

COMPARATIVE ANALYSIS OF ML AND DL CLASSIFIERS FOR EEG-BASED EPILEPTIC SEIZURE DETECTION USING PERFORMANCE METRICS

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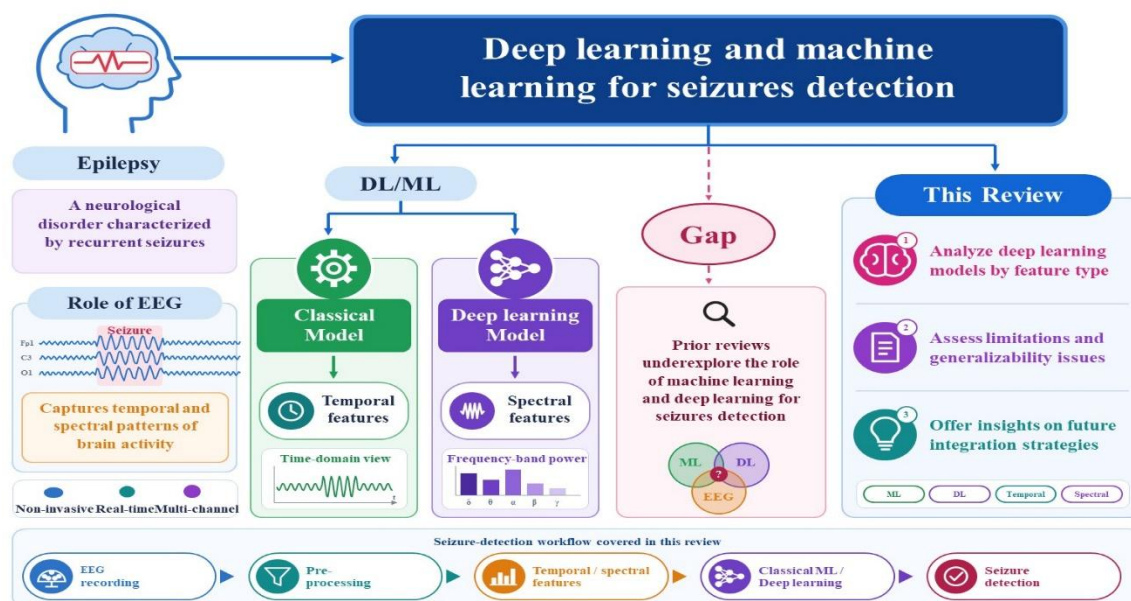
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ABSTRACT

Neurological disorder known as epilepsy is typified by aberrant brain neuronal activity that results in frequent, unprovoked seizures. It represents about 1% of all diseases worldwide and affects more than 70 million people. The mortality rate for people with epilepsy is almost three times that of the total population. However, research indicates that with the right diagnosis and care, up to 70% of epilepsy cases can be effectively managed and possibly resolved. Using a variety of machine learning (ML) and deep learning (DL) classifiers, the goal of this review is to suggest appropriate seizure detection methods that are customized for specific medical datasets. The feature extraction methods employed, such as Multi-Fractal Detrended Fluctuation Analysis (MFDA), Variational Mode Decomposition (VMD), and Discrete Wavelet Transform (DWT), have a major impact on these classifiers' performance. Accurate seizure detection depends on choosing the best feature and classifier combination. Machine learning techniques that have achieved 100% accuracy include Random Forest with L1-PRR and LS-SVM with Tunable Q-Factor Wavelet Transform (TQWT) with fractal dimension. An Artificial Neural Network (ANN) that used Local Neighborhood Difference Pattern (LNDP) and 1-D Local Gradient Pattern (LGP) for feature extraction demonstrated 98.96% accuracy, 98.56% sensitivity, and 99.38% specificity, demonstrating the immense promise of deep learning models. Additionally, 10-fold cross-validation was used to achieve 100% accuracy for ED-LSTM. Convolutional Neural Networks (CNN) and K-Nearest Neighbours (KNN) are two more classifiers that have demonstrated impressive performance. In order to improve the identification of epileptic seizures, this study highlights the significance of choosing the best EEG-based ML and DL classifiers in addition to suitable feature extraction techniques.

Keywords: Epileptic Seizure, EEG, Deep Learning, LS-SVM, ANN, L1PRR, MFDFA

Graphical Abstract



INTRODUCTION

Evidence of epilepsy, one of the earliest neurological conditions, may be found in Babylonian medical manuscripts that date back 3,000 years. [1]. In terms of prevalence and symptoms, disorder is fairly uniformly distributed worldwide and affects both humans and animals [2]. Recurrent seizures combined with typical symptoms such as behavioral abnormalities, sensory abnormalities, and transient unconsciousness are indicative of

epilepsy [3]. The hazards associated with these epileptic seizures are high and can include anything from burns and physical harm to death, particularly if the seizures persist for an extended period [4, 5]. Although the specific cause is still unknown, research has found out that aberrant electrical discharges in the brain which could be caused by things such as hypoglycemia and oxygen deprivation after birth is a significant contributor to seizure production. Figure 1 presented the current study [1,2,6].

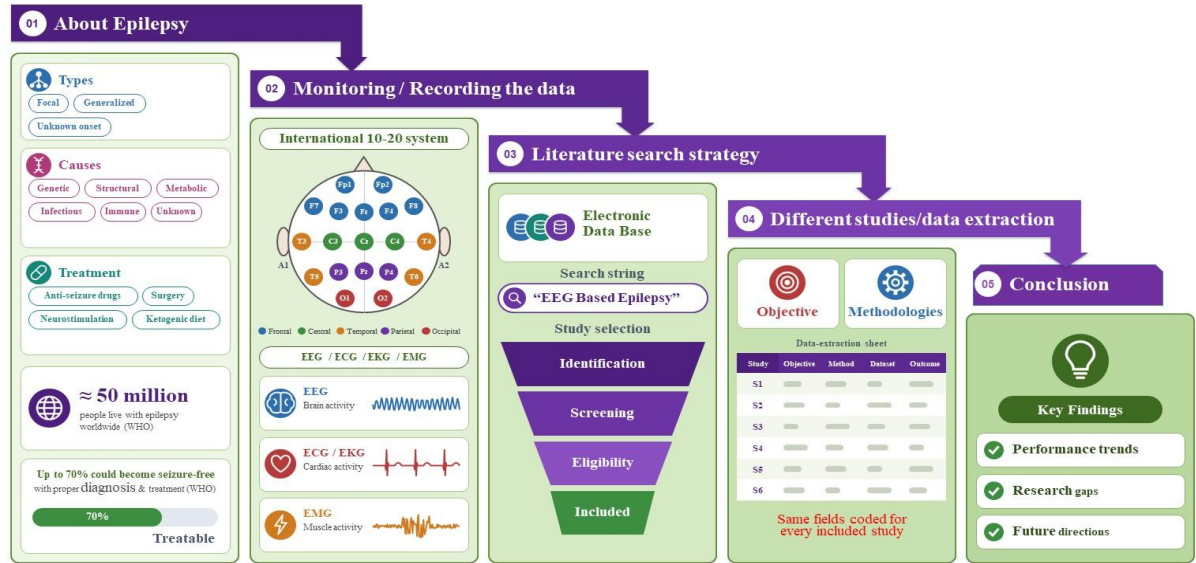


Figure 1. Structure of the present study [4]

Although pharmacotherapy is the primary form of treatment, around 30% of patients suffer from drug-resistant epilepsy that requires other methods of control [7]. The surgical treatment of epilepsy is also quite tricky, with the success rate being about 75% for lesioned temporal lobes and 50% for non-lesional temporal lobes, while frontal lobe epilepsy surgery has a smaller efficacy rate of 35-60%. Such outcomes are explained by the low accuracy of current methods of video-EEG monitoring and PET scans that are unable to identify the focus of seizures in some patients [8,9], thus making it harder to remove. In this essay, I will discuss different aspects of epilepsy, such as history, classification, diagnostics, and treatment. Furthermore, I will also analyze the modern trends in the identification and control of seizures. Three types of epileptic seizures occur in patients: focal (partial) seizures that affect limited areas of the brain, generalized seizures that impact the whole brain, and rare adductor seizures [10,11]. The symptoms of these three types vary greatly, which is visible in Figure 2 [11]. Due to the complexity of the EEG and ECG signal patterns, their interpretation remains difficult in both humans and machines. The analysis of such data requires advanced mathematics, which is why manual patient-specific feature extraction and classification are not enough, and new machine learning methods should be used. Figure 2. shows the classification of epileptic seizures [12].

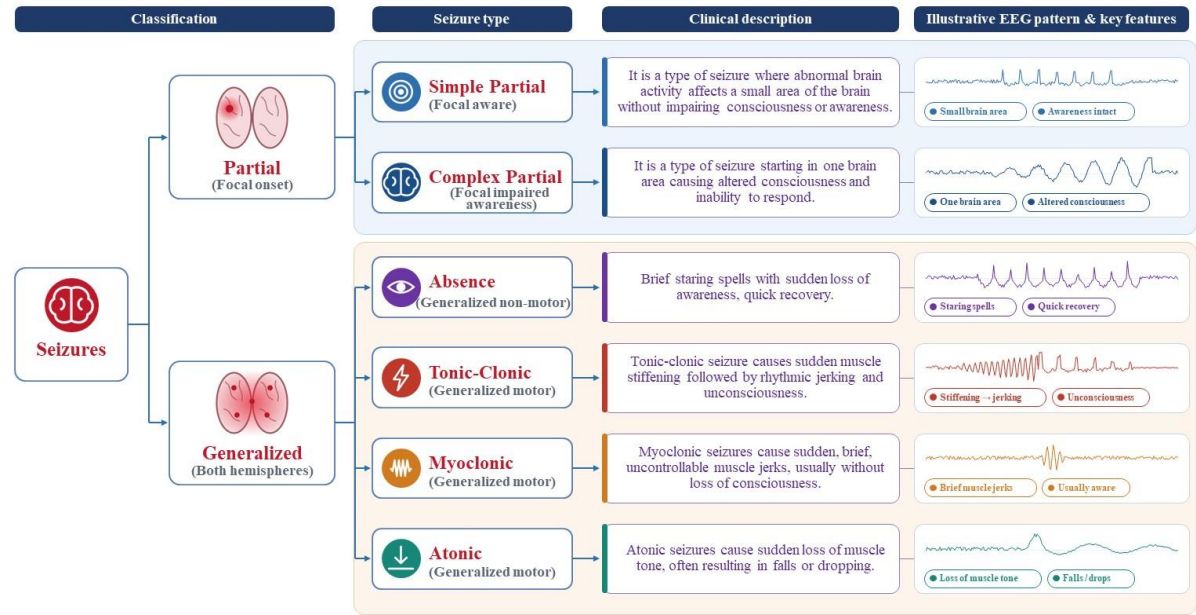


Figure 2: Type of Seizures [11]

Although ECG offers technical advantages over traditional EEG such as its superior spatial outcome, signal to noise ratio, both techniques require advanced computational analysis [13]. To date, the field faces dual challenge

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of the selection of optimal machine learning classifiers and identification of the most discriminatory signal characteristics from the huge amounts of noisy data sets. An effective seizure detection system should account for multiple clinical parameters that include seizure triggers, temporal change patterns, behavioral signs and recovery characteristics. This multivariate approach is needed for development of personalized treatment strategies and improvement of treatment outcomes. The modern management of epilepsy relies more and more on technological integration, where recording devices (EEG/ECG) capture the neural activity and machine learning algorithms extract the clinically relevant patterns. Paradigm shift from traditional signal processing to artificial intelligence analysis is seen in the epileptology field. The automating seizure detection process has been successful with deep learning models, particularly convolution neural networks (CNNs) and long short-term memory (LSTM) networks. [13]. Nevertheless, challenges remain concerning the interpretation of model results, generalizability across diverse population and limitation in real-time applications. Future directions include the development of explainable artificial intelligence systems that leverage clinical expertise and computational power to integrate multi-modal data from wearable devices for continuous monitoring. As the field advances, it is anticipated that synergistic approach between clinical epileptology and machine learning will revolutionize both diagnosis and treatment, eventually raising the standard of living of the people suffering from epilepsy. In this comprehensive review, we take up the historical perspectives, clinical classifications, technological advances and prospects to present holistic understanding of epilepsy management in the era of computational neuroscience. The epileptic seizures detection, classification, management and their limitations are presented in table 1.

Table 1. Epilepsy Detection, Classification, and Management

Ref.	Key Contribution	Method/Approach	Limitations
[1]	Historical review of epilepsy concepts from ancient to modern times.	Qualitative analysis of historical texts.	Lacks modern clinical or technical insights.
[2]	WHO report on neurological disorders, including epilepsy burden.	Public health data synthesis.	Limited technical details on detection methods.
[3]	Overview of epilepsies and seizures by NINDS.	Clinical and epidemiological review.	No focus on automated detection techniques.
[4]	Highlights underdiagnosis of nonconvulsive status epilepticus.	Clinical case review.	No technical solutions proposed.
[5]	Discusses epilepsy and learning disabilities.	Literature review.	Outdated (1998), lacks modern ML/DL insights.
[6]	Comprehensive textbook on epilepsy.	Theoretical and clinical overview.	Not focused on computational methods.
[7]	WHO 2019 epilepsy fact sheet (global prevalence).	Epidemiological report.	No technical contributions.
[8]	Review of seizure prediction challenges.	Literature survey.	Highlights lack of reliable real-world prediction models.
[9]	Reviews failures in temporal lobe epilepsy surgery.	Clinical case analysis.	Does not propose computational solutions.
[10]	ILAE 2017 seizure classification update.	Clinical guidelines.	No technical implementation.
[11]	Describes seizure types (Ontario Epilepsy Foundation).	Educational resource.	Lacks scientific rigor.
[12]	Explains ILAE 2017 classification changes.	Review article.	No novel detection methods.
[13]	Compares fMRI, ECoG, EEG correlations.	Multi-modal signal analysis.	Small sample size, no seizure-specific focus.
[14]	ML review for seizure detection (up to 2020).	Survey of classifiers (SVM, RF, etc.).	Excludes deep learning advancements post-2020.
[15]	Medical causes of seizures (e.g., metabolic, trauma).	Clinical review.	No technical detection methods.
[16]	Early ANN-based seizure detection using time-frequency features.	STFT + ANN.	Outdated (2007), low accuracy by modern standards.
[17]	Local pattern transforms for EEG classification.	Texture-based features + SVM.	Handcrafted features may not generalize.
[18]	Sample entropy + extreme learning machine.	Entropy-based features.	Limited to offline analysis.
[19]	VMD + AR features + Random Forest.	Variational mode decomposition.	Computationally heavy.

[20]	DT-CWT + nonlinear features.	Dual-tree wavelet transform.	Requires manual feature engineering.
[21]	Tunable-Q wavelet + Kraskov entropy.	Wavelet-entropy fusion.	Sensitive to noise.
[22]	Tunable-Q wavelet + fractal dimension.	Fractal analysis.	May overfit small datasets.
[23]	Ensemble classifiers with weighted voting.	SVM, k-NN, NB fusion.	Complex ensemble, no deep learning.
[24]	Multifractal EEG subband analysis.	Multifractal detrended fluctuation.	Theoretically complex for clinical use.
[25]	Robust seizure classification methodology.	Feature selection + SVM.	Validated only on small datasets.
[26]	L1-penalized robust regression for EEG.	Sparse signal processing.	May miss non-linear patterns.
[27]	Deep learning for epilepsy detection.	CNN on raw EEG.	Requires large labeled datasets.
[28]	Cost-sensitive active learning for seizure detection.	Deep active learning.	High computational cost.
[29]	Wavelet-based deep learning.	CNN on wavelet coefficients.	Dependent on wavelet choice.
[30]	Grid search-optimized Random Forest.	RF + hyperparameter tuning.	Limited to traditional ML.
[31]	Statistical sampling + novel feature selection.	Feature selection algorithm.	Not compared to deep learning.
[32]	Optimized DNN for EEG seizure detection.	Custom CNN architecture.	Black-box model, lacks interpretability.
[33]	Wavelet + arithmetic coding + ML.	Signal compression + SVM.	Lossy compression may discard key features.
[34]	Modified distribution entropy for seizures.	Entropy-based detection.	Unproven on diverse epilepsy types.
[35]	Deep metric learning for seizure detection.	Siamese networks.	Requires triplet loss tuning.
[36]	Fusion of handcrafted + deep features.	Hybrid (SVM + CNN).	Complex pipeline.
[37]	1D CNN + ML hybrid.	CNN + feature fusion.	May not generalize across datasets.
[38]	VMD + Deep Forest.	Variational mode decomposition.	Less interpretable than traditional ML.
[39]	CNN with feature fusion.	Multi-feature CNN.	Risk of overfitting with small data.
[40]	Combined deep learning for multi-class EEG.	Multi-model fusion.	High computational demand.
[41]	DL for seizure detection (2024).	Advanced CNN/Transformer.	Limited clinical validation.
[42]	Line length for burst detection in EEG.	Signal processing metric.	Only tested on neonatal EEG.
[43]	RF for intracranial EEG seizure detection.	Random Forest on iEEG.	Invasive EEG only.
[44]	Pattern recognition for EEG classification.	Statistical features + SVM.	Handcrafted features limit scalability.
[45]	Comparative study of classifiers.	SVM, RF, k-NN comparison.	No deep learning benchmarks.
[46]	Multi-view deep learning (STFT).	CNN on STFT spectrograms.	STFT loses temporal resolution.
[47]	LSTM for seizure prediction.	Time-series deep learning.	High false-alarm rates in practice.
[48]	DL for high-risk epilepsy symptom prediction.	Clinical data + DL.	Requires EHR integration.
[49]	EMD vs. DWT vs. WPD for seizure detection.	Decomposition methods.	EMD suffers from mode mixing.
[50]	Algorithm for childhood vs. structural epilepsy.	EEG classification.	Limited to two epilepsy types.
[51]	Time-domain CNN improvements.	1D CNN on raw EEG.	May miss frequency-domain features.

[52]	Third-order cumulant for focal EEG detection.	Higher-order statistics.	Computationally intensive.
[53]	Gramian Angular Summation Field + DNN.	Image-encoded EEG + CNN.	Loses sequential EEG information.

Monitoring and recording the data

Electroencephalography (EEG) records voltage fluctuations between electrodes placed on the scalp. The international 10-20 system determines the positions of electrodes, which usually include 21 recording electrodes and one ground electrode, with a significant amount of signal distortion in the process. Additional electrodes such as EOG, ECG, EMG are used to eliminate artifacts and improve spatial resolution [14,15]. The complex nature of brain activity and the associated EEG signals makes them difficult to analyze, and the use of ML methods is necessary. The standard procedure involves collecting EEG data, preprocessing, extracting features, and selecting features that are relevant to the problem. Classifiers are then selected and trained to recognize these features, among which feature selection plays a vital role [14]. Research papers were searched in the Scopus and Google Scholar databases using the keywords “epilepsy,” “EEG-based seizure detection,” and “black-box and non-black-box models.” Among the many findings, manuscripts published in 2007-2020 were considered, including those with at least four patient EEG datasets. Articles were screened, and those that met the inclusion criteria were analyzed by extracting information on ML methods, performance, datasets, and accessibility. This review aims to demonstrate how the field has shifted from conventional ML classifications to deep learning methods and identify the need for interpretable and generalizable systems for epileptic seizure detection. Findings highlight the importance of standardized datasets and open-access research to advance EEG-based epilepsy diagnosis. A basic model of seizure detection is presented in **Figure 3**.



Figure 3. A basic model of seizure detection

Black-box and non-black-box classifiers are the two primary types. black-box classifiers, such as support vector machines (SVMs) and artificial neural networks (ANNs) [16, 17], provide high accuracy but do not reveal the details behind the results. They cannot explain the steps involved in the classification process. Non-black-box classifiers, such as decision trees and random forests, on the other hand, can provide an explanation of every stage of the processing, enabling a better comprehension of the entire procedure. Meaningful patterns might not be able to be found in a raw EEG dataset before a machine learning classifier is applied. Finding significant and pertinent statistical patterns in unprocessed EEG data is a difficult but crucial endeavour. Identifying seizure stages and guaranteeing precise and quick seizure detection are just two of the neurological issues that may be resolved with the help of the data processing and application of an appropriate machine learning classifier.

Performance Metrics for Evaluation

Accuracy, sensitivity, specificity, FDR, and other metrics can be measured to assess the classifier's performance. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four classification results that are used to compute these measuring parameters [14].

TP: If a seizure is occurring in a person and is accurately detected by the classifier.

TN: If a person is experiencing a seizure and it is correctly identified by the classifier.

FP: If classifier detects patient having seizure as a normal person

FN: If classifier detects a normal person as having seizure

Accuracy: The ratio of results, including both true positives and true negatives.

$$\text{Accuracy} = \left[\frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \right] * 100$$

Specificity: Proportion of the TN identified correctly.

$$\text{Specificity} = \left[\frac{\text{TN}}{\text{TN} + \text{FP}} \right] * 100$$

Sensitivity/ Recall: The ratio of actual positive instances to true positive cases.

$$\text{Sensitivity/Recall} = \left[\frac{\text{TP}}{\text{TP} + \text{FN}} \right] * 100$$

Precision: High precision indicates a low false positive rate.

$$\text{Precision} = \left[\frac{\text{TP}}{\text{TP} + \text{FP}} \right] * 100$$

False Detection Rate (FDR): A set of predictions represent the expected percentage of false predictions inside that set

$$FDR = \left[\frac{FP}{\text{Total Time(Hours)}} \right] * 100$$

F1 Score/ F-measure:It strikes a balance between precision and recall.

$$F - \text{measure} / F1 \text{ Score} = 2 \times \left[\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \right]$$

Area Under Curve (AUC) score: A model with a higher AUC is superior in predicting True Positives and True Negatives.

ROC curve: A graph displaying the effectiveness of a classification model, anywhere the curve plots two parameters: TP Rate and FP Rate. A performance comparison of various important works done earlier by different authors based on the dataset of Bonn University from 2007 to 2024 is specified in Table 3.

Machine learning and Deep learning classifiers

In order for traditional machine learning (ML) models to identify patterns and generate predictions, they mostly rely on manual feature engineering, in which subject matter experts choose and extract significant features from the data [54]. These models are often easier to understand and explain and work best with small, structured sets of data. The examples of such models are support vector machines, logistic regression, and decision trees [55, 56]. Meanwhile, deep learning (DL) is a set of multi-layer neural networks that mimic the function of the human brain in order to automate the process of feature extraction. This allows DL to learn complex patterns from huge amounts of unstructured data, such as text, sound, and images. DL models are excellent at identifying complicated patterns and attaining high accuracy in challenging tasks, despite the fact that they need significant computer resources and big datasets to train efficiently [57]. The tradeoff between the two lies in DL's requirement for extensive data and hardware versus ML's interpretability and effectiveness with smaller datasets, making each suitable for different kinds of problems and data types. The key differences of traditional ML and Deep Learning is shown in Table 2. [58].

Table 2. Key Differences at a Glance

Aspect	Traditional ML	Deep Learning
Feature Engineering	Manual, requires domain expertise	Automated, learns features from data
Data Dependency	Less data needed, works well with small datasets	Requires large-scale datasets
Complexity	Simpler algorithms	Complex multi-layered neural networks
Interpretability	Generally interpretable	Largely black box, harder to explain
Hardware	Runs on CPUs	Needs GPUs/TPUs for training
Performance	Good for structured data, plateaus on complexity	High accuracy on complex, unstructured data

Table 3. Summary of existing work (EEG-based epileptic seizure detection using ML and DL classifiers, features) on a dataset of Bonn University, Germany during (2007-2024)

S.NO	Ref.	Classifier(s)	Feature(s)	Performance metrics	Performance (%)
1	[16]	ANN	Time-frequency	Overall Accuracy	97.72 - 100
2	[18]	ELM	Sample Entropy (SampEn)	Accuracy, Sensitivity, Specificity	95.67,97.26,98.77
		BPNN		Accuracy, Sensitivity, Specificity	95.33,95.81,75.54
3	[19]	AR based quadratic element and random forest	VMD	Accuracy	97.35
4	[17]	NN	LNDP feature extraction techniques	Accuracy	96.025
		SVM		Accuracy	96.76
		DT		Accuracy	93.6
		ANN		Accuracy, Sensitivity, Specificity	98.96,98.56,99.48
		NN	1D-LGP feature extraction techniques	Accuracy	94.22
		SVM		Accuracy	95.97
		DT		Accuracy	91.8
		ANN		Accuracy, Sensitivity, Specificity	98.96,98.68,99.38
5	[20]	SVM	DT-CWT-based non-linear features	Accuracy, Sensitivity, Specificity	96,96.9,97

6	[21]	LS-SVM classifier	TQWT	Accuracy, Sensitivity, Specificity Matthew's correlation coefficient	97.75,97.99,96
7	[22]	LS-SVM classifier	TQWT and fractal dimension	Accuracy, Sensitivity, Specificity	100,100,100
8	[23]	SVM and NN	DWT and CWT	Overall Accuracy	99.1
9	[24]	SVM	MFDFA	Accuracy	99.60
10	[25]	Random forest	STFT, mean, energy and std dev	Class Accuracy	96.7
11	[26]	Random forest	LIPRR	Class Accuracy	100
12	[27]	P-1D-CNN	10-fold cross validation	Accuracy	99.1 ± 0.9%
13	[28]	1D CNN	-	Accuracy, Precision, Recall	97.27,99.54,92.37
		LSTM		Accuracy, Precision, Recall	96.82,97.75,92.55
		GRU		Accuracy, Precision, Recall	96.67,99.08,91.52
14	[29]	CNN	DWT	Accuracy, Sensitivity, Specificity	100,100,100
15	[30]	SVM	15-features	Accuracy	95.91
		NB		Accuracy	95.38
		KNN		Accuracy	94.02
		Random Forest		Accuracy	97.06
		LMT		Accuracy	96.72
16	[31]	Random forest	DWT	Sensitivity, FPR	99.74,0.21/hr
17	[32]	ESD-LSTM	10-folds cross-validation	Accuracy, Sensitivity, Specificity	100,100,100
18	[33]	KNN	Discrete Wavelet + Arithmetic coding	Accuracy	100
		Naïve Bayes			
		MLP			
		SVM			
19	[34]	Random forest	IMF	Accuracy, Sensitivity, Specificity	98.4,98.6,96.4
20	[35]	Deep metric learning	Deep feature extractor	Accuracy, specificity	98.6,100
21	[36]	CNN-RNN	TQWT	Accuracy	99.71
22	[37]	CNN	Class 2, Class 3, Class 4, Class 5	Accuracy	100,99,94.6,94
23	[38]	VMD and DF Model	LECM	Sensitivity, Specificity	99.32,99.31
24	[39]	CNN	DWT decomposition	Accuracy, Sensitivity, Specificity, Precision	99.9,100,99.8,99.81
25	[40]	CNN	CWT	Accuracy	99.07
			STFT	Accuracy	99.28
26	[41]	CNN and RNN with LSTM	STFT	Accuracy	99.57
			CWT	Accuracy	99.26

Performance Metrics for Evaluation

We began by reviewing papers in which the performance metrics accuracy, precision, and sensitivity were calculated on various datasets. Among the classifiers tested, the LS-SVM with TQWT, CNN with DWT, and ESD-LSTM using 10-fold cross-validation consistently yielded the best results matched to other feature extraction methods. SVM classifiers with different features applied to the Bonn University dataset are present in **Table 3**, in which LS-SVM classifier with TQWT shows better results among other features.

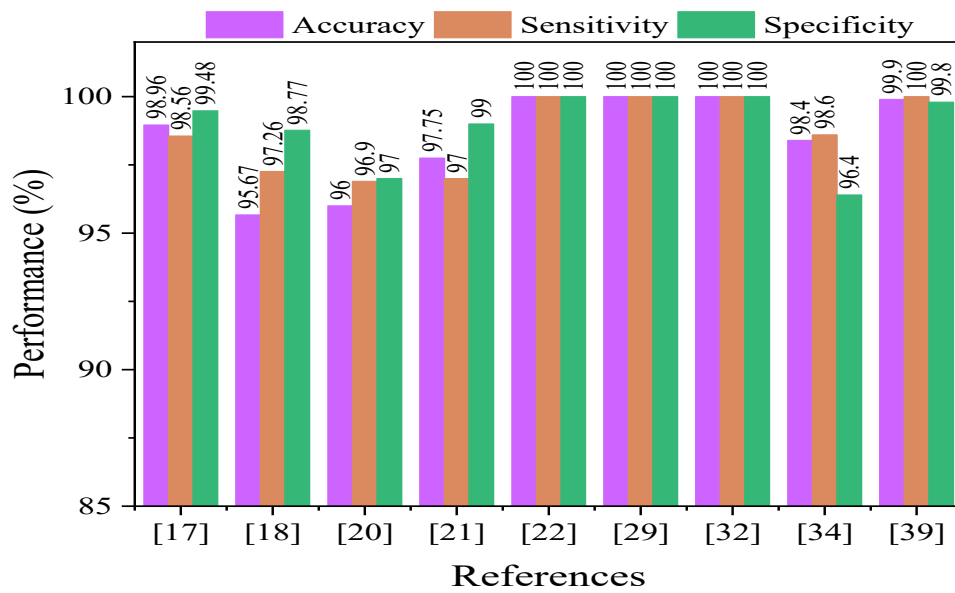


Figure 4. Performance comparison of classifiers which have three parameters accuracy, precision and sensitivity

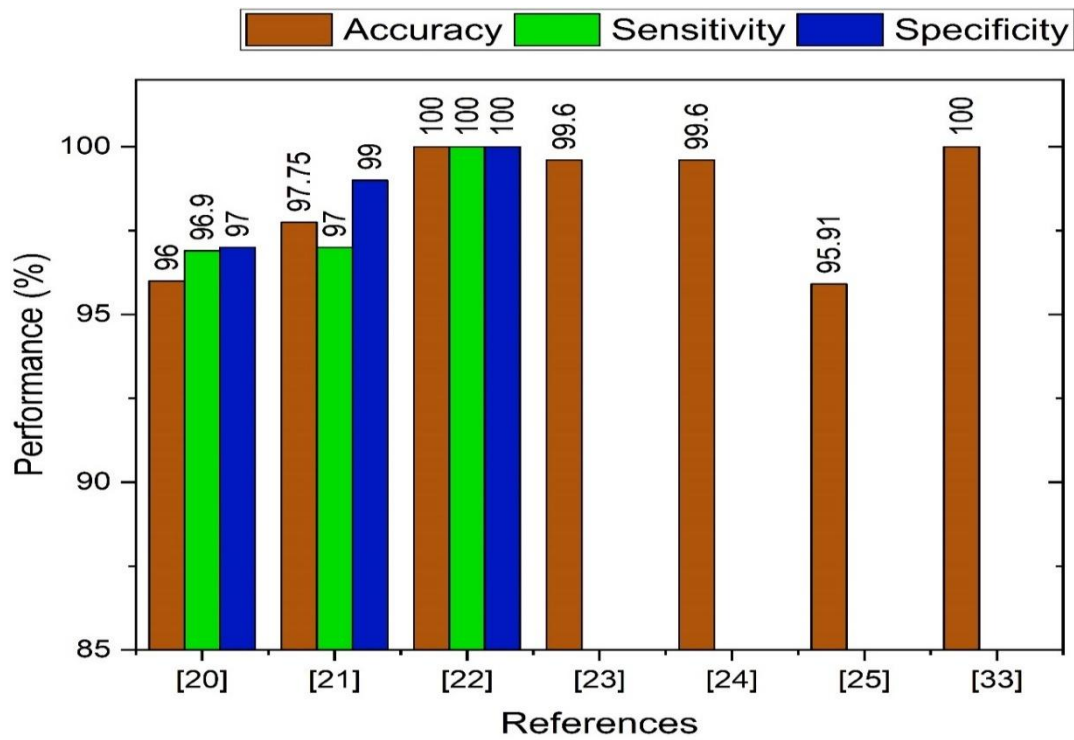


Figure 5. Performance comparison of existing SVM classifiers on the Bonn University dataset

Table 4. Performance comparison of existing SVM classifiers on the Bonn University dataset

Ref	Accuracy (%)	Sensitivity (%)	Specificity (%)
[20]	96	96.9	97
[21]	97.75	97	99
[22]	100	100	100
[23]	99.6.	-	-
[24]	99.60	-	-
[25]	95.91	-	-
[33]	100	-	-

Neural Network classifiers (Deep learning) applied on the Bonn University dataset have been discussed shown in **Table 5**, in which CNN with DWT, ANN (several features are extracted based on time-specific methods), and KNN show promising results.

Table 5. Performance comparison of existing Neural Network classifiers on the Bonn University dataset

Ref	Accuracy (%)	Sensitivity (%)	Specificity (%)
ANN [16]	97.72 - 100		
BPNN [18]	95.33	95.81	7.54
ANN-LNDP [17]	98.96	98.56	99.48
ANN-1D LGP [17]	98.96	98.56	99.38
CNN [27]	99.1		
CNN [28]	97.27		
CNN [29]	100	100	100
KNN [30]	94.02		
KNN [33]	100		
CNN-RNN [36]	99.71		
CNN [37]	100,99,94.6,94		
CNN [39]	99.9	100	99.8
CNN [40]	99.07,99.28		
CNN-RNN [41]	99.57,99.26		

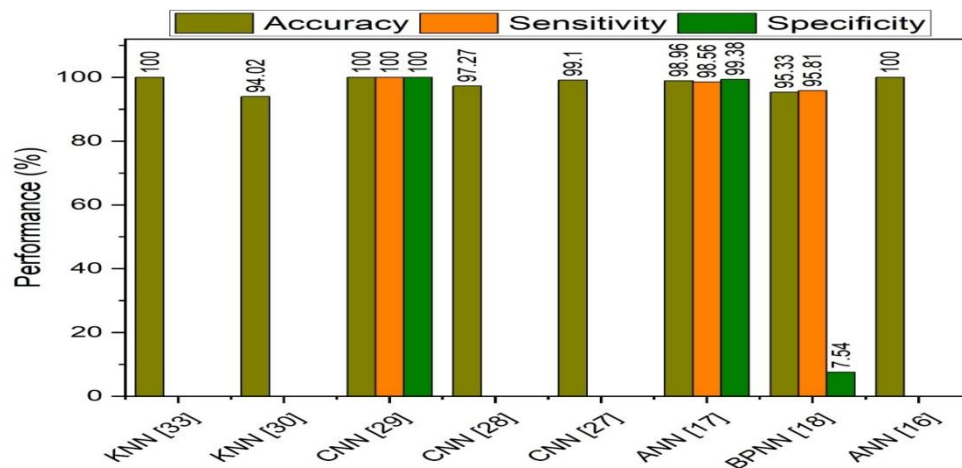


Figure.6 Performance comparison of existing Neural Network classifiers on the Bonn University dataset
Table 6 discusses Random Forest classifiers with different features applied to the Bonn University dataset, and shows that Random Forest classifiers with L1-penalized robust regression (L1PRR) are a powerful way to diagnose epilepsy, as they show very good results.

Table 6. Performance comparison of existing Random Forest classifiers on the Bonn University dataset

Ref	Accuracy (%)
[19]	97.35
[25]	96.7
[26]	100
[30]	97.06
[31]	98.4
[38]	--

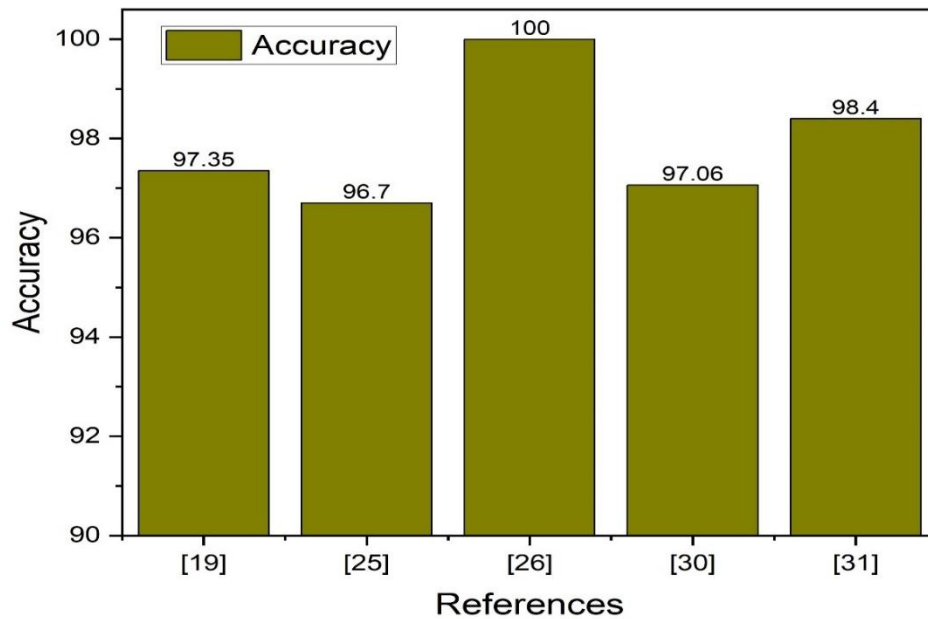


Figure.7 Performance comparison of existing Random Forest classifiers on the Bonn University dataset

Literature Review of existing work (EEG-based epileptic seizure detection using ML and DL classifiers, features) on a dataset of Bonn University, Germany during (2007-2024)

In 2007, Tzallas et al. used time-frequency methods to analyze EEG data and extracted several features for each segment based on time-specific techniques. These features were applied to ANNs, providing very promising accuracy rates of 97.72% to 100% [16]. Yuedong Song et al. proposed an automatic diagnosis system using sample entropy and ELM models, which shows high accuracy (95.67%) with high speed [18]. Tao Zhang et al. proposed an AR-based quadratic element and RF with VMD integration program, logarithmic performance, and the highest classification accuracy of 97.352%. This technique can be added to software and may help doctors detect seizures in hospitals [19]. Abeg Kumar Jaiswal et al. used time-frequency methods to analyze EEG data and extracted several features for each segment based on time-specific techniques. These features were applied to ANNs, providing very promising accuracy rates of 97.72% to 100% [16]. It has been suggested that LNDP and 1D-LGP may be effective means to extract factors in the separation of epilepsy EEG signals by NN, SVM, DT, and ANN techniques. In all these techniques, ANN classifiers achieve the highest average classification accuracy of 99.82% and 99.80% [17]. Mingyang Li et al. proposed SVM with the effect of various filter types on DT-CWT with several features and found that it achieves a satisfactory classification accuracy of 98.87%, higher than DWT-based features. This performance validates that their proposed method can provide something important at less computational cost as well as being easily implemented. It is a technique that could be used for real applications ranging from improving instantaneous brain monitoring systems [20]. By employing the Kraskov entropy of TQWT based on rotten bands, Shivnarayan Patidar et al.'s promising method, TQWT, aids in the development of distinctive traits. It was possible to identify and utilise this Kraskov entropy-based feature without the use of LS-SVM. The Matthews correlation coefficient, sensitivity, specificity, and classification accuracy were all markedly enhanced by the experimental findings of this investigation [21]. Additionally, Manish Sharma et al. suggested a TQWT-based automatic seizure detection machine learning model. The RBF kernel in LS-SVM is used for separation. One significant finding of the proposed study is that, in all three steps, the model's performance was estimated to be rather near to the full model [22]. Satapathy et al. (2017) verified that the model's estimated performance was nearly identical to the full model in each of the three steps [23]. created SVM and neural networks to categorize EEG patterns and identify individuals with epilepsy. Several kernel techniques, including linear, polynomial, and RBF, were assessed empirically for SVM. Lastly, the study recognises that recurrent neural networks consistently produce subpar outcomes on conditioned epilepsy data. SVM and probabilistic neural networks, on the other hand, are reasonably effective and cost-effective [23]. Considering the fraudulent and unethical practices in EEG, to capture the random and sudden changes, Debdeep Sikdara et al. presented a fictitious nonlinear method of MFDFA. In this journal, to address healthy behavior (Group B), interictal (Group ID pattern-ictal (Group E), a hold-up vector (SVM) machine is trained to distinguish between groups in different EEG bands. An accuracy of 99.6% was found in limited band EEG [24]. Tzimourta et al. introduced a method to obtain automatic recordings based on DWT. Five levels of attenuation are used for each phase of EEG, and five elements are extracted from the wavelet coefficients. The results of both data divisions were more than 95% accurate, and the frequent conflict rate and error rate reached 99.74% and 0.21/h, respectively, ensuring the robustness of the method [25]. Hussein et al. introduced a powerful method to distinguish epilepsy. The efficiency of the planned model is evaluated under favorable practical life situations, achieving 100% accuracy under suitable conditions [26]. In this paper, P-1D-CNN focuses on enhancing the proper configuration of the model, resulting

in 61% fewer parameters compared to standard CNN models and improved efficiency. To address the challenge caused by data scarcity, the authors planned two data augmentation methods. The system was tested on the benchmark dataset, the University of Bonn dataset, and achieved an accuracy of $99.1 \pm 0.9\%$ in almost all cases related to epilepsy detection. The strength of the P-1D-CNN model lies in its compact space requirements (61% smaller) and very short detection time (< 0.000481 seconds), making it suitable for real-time clinical applications [27]. Xuhui Chen et al. introduced a novel generic double DNN movement that provides cost-sensitive advantages for sample classification in the labeling process. 1D The CNN was integrated within the double DNN framework along with three types of basic neural networks, namely a recurrent neural network with LSTM units and a recurrent neural network with GRUs, to evaluate its performance. Results showed that the proposed system can reduce the number of labeled samples by up to 33% compared to uncertainty sampling and 80% compared to random sampling. Summary of existing work (EEG-based epileptic seizure detection using—ML classifiers, and features) on other available datasets (2014-2024) are available in **Table 7**.

Table 7. Summary of existing work (EEG-based epileptic seizure detection using ML classifiers, and features) on available datasets other than Bonn University (2014-2024)

S. No.	Ref.	Classifier(s)	Feature(s)	Performance metrics	Performance (%)
	[42]	Burst detection algo	Line length	Accuracy, Sensitivity, Specificity	84.27,84,85.7
1.	[43]	Random forest	IMF	Accuracy	98.4
2.	[44]	SVM	Energy	Accuracy, Sensitivity, Specificity	99.11,99.28, 98.93
		MLP		Accuracy, Sensitivity, Specificity	97.14, 96.48, 97.83
		KNN		Accuracy, Sensitivity, Specificity	98.21, 96.88 99.63
		Naïve		Accuracy, Sensitivity, Specificity	89.63, 88.24, 90.77
3.	[45]	Random forest	DWT 9 statistical features	Specificity, Precision	96.4, 96.67
4.	[46]	STFT mSSDA		AUC-ROC, AUC-PR, F1-score, Accuracy	0.9833, 0.9549, 0.9605 0.9382
5.	[47]	LSTM	Statistical moments, zero crossings, Wavelet Transform coefficients, PSD, cross correlation, graph theory	Accuracy, Sensitivity, Specificity, FPR	100, 99.28, 99.28 0.107
6.	[48]	LDA		Max AUC	0.748
		LR			0.684
		CNN			0.790
		RNN			0.557
7.	[49]	MSPCA + WPD + SVM	WPD, DWT and EMD	Accuracy	99
8.	[50]	ANN	Mathematical morphological filter based method	Accuracy	72
		SVM			69
9.	[51]	CNN	Time-domain waveform	Accuracy, Sensitivity, Specificity	81, 70, 92
			MIDS	Accuracy, Sensitivity, Specificity	83, 92, 74
			Data augmentation method	Accuracy, Sensitivity, Specificity	84, 72, 95
10.	[52]	SVM	LSDA	Accuracy	99
11.	[53]	AlexNet		Precision, Recall, F1-score,AUC	0.7451,0.7435,0.7436,0.71
		VGG16		Precision, Recall, F1-score, AUC	0.7701,0.7574,0.7518,0.75
		VGG19		Precision, Recall, F1-score, AUC	0.7761,0.7534,0.7499,0.75
		Custom CNN		Precision, Recall, F1-score, AUC	0.8370,0.8021,0.7981,0.85

		Feature-based ANN		Precision, Recall, F1-score, AUC	0.885, 0.92, 0.90, 0.92
12.	[35]	Deep metric learning	Deep feature extractor	Accuracy, Specificity	86.68, 93.71
13.	[36]	CNN-RNN	TQWT	Accuracy	99.13
14.	[37]	CNN	Binary Classification	Accuracy	98
15.	[38]	VMD and DF Model	LECM	Sensitivity, Specificity	95.2, 98.56
16.	[39]	CNN	DWT decomposition	Accuracy, Sensitivity, Specificity, Precision	100, 100, 100, 100
17.	[40]	CNN	CWT & STFT	Accuracy	96.23
18.	[41]	CNN and RNN with LSTM	CWT	Accuracy	99.57
			STFT	Accuracy	97.12

Table 8. Performance comparison of different classifiers on Epilepsy Center, University Hospital of Freiburg, Germany dataset

Ref	Accuracy (%)	Sensitivity (%)	Specificity (%)
RF [43]	98.4		
SVM [44]	99.11	99.28	98.23
MLP [44]	97.14	96.48	97.83
KNN [44]	98.21	96.88	99.63
Naive [44]	89.63	88.24	90.77
CNN-RNN [36]	99.13		
DF [38]		95.2	98.56

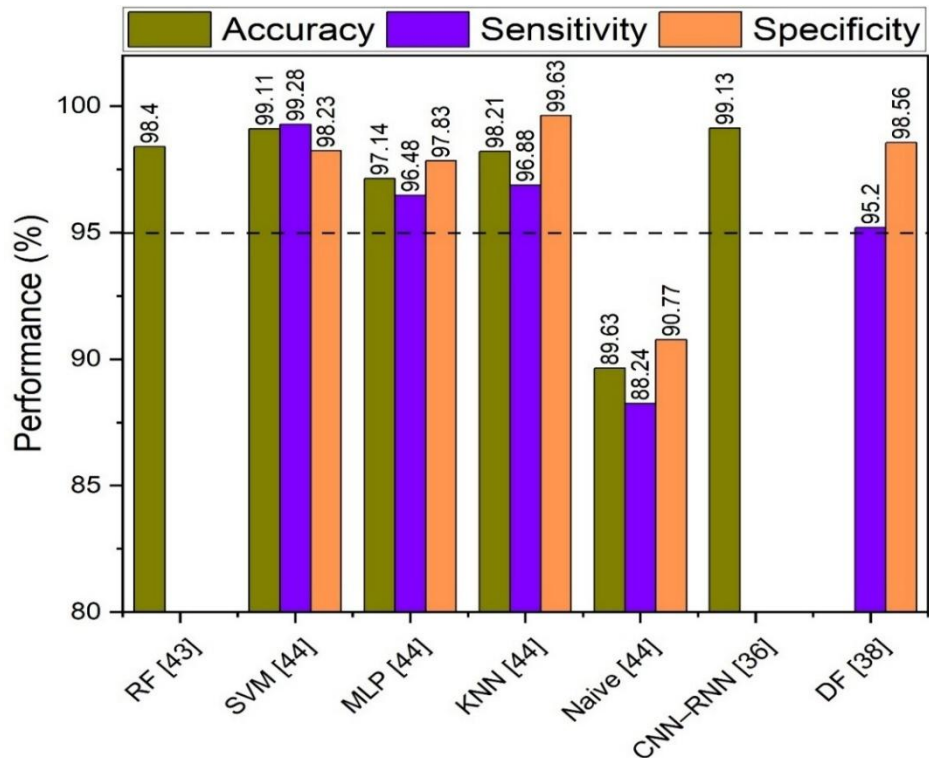


Figure 8. Epilepsy Center, University Hospital of Freiburg, Germany

In **Table 9** different classifiers applied to the Children’s Hospital, Boston dataset, have been discussed in which LSTM machine classifier and CNN deep learning classifier with Data augmentation method show the promising result.

Table 9. Performance comparison of existing classifiers on Children’s Hospital, Boston dataset

Ref	Accuracy (%)	Sensitivity (%)	Specificity (%)
Random forest [45]			96.8
STFT [46]	93.82		
LSTM [47]	100	98.28	99.28
SVM [49]	99		

CNN-MIDS [51]	81	70	92
CNN-TIME [51]	83	92	74
CNN-DATA [51]	84	72	95
Deep Metric Learning [35]	86.68		93.71
CNN [37]	98		
CNN [40]	96.23		
CNN [41]	99.57		
RNN-LSTM [41]	97.12		

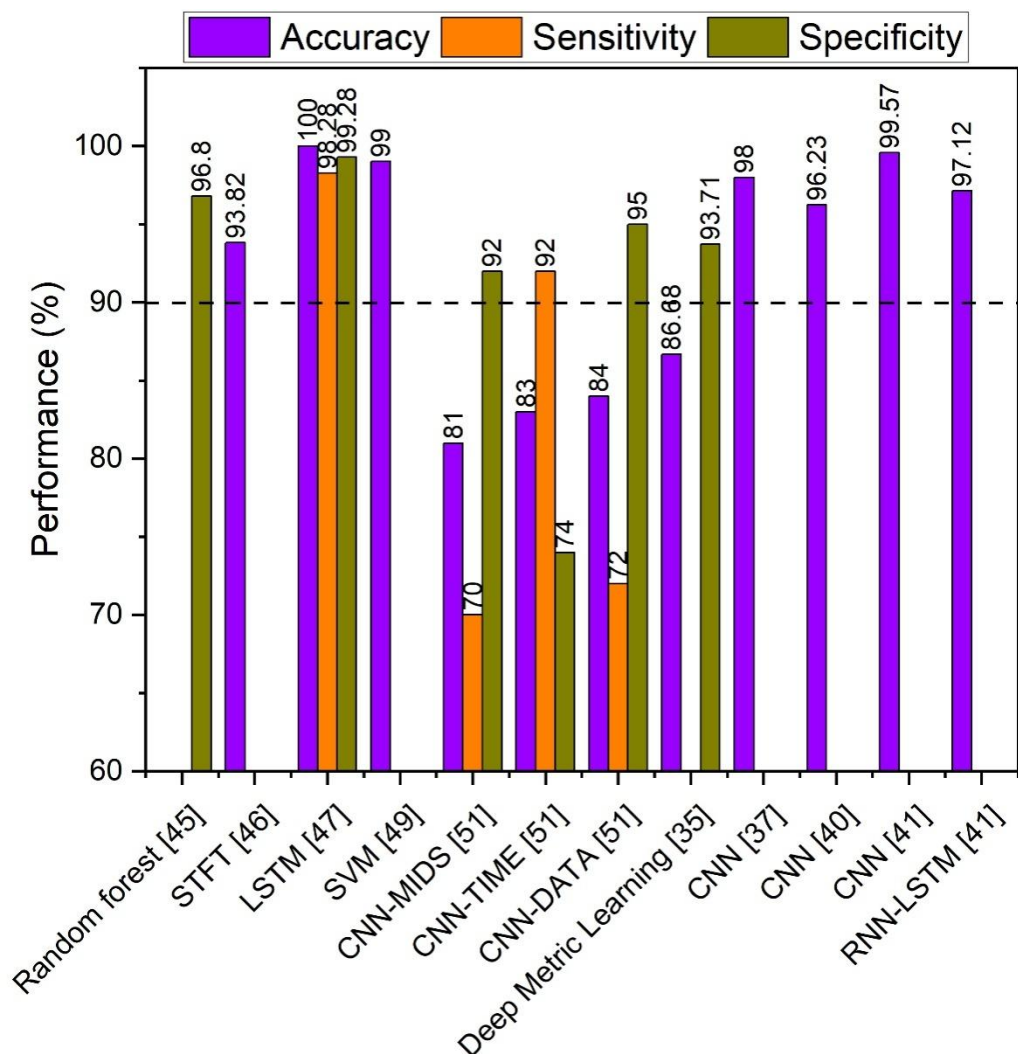


Figure 9. Performance comparison of existing classifiers on Children's Hospital, Boston dataset

Table 10. Different parameter values related to existing classifiers on the Bern-Barcelona (Bern) dataset

Ref	Precision	Recall	F1-score	AUC	Accuracy (%)
SVM [52]					99
AlexNet [53]	0.7451	0.7435	0.7436	0.71	-
VGG16 [53]	0.7701	0.7574	0.7518	0.75	-
VGG19 [53]	0.7761	0.7534	0.74995	0.75	-
Custom CNN [53]	0.837	0.8021	0.7981	0.85	-
Feature-based ANN [53]	0.885	0.92	0.9	0.92	
CNN [40]					95.46

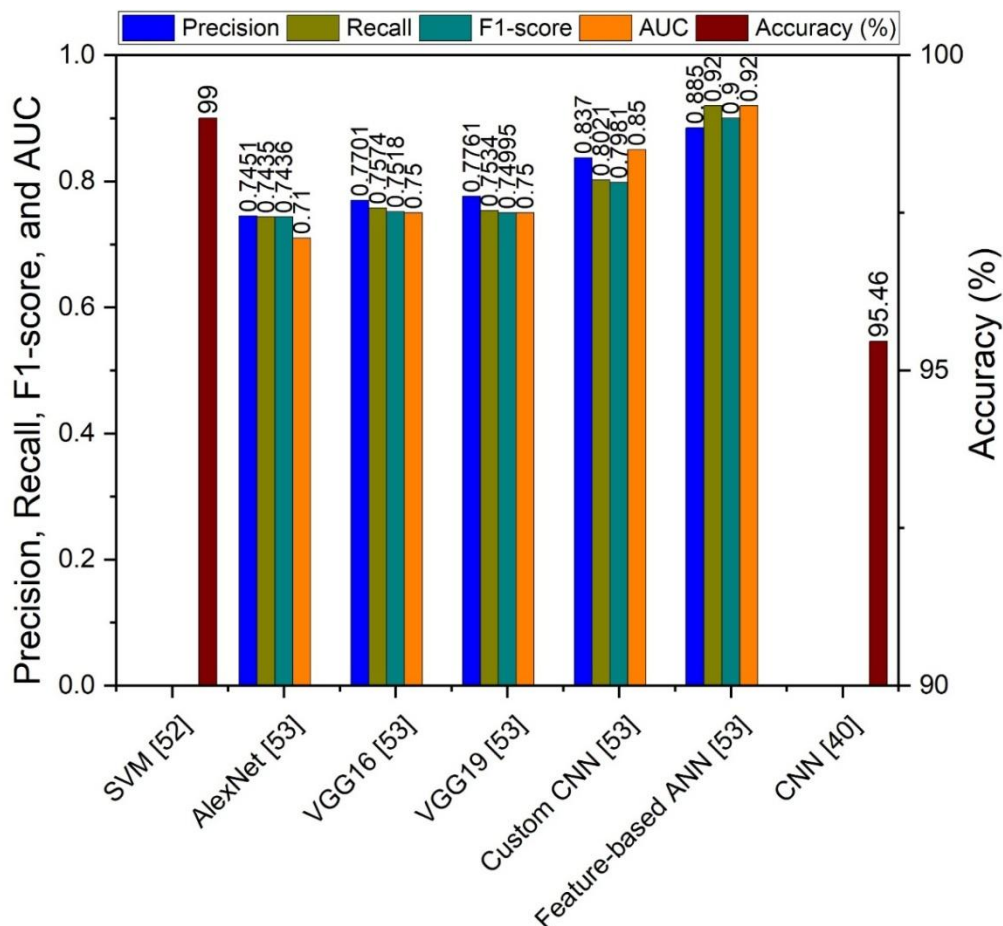


Figure 10. Performance comparison of existing classifiers on the Bern-Barcelona (Bern) dataset
Review literature of existing work (EEG-based epileptic seizure detection using ML classifiers, and features) on other than Bonn University available datasets (2014-2024)

Koolen et al. introduced a new method for proactively detecting automatic bursts in EEG recordings using a line length based on content height and signal density. The burst detection accuracy ranged from 79.54 to 89.82% with both high sensitivity and high specificity, with moderate comparative agreement [42]. Cristian Donos et al. selected a collection of 11 domain features and a simple computer-generated time option from a single unidentified EEG contact first. Classification of features was done using random forest classification, with the presentation being: average sensitivity 93.84% (100% moderate sensitivity), average detection latency of 3.03 seconds (median 1.75 seconds), and average false positives per hour of 0.33/h (median 0.07/h) [43]. Amin et al. demonstrated an accuracy of 99.11% using classifiers like naïve Bayes (NB), multi-layer perceptrons (MLP), support vector machines (SVM), and K-nearest neighbours (KNN) [44]. Siddiqui et al. applied four distinct split-two black box types (KNN and SVM) as well as two additional black boxes (ensemble and decision tree) to two patient syncope datasets. According to their research, non-black box classifiers primarily perform better than other classifiers. Notably, when compared in multiple combinations, excellent accuracy is achieved [45]. To train a seizure detector, Ye Yuan et al. introduced multi-view features that are collectively collected through a feature fusion approach and input into a fully correlated SSDA model. Using the CHB-MIT scalp EEG dataset, the suggested approach was evaluated and contrasted with a number of baseline techniques. The outcomes validate the efficacy and superiority of the intended model in detecting epileptic seizures. [46]. To assess seizure prediction performance over four distinct preictal window durations, spanning from 15 minutes to 2 hours, Kostas M. Tsiouriset et al. developed a two-layer LSTM network. With a low false prediction rate (FPR) and good seizure calculation sensitivity, the suggested approach was able to accurately predict 185 seizures. Depending on the preictal window length, the false prediction rate varied between 0.11 and 0.02 false alarms per hour. Compared to convolutional neural networks and conventional machine learning methods that have already been assessed in the literature, this LSTM-based method greatly improves the presentation of seizure prediction [47]. In this work, MINGRUI SUN et al. introduced a patient-specific model that extracts features from time series and frequency domain data using a two-layer CNN. The time domain EEG signal is converted to a frequency domain signal using a data preprocessing technique based on the independent Fourier transform. Using preictal clips of EEG datasets, an LSTM network is used to infer seizures, improving the use of RNN-based deep learning methods. The technique effectively extracts latent information with meaningful interpretation and achieves good presentation in forecasting preictal states, as evidenced by extensive experimental data [48]. A model that can discriminate between ictal and interictal states with 100% accuracy, interictal, preictal, and ictal EEG states with 99.77%

accuracy, and interictal and preictal EEG states with 99.70% accuracy was presented by Emina Alickovica et al. [49]. A new algorithm for the computational classification of interictal EEG Rolandic spikes by type of epilepsy was proposed by Andrius Vytautas et al. (Group I: paediatric epilepsy, spontaneous, patients without brain tumours, Group II: patients with epilepsy). EEG separation accuracy increased by 75% [50]. An automatic novel CNN-based EEG acquisition system with two novel developments was proposed by Zuochen Wei et al., who treated this function as a significant data editing challenge. The CNN with MIDS and increased data production reached 77.08%, 92.46%, and 72.11% sensitivity and 95.89% specificity, respectively, whereas CNN with EEG epilepsy separation initially achieved 70.68% sensitivity and 92.30% specificity [51]. With limited LSDA features and support vector machine (SVM) output, Rahul Sharma et al. were able to attain a high accuracy of 99%. To win psychiatric surgery, this method can assist clinicians in determining the location of epilepsy [52]. In this study, K. Palani Thanaraj et al. assessed the use of deep neural networks (DNNs) on focal GASF pictures in order to detect epilepsy from EEG time series data. They validated three pre-trained DNN models (AlexNet, VGG16, and VGG19) using transfer learning. The results indicated that the custom CNN model had an average area under the curve (AUC) of 0.92, a ROC curve precision of 0.885, a recall of 0.92, and an F1 score of 0.90 [53].

CONCLUSION:

With the increasing number of epileptic seizure patients, accurate diagnosis is very important. Therefore, the adoption of machine learning classifiers and features should be taken seriously. This paper is about choosing a completely updated method of machine learning to find the right classification and features. As a result, it is concluded that the "non-black box" delimitation of decision forests with decision tree combinations is very effective. This is because it can increase the accuracy of prediction and produce many reasonable, exciting and logical rules. It also helps to find valuable details such as the localization of syncope and the type of test. In contrast, the "black box" delimitation cannot produce reasonable rules even if it can reach the highest prediction accuracy. Among the numerous black box classifiers available this year, While Random Forest and L1 Punitive Robust Regression (L1PRR) [Class Accuracy 100%], DWT [Sensitivity and FPR are 99.74 and 0.21/h respectively], and SVM machine learning classifiers with Tunable-Q Wavelet Transform (TQWT) [Accuracy, Sensitivity, and Specificity are 100% each], Multifractal Detrended Fluctuation Analysis (MFDFA) [Accuracy 100%], and Locality Sensitive Discriminant Analysis (LSDA) [Accuracy 99%] have demonstrated promising results over other classifiers. In the meantime, deep learning classifiers like CNN, KNN, and ED-LSTM utilizing 10-fold cross-validation (accuracy 100%), ANN employing LNDP and 1-D LGP feature extraction approaches (accuracy 98.96%, sensitivity 98.56%, specificity 99.38%), have also demonstrated encouraging results.

Future Perspectives

EEG-based epileptic seizure detection using machine learning (ML) and deep learning (DL) classifiers has shown promising high accuracy, sensitivity, and specificity metrics, enhancing early diagnosis and seizure management. Future research aims to address the issue of limited, imbalanced data sets, sensitivity to noise, overfitting, and a lack of interpretability, as well as the use of more effective DL methods, including attention mechanisms, to manage data sets in real-time. To make such devices widely useful and reliable, clinical validation on larger, more diverse data sets is necessary. Furthermore, DL models should be made more interpretable and transparent to encourage healthcare professionals to adopt and use them. Finally, further research into the application of wearable and portable EEG devices in clinical practice and epileptic seizure prediction is required to make such devices a part of everyday patient monitoring and offer better care for patients with epilepsy. The area of epileptic seizure prediction is entering a new era of intelligent, real-time monitoring using ML and DL methods and technologies that can be implemented in actual practice.

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Conflict of Interests

The authors declare no conflict of interest.

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