Enhanced Detection of Epileptic Seizure Using Supervised and Unsupervised Algorithms

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Abstract

This study is dedicated to advancing the accuracy of epileptic seizure identification using electroencephalogram (EEG) data, a crucial tool in epilepsy diagnosis. Traditionally, medical experts have relied on visually assessing EEG waveforms, a time-consuming and error-prone process. Numerous pattern identification approaches have been developed in response to these difficulties, including techniques like the Discrete Wavelet Transform (DWT) for removing important patterns from EEG data. The overarching goal is to enhance seizure detection precision by translating EEG data into numerical values via DWT. The dataset used in this study comprises 668 columns representing brainwave readings, signal standard deviations from individual electrodes, and a binary representation of illness presence. To distinguish epileptic episodes, four classifiers were employed: Support Vector Machine (SVM), Random Forest Classification, K Nearest Neighbor (KNN), and K-means clustering. Remarkably, the unsupervised K-means clustering method outperformed supervised methods, achieving an impressive 98.1% classification accuracy. This finding is significant as it suggests that unsupervised learning techniques may offer a more efficient and accurate alternative to traditional methods for identifying epileptic seizures. Additionally, the study proposes future research into deep learning approaches, renowned for their enhanced classification accuracy in epilepsy detection. This research sets the stage for further investigations into leveraging advanced machine learning techniques to refine seizure identification systems, potentially revolutionizing the field of epilepsy diagnosis and management.

Keywords

Electroencephalogram (EEG), Machine Learning, Epileptic Seizure, Supervised Learning, Unsupervised Learning, Discrete Wavelet Transform (DWT), Support Vector Machine(SVM), Random Forest Classifier, k-means classifier, k-nearest Neighbor(KNN)

1. Introduction

One of the most serious neurological conditions that have an impact on human existence is epilepsy. Analyzing the Electroencephalogram (EEG) signal patterns, a common method for identifying brain abnormalities, can be used to detect this disease. To investigate epilepsy, medical professionals and researchers frequently employ EEG signals. Since epileptic seizures result in aberrant changes in the brain, experienced doctors have long used traditional methods

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to identify unexpected epileptic seizures [1]. Visual examination of the EEG waves is a common method used by experts to spot irregularities. This process typically requires a lot of time and is subject to human error.

The most common technique for detecting epileptic seizures is pattern recognition, which entails sifting through EEG for hidden patterns. Researchers have employed a range of feature extraction methods, including DWT, IDFT, FT, CWT, FFT, DFT, and STFT, to extract the hidden patterns from EEG data [2]. Other methods, such as Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Optimization (ACO), and many others, have also been investigated to determine the best qualities. To identify epileptic episodes from the EEG signals, the researchers looked at several classifiers, including support vector machines, decision trees, k-nearest neighbors (k-NN), Naive Bayes (NB), and Gaussian mixture [3, 4]. All the aforementioned pattern recognition techniques combine different feature extraction, selection, and classification techniques to increase the precision of diagnosing epileptic episodes.

The goal of this research is to increase detection accuracy for a dataset of EEG signals which is converted into numerical values using Discrete Wavelet Transform (DWT). The dataset consists of 668 columns. It is a public dataset available on Kaggle. The standard deviation of the signal from the T5 and T6 electrodes as well as the brain waves detected at the FP1, FP2, F3, and F4 electrodes are among these characteristics. The disease is depicted in binary form in the final column. To determine whether the output is an epileptic seizure, the four classifiers are analyzed in conjunction with the selected characteristics.

2. Literature Survey

Several AI in healthcare state of the art works are recently published and researchers applied machine learning models to detect and diagnose several human diseases [5, 6, 7, 8]. Here, we analysed some recent research contributions done for epileptic seizure detection.

Table 1
Various papers on the detection of Epileptic Seizure and the methodologies used

S.no	Title	Authors	Summary and Outcomes
1	Classification of epileptic EEG signals based on simple random sampling and sequential feature selection [9]	Hadi Ratham Al Ghayab . Yan Li . et.al.	This study presents a unique method for feature extraction and selection from multi-channel EEG signals using sequential feature selection (SFS) and simple random sampling (SRS) approaches. It achieves impressive classification accuracy, sensitivity, and specificity of 99.90%, 99.80%, and 100%, respectively, showcasing its potential for EEG-based disease diagnosis and treatment in medical applications.
2	A review of epileptic seizure detection using machine learning classifiers [10]	Mohammad Khubeb Siddiqui1 , Ruben Morales-Menendez1 et.al	The difficult task of seizure identification and classification in EEG and ECoG signals is covered in-depth in this work through machine learning-based methods. It divides these methods into "black-box" and "non-black-box" categories based on statistical characteristics and machine learning classifiers, providing insights into the changing seizure detection and localization environment. This study provides insight into the state-of-the-art and potential prospects for epilepsy-related signal analysis research
3	Machine Learning Algorithms for Epilepsy Detection Based on Published EEG Databases: A Systematic Review [11]	Andreas Miltiadous , Katerina D. Tzimourta et.al.	This comprehensive systematic review delves into the realm of automated epilepsy detection through EEG signal analysis. It assesses 190 studies, highlighting trends such as the increasing use of Convolutional Neural Networks and Time-Frequency decomposition methodology in this field. This research serves as a valuable resource for understanding the landscape of machine-learning approaches for epilepsy diagnosis, making it an essential reference for future work in this domain.
4	Detection of Epileptic Seizures from EEG Signals by Combining Dimensionality Reduction Algorithms with Machine Learning Models [12]	Muhammad Zubair ID et.al.	This paper addresses the challenge of epilepsy detection using EEG signals and introduces innovative dimensionality reduction techniques (SPPCA and SUBXPCA) applied after the Discrete Wavelet Transform (DWT). These methods choose essential time-frequency domain variables associated with epileptic seizures, which improve the classification precision of machine-learning models. Results indicate that SPPCA achieves 97% accuracy with the CatBoost classifier, while SUBXPCA reaches 98% accuracy with the random forest classifier, surpassing other state-of-the-art approaches in both accuracy and computational efficiency.
5	Machine Learning for Predicting Epileptic Seizures Using EEG Signals: A Review [13]	Khansa Rasheed1 , Adnan Qayyum1 , Junaid Qadir1 , et.al.	The use of artificial intelligence (AI) and machine learning (ML) in healthcare is examined in this research, with an emphasis on the early diagnosis and prediction of epilepsy, a disorder marked by unpredictable and repetitive convulsions. Despite historical challenges, recent ML-based algorithms show promise in revolutionizing seizure prediction. The paper conducts a thorough review of current ML techniques using EEG signals for early seizure prediction, highlighting existing gaps, challenges, and potential future directions in this critical area of research.

Table 2
Various papers on the detection of Epileptic Seizure and the methodologies used (Contd..)

S.no	Title	Authors	Summary and Outcomes
6	Enhanced Detection of Epileptic Seizure Using EEG Signals in Combination With Machine Learning Classifiers [14]	Wail Mardini, Muneer Masadeh Bani Yasseinet.al.	The architecture for automated epileptic seizure identification from EEG signals is presented in this research to improve accuracy while lowering processing costs. It makes use of the Genetic Algorithm (GA), four machine learning classifiers (SVM, KNN, ANN, and NB), as well as a 54-DWT mother wavelet analysis. The findings show that ANN outperformed the other classifiers in terms of accuracy, proving its efficacy in identifying epileptic episodes using the statistical features derived from the 54-DWT mother wavelets in EEG signals.
7	A Unified Framework and Method for EEG-Based Early Epileptic Seizure Detection and Epilepsy Diagnosis [15]	Zixu Chen, Guoliang Lu, Zhaohong Xie, Wei Shang et al.	In this study, we present a unified framework for electroencephalogram (EEG) data-based epilepsy diagnosis and early epileptic episode detection. The autoregressive moving average (ARMA) model is used to examine EEG dynamics and find anomalies suggestive of epileptic seizures. Experiments conducted on publicly available EEG databases demonstrate impressive classification accuracy of 93% and 94%, highlighting the framework's potential for real clinical applications, especially in scenarios where EEG data may contain various brain disorders alongside epilepsy.
8	Identifying Refractory Epilepsy Without Structural Abnormalities by Fusing the Common Spatial Patterns of Functional and Effective EEG Networks [16]	Yuhang Lin, Peishan Du, Hongze Sun et.al.	This study explores the use of spatial pattern of network (SPN) features extracted from resting-state scalp electroencephalogram (EEG) data to differentiate between drug-refractory epilepsy patients without significant structural abnormalities (RE-no-SA) and medically controlled epilepsy patients (MCE). The SPN features, particularly when combining functional and effective EEG networks, exhibited high accuracy, reaching 96.67%, with 100% sensitivity and 92.86% specificity. These findings suggest that fused SPN features can serve as reliable tools for distinguishing between these patient groups and offer new insights into the complex neurophysiology of refractory epilepsy.
9	Mapping Propagation of Interictal Spikes, Ripples, and Fast Ripples in Intracranial EEG of Children with Refractory Epilepsy [17]	Saeed Jahromi; Margherita A.G. Matarrese; et.al.	To find accurate biomarkers for the epileptogenic zone (EZ). The study suggests a novel approach to calculate the timing of the spread of epilepsy biomarkers across different brain regions and evaluates their common beginning. Moreover, this study provides preliminary evidence that fast ripples also propagate across large brain regions. These findings offer valuable insights into epilepsy biomarker detection and EZ localization using icEEG data.
10	Simple Detection of Epilepsy From EEG Signal Using Local Binary Pattern Transition Histogram [18]	Muhammad Yazid, Fahmi Fahmi, Erwin Sutanto et.al.	The Local Binary Pattern Transition Histogram (LBPTH) and Local Binary Pattern Mean Absolute Deviation (LBP-MAD) are unique features that this research introduces as an effective feature extraction method for epilepsy identification from EEG signals. This method surpasses 99.6% accuracy in identifying ictal from non-ictal EEG data utilizing Support Vector Machine (SVM) and k-nearest neighbor (KNN) classification, It is suited for transportable, low-power, and reasonably priced wearable medical devices for epilepsy detection since it retains more than 99.1% SVM classification accuracy even with brief input data (2.95 seconds).

3. Machine Learning Techniques

With the use of the EEG signals that are gathered with the aid of electrodes, machine learning algorithms are utilized to categorize the data into epilepsy positive or negative. The classification is implemented using the following Machine learning algorithms:

1. K- Means Clustering
2. Support Vector Machines (SVM)
3. Random Forest classifier
4. k-nearest Neighbors (KNN).

A brief introduction of the above-said algorithms is presented in this subsection. Certainly, here is a rewritten version of the provided information:

3.1. K-Means Clustering:

K-Means clustering is a fundamental unsupervised machine learning technique known for its simplicity and effectiveness in grouping data into distinct clusters. Its primary objective is to minimize the variation within each cluster. The technique accomplishes this by updating centroids until convergence and iteratively allocating data points to the closest cluster centroid.

K-Means finds applications in various fields, including image segmentation, customer segmentation, and anomaly detection, due to its ease of use and scalability. Researchers and professionals value its ability to reveal hidden patterns within data without relying on pre-labeled data [19].

The simplicity and speed of K-Means have solidified its status as a foundational clustering approach, advancing our understanding of data structures and pattern recognition in the domain of unsupervised learning.

3.2. Support Vector Machines (SVM):

Support Vector Machines (SVMs) are a versatile and widely used machine learning technique applicable to various domains. They excel in handling both linear and nonlinear classification and regression tasks, particularly when data separation is not obvious.

By maximizing the margin—the distance between the closest data points and the decision boundary (the support vectors), SVMs seek to identify the best hyperplane. This reduces classification errors and enhances the generalization of new data [20]. SVMs can be customized using different kernel functions (linear, radial basis, polynomial) to handle complex decision boundaries encountered in real-world datasets.

SVMs are valued for their ability to handle high-dimensional data and nonlinear relationships, making them suitable for tasks such as image classification, text categorization, and bio-informatics [21]. Their track record of accuracy and resilience has significantly contributed to predictive modeling in various research and application domains.

3.3. Random Forest Classifier:

The Random Forest classifier is a sophisticated and adaptable machine learning method widely accepted in data science and predictive modeling [22]. It falls under the umbrella of ensemble learning, which combines forecasts from various decision trees to produce a reliable and precise model. To reduce over-fitting and increase generalization, each decision tree in the Random Forest is built using a random subset of the training data and a random selection of features.

Random Forest excels in both classification and regression tasks, making it suitable for a broad range of applications. It offers feature relevance scores and handles high-dimensional data effectively, making it valuable for feature selection and data exploration [23]. Random Forest is a key tool for machine learning practitioners, enabling the development of robust prediction models by handling complex interactions within data and demonstrating resilience to outliers and noise.

3.4. k-Nearest Neighbors (KNN):

A fundamental and simple machine learning algorithm that is frequently used in classification and regression issues is called k-nearest neighbors (KNN). According to the proximity principle, which governs how it operates, [24] a new data point's prediction is based on the average value or majority class of its k-nearest neighbors in the training dataset.

KNN is a powerful tool, especially for small to medium-sized datasets, owing to its simplicity and ease of implementation [25]. It makes no assumptions about the underlying data distribution, making it a non-parametric approach suitable for diverse data types. However, the effectiveness of KNN depends on factors like the number of neighbors (k) and the selected distance measure, necessitating careful adjustment [26]. Despite being straightforward, KNN may produce outstanding results in situations where local patterns and neighborhood links are crucial, making it a crucial part of the machine learning toolkit [27].

4. Methodology

To implement the above-mentioned machine learning algorithms on the dataset, data should be cleaned, analyzed, and pre-processed for extracting the important features. Fig. 1 shows the methodology of work carried out in this paper.

4.1. Data Collection:

The dataset was obtained from Kaggle and comprises EEG signals converted into numerical values. It includes readings of alpha, beta, and gamma brainwaves measured through various electrodes, along with the standard deviation of these signals, obtained through Discrete Wavelet Transform (DWT). The dataset consists of 668 columns and 2216 rows, with the last column serving as the target variable, indicating '0' or '1'.

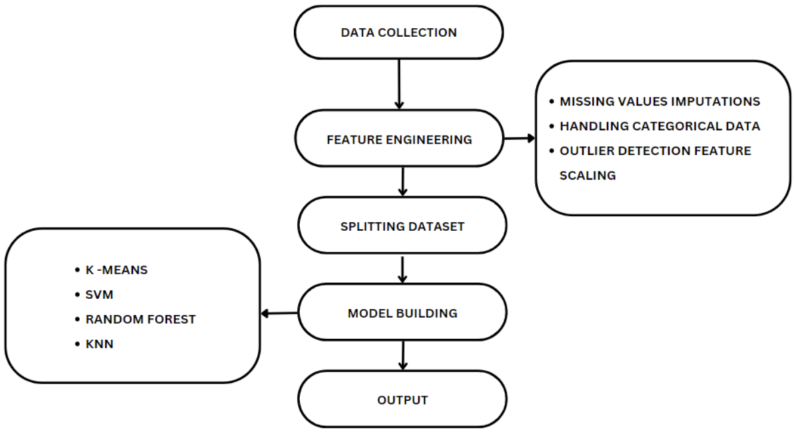

Figure 1: Proposed architecture to detect epileptic seizure using ML algorithms

4.2. Feature Engineering:

Feature engineering is the process of transforming unstructured data into informative input variables for machine learning models. It involves three main steps:

Missing Values Imputation Dealing with missing data is crucial for model performance. Strategies include removing rows with missing values, filling them with mean, median, or mode [28] values, or using forward/backward fill [29].

Handling Categorical Data. Categorical data, which consists of limited, fixed categories, can be processed using techniques like Label Encoding [30], One-Hot Encoding, or Binary Encoding [31].

Outlier Detection and Feature Scaling. Outliers are data points significantly different from the majority. Feature scaling standardizes [32] numerical features to ensure they have comparable magnitudes. This step is important for algorithms sensitive to feature scale, such as K-Means [33].

4.3. Splitting Dataset:

The 2216 rows of the dataset are divided in an 80:20 ratio. The model is trained using 80% of the data, and its accuracy is tested and validated using the remaining 20%. This division enables evaluation of the model's performance on unknown data.

4.4. Model Building:

After data pre-processing, machine learning models are constructed using Python and relevant libraries. The following methods are employed to evaluate model accuracy:

K-Means Clustering K-Means is used to create clusters with a silhouette average of 98.1%, indicating strong clustering significance.

Support Vector Machines (SVM) The accuracy, precision, recall, and F1 score [34] of SVM for binary classification (epilepsy vs. non-epilepsy) are 83.5%, 70.8%, 54.2%, and 40.3%

respectively.

Random Forest The Random Forest model classifies epilepsy patients and non-epilepsy patients with an accuracy of 83.5%, precision of 83.6%, recall of 83.5%, and F1 score of 83.5%.

k-Nearest Neighbors (KNN) A non-parametric supervised learning technique called KNN [35] achieves classification accuracy, precision, recall, and F1 score of around 80% respectively.

These results provide insights into the performance of various machine-learning approaches in classifying patients with and without epilepsy based on EEG signals and derived features.

5. Result and Discussion

To categorize whether a patient has epilepsy or not, many types of machine learning algorithms are used and evaluated. The bar graph in Fig. 2 shows the Precision value of different algorithms on the dataset.

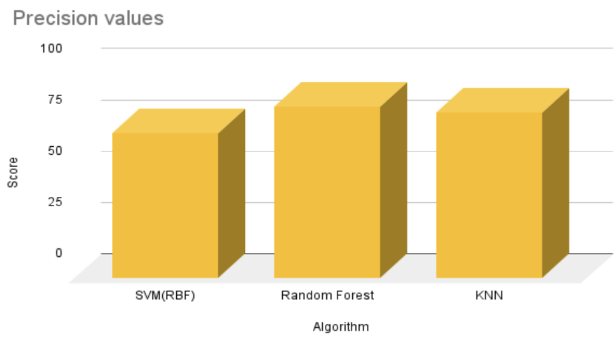

Figure 2: Precision Score vs. Supervised Algorithms

From fig. 2 it is clear that the random forest algorithm shows the highest precision value of 83.6% followed by KNN with 80.7% when compared with other supervised algorithms.

Fig. 3 represents the variation in recall values concerning the supervised algorithms used.

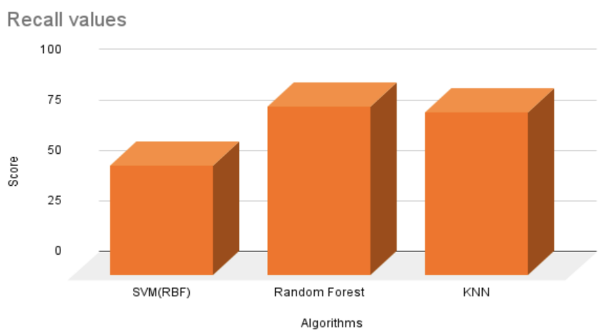

Figure 3: Recall Value vs. Supervised Algorithms

From the graph in fig. 3, it is evident that SVM's recall value, which stands at 54.2%, is the lowest, just like the precision score. With a recall rating of 83.5%, the random forest method tops KNN, which comes in at 80.6%.

Fig. 4 shows the F1 score of the algorithms while used on the dataset.

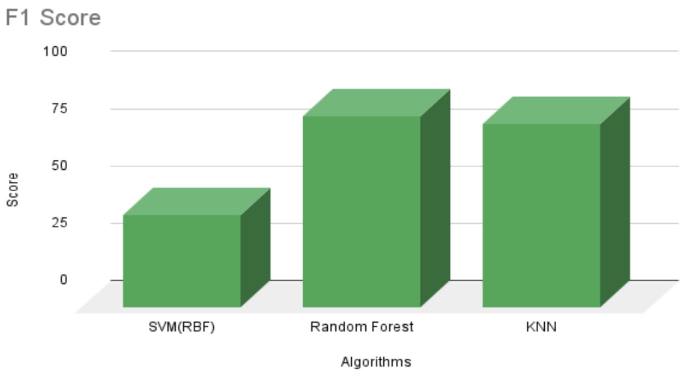

Figure 4: F1 Score vs Supervised Algorithms

SVM gives a very low F1 score of 40.3%, KNN shows 80.5%, and the Supervised algorithm that gives the highest F1 score is Random Forest with 83.5%.

As supervised algorithms did not give a significantly good prediction, Unsupervised models were created and executed with the same dataset for better accuracy. The accuracy of k-means clustering, an unsupervised technique, is 98.1%, which is significantly higher than that of any supervised algorithms previously employed. A clear comparison of the algorithms and the corresponding accuracy values has been mentioned in the table 3.

Table 3

Various papers on the detection of Epileptic Seizure and the methodologies used (Contd..)

S.no	Algorithm	Accuracy(%)
1	K-means	98.1
2	SVM	83.5
3	Random Forest	83.5
4	KNN	80

6. Conclusion and Future Work

In this study, brainwaves measured from several EEG electrodes are used to classify whether a patient is experiencing an epilepsy seizure or not using a range of machine learning methods. The supervised algorithms used are Support Vector Machine (SVM), Random Forest Classification, K Nearest Neighbor (KNN), and K-means clustering an unsupervised algorithm is also used. On comparing the accuracy of each algorithm, it is quite clear that K-Means clustering (unsupervised algorithm) gives a better classification accuracy of 98.1% than supervised algorithms. Deep learning methods, which are more accurate than other ML classifiers, can be used to broaden this proposed study in the future.

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