity and sensitivity are 100% accurate in SVM classifier for both datasets A-E and B-E.

Results from Deep Learning

Fig 4 shows the classification results of the CNN classifier on the datasets, from which it is clear that the CNN has improved all the classification results achieved for the feature values obtained from the DWT, with an average accuracy of 97.45%, and for the datasets A-E, both SVM and CNN have the best results.

Conclusion

Examination and judgement of EEG by experts is a very time consuming and expensive way, for these problems EEG signal-based epilepsy detection algorithms are very important, in medical diagnostic systems, pattern recognition methods are required to detect the medical data in a shorter period of time and to ensure a high level of accuracy.

The novelty of this paper is to compare for the first time the work done by deep learning and traditional machine learning for EEG based detection, comparing the accuracy of both pattern recognition approaches using the same dataset. We extracted features from the dataset by using low pass filter, functions such as stat feat, wave feat, etc., and in stat feat we extracted the mean, maximum and minimum values as features. The results show that pattern recognition of normal eyes open and seizure EEG dataset using traditional machine learning SVM classifier can achieve more than 95% accuracy. Recognition of the same epileptic EEG data using deep learning was achieved with more than 98% accuracy, obtaining better accuracy and shorter time. Overall, experiments using deep learning CNN obtained higher accuracy than experiments using DWT wavelet transform function and SVM. In recent years, more and more new methods are being applied to automatic epilepsy detection, so faster and more accurate epilepsy detection algorithms will help doctors in clinical diagnosis, and future epilepsy detection models will be developed in the direction of more simplicity, efficiency and accuracy.

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