IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 2, October 2023

Automatic Machine Learning-Based Epilepsy Detection

Mr. Satish Ukade and Dr. S. K. Sonkar
Department of Computer Engineering
Amrutvahini College of Engineering, Sangamner, Maharashtra, India
satish.ukade@gmail.com and sonkar83@gmail.com

Abstract: *Epilepsy is a neurological condition characterized by disrupted nerve cell activity in the brain, leading to recurrent seizures that can significantly disrupt an individual's daily life. The communication between nerve cells, intricately interconnected, is perturbed in epilepsy, resulting in atypical functioning. Electroencephalogram (EEG) and Electrocorticography (ECoG) monitoring are commonly employed to evaluate this disorder. EEG captures brain signals through images, offering insights into abnormal brain activity. Machine learning systems utilizing these monitored signals aim to assist in diagnosing epilepsy. Through the analysis of vast data volumes, machine learning classifiers and statistical features are applied to classify this disorder. A Convolutional Neural Network (CNN) system is implemented to process large datasets containing EEG signal images, facilitating the classification of epilepsy. Ongoing research evaluates system performance using various classifiers and features to enhance the accuracy and effectiveness of epilepsy diagnosis.*

Keywords: epilepsy detection, brain disorder, EEG signals, Image processing, CNN

I. INTRODUCTION

The brain is a vital part of the human body, functioning through a complex network of nerves. Disruptions within this network can result in the dysfunction of normal brain activities, causing the overtaking or 'seizing upon' of other brain functions. This disorder, originating from the Greek word "epilepsies," meaning "to seize upon," is termed epilepsy. Epilepsy is a neurological condition where normal brain activities are overtaken by abnormal behavior, potentially leading to severe injuries within a short time frame due to recurrent seizures [1]. Ancient Babylonian scripts reference epilepsy and include mentions of medicinal treatments to alleviate its effects [2, 3]. Importantly, epilepsy is not exclusive to humans but extends across various mammalian species such as dogs, cats, and rats. This neurological disorder's impact reaches beyond human beings and affects a wide range of animal species.

The intricate network of nerves in the brain operates through electrical signals, and disturbances within this network lead to the manifestation of disorders such as epilepsy. Multiple factors contribute to these disturbances, including oxygen deprivation during childbirth or low blood sugar levels. Epilepsy affects one out of 100 million people at some point in their lifetime, with an estimated 50 million individuals affected globally [5, 10]. This disorder accounts for approximately 1% of the world's population.

Epilepsy is often characterized by seizures, which can be considered the main symptom of the disorder. A seizure represents a disturbance in brain cell activity, leading to unusual behavior in individuals and transient loss of consciousness. These episodes of unconsciousness can occur at any time during the day, lasting from a few seconds to a few minutes, and may result in minor injuries, burns, or more serious consequences such as fractures or sudden death.

Neurological experts have broadly categorized epilepsy into two primary types: partial and generalized seizures. Partial seizures, also referred to as focal seizures, impact only a specific portion of the brain. There are two types of partial seizures: simple-partial and complex-partial. In simple-partial seizures, the individual may not lose awareness but might face difficulties in communication. Conversely, in complex-partial seizures, the affected person experiences confusion about their surroundings and might engage in abnormal behaviors like chewing or mumbling; this is known as 'focal impaired awareness seizure.' On the contrary, in generalized seizures, all brain regions are affected simultaneously, impacting the entire brain network promptly [14]. Generalized seizures come in various forms but are broadly divided into convulsive and non-convulsive types.

Numerous studies have been conducted on seizure detection, incorporating various features, classifiers, and claimed accuracies, yet overlooking the challenges encountered by data scientists when exploring datasets related to neurological disorders. This composition provides a detailed exploration of machine learning methodologies in detecting epileptic seizures and associated data analysis. The collected papers in this review are sourced from reputable journals and databases like SCOPUS or Web of Science (WOS), including well-ranked conference papers. A wealth of literature exists, delving deeply into the analysis of different features and classifiers applied to EEG datasets for seizure detection. However, the establishment and application of such methodologies are challenging tasks. Prior research indicates an increasing interest in utilizing machine learning classifiers for this purpose

The quest for discerning significant patterns from EEG signals plays a pivotal role in detecting seizures, determining their location in the brain, and uncovering other emotionally related information. Approximately three decades ago, Jean Gottman established a model for effectively handling EEG signals by employing diverse computational and statistical methods to automatically detect seizures. Furthermore, various signal processing and data analysis approaches have been explored to improve the methodologies.

The paper is structured as follows: Section I provides a comprehensive introduction, while Section II entails an extensive survey of previous systems. Section III outlines the architecture for seizure detection, along with a detailed discussion of the methodology employed. Finally, Section IV presents the results and analysis derived from the implementation.

II. LITERATURE SURVEY

Machine Learning Algorithms for Epilepsy Detection Based on Published EEG Databases: A Systematic Review

The study focused on the Signal Transformation methodologies and the Classification Algorithms applied and evaluated which is prevailing during the latest years. This review concluded on the following observations: 1) the future on automatic epilepsy detection lies on methodologies that employ a combination of Time-Frequency transformations to produce images and feed CNN classifiers, as well as on methodologies that employ Neural Networks on raw EEG signal. Also, CNN seems to outperform other classifiers regarding the Seizure Detection and Healthy-Interictal problems. 2) the most popular database is Bonn DB, however more databases such as Neurology and Sleep Center DB, Freiburg DB, Temple DB provide more appropriate EEG recordings (meaning no combination of scalp EEG and intracranial EEG) for classification tasks and are increasingly employed in combination with the most well-established Bonn and CHB-MIT databases. 3) limitations regarding each DB exist.

Energy-Efficient Tree-Based EEG Artifact Detection

This work presented the analysis and implementation of an artifact detection framework with minimal EEG setups (4 temporal channels), considering different classifcation approaches (binary, multi-label, multi-class multi-output). We used a combination of FFT and DWT for signal pre- processing and an automated machine learning framework (TPOT) to search for the optimal model for each scenario.

Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances

The use of hybrid algorithms and a combination of supervised with unsupervised and ML with DL methods are promising to provide better results. Even, various fine tunings can sometimes offer promising improvements. , 3D-CNN is used first to extract primary features, and next, instead of the general FC layer, the FSBi-LSTM is used. This slight change in a part of the system eventually resulted in superior performances.

Simple Detection of Epilepsy From EEG Signal Using Local Binary Pattern Transition Histogram

The work presents, the machine learning classification of epilepsy from EEG signals. Based on Discrete Wavelet Transform combined with two newly proposed features: Local Binary Pattern Transition Histogram (LBPTH) and

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 2, October 2023

Local Binary Pattern Mean Absolute Deviation (LBPMAD), our proposed method allows efficient feature extraction from a time series signal such as EEG signals, achieving high classification accuracy with relatively small feature vector size of only 18.

Enhanced Detection of Epileptic Seizure Using EEG Signals in Combination With Machine Learning Classifiers

In this work, authors propose a novel approach to diagnosis the EEG signals using Multi-DWT, and Genetic algorithm coupled with four classifiers such as SVM, ANN, KNN, and Naive Bayes. The experimental results showed that the DWT features coupled with some machine learning algorithms had provided noticeable results, and the ANN classifier outperforms all tested classifiers.

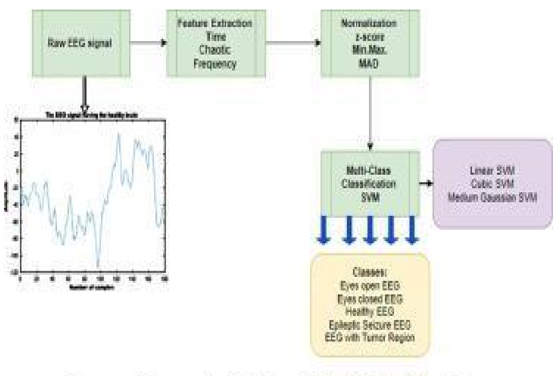
A Unified Framework and Method for EEG-Based Early Epileptic Seizure Detection and Epilepsy Diagnosis

In this paper, authors develop a unified framework for early epileptic seizure detection and epilepsy diagnosis, which includes two phases. In the first phase, the signal intensity is first calculated for each data point of the given EEG, enabling the well-known autoregressive moving average (ARMA) model to characterize the dynamic behavior of the EEG time series. The residual error between the predicted value of learned ARMA model and the actually observed value is used as the anomaly score to support a null hypothesis testing for making epileptic seizure decision. The epileptic seizure detection phase can provide a quick detection for anomaly EEG patterns, but the resulting suspicious segment may include epilepsy or other disordering EEG activities thus required to be identified. Therefore, in the second phase, we use pattern recognition technique to classify the suspicious EEG segments

	Author Name	Description
01	L. Hussain, W. Aziz, A. S. Khan, A. Q. Abbasi, and S. Z. Hassan	Classification of electroencephlography (EEG) alcoholic and control subjects using machine learning ensemble methods
02	A. Hamad, E. H. Houssein, A. E. Hassanien, and A. A. Fahmy	Feature extraction of epilepsy EEG using discrete wavelet transform
03	U. R. Acharya, S. Vinitha Sree, G. Swapna, R. J. Martis, and J. S. Suri	Automated EEG analysis of epilepsy: A review
04	P. Sarma, P. Tripathi, M. P. Sarma, and K. K. Sarma	Pre-processing and feature extraction techniques for EEGBCI applications-a review of recent research
05	C. Umale, A. Vaidya, S. Shirude, and A. Raut	Feature extraction techniques and classification algorithms for EEG signals to detect human stress-a review

III. METHODOLOGY

A. System Architecture



The stages of the proposed method in the multi-class EEG signals classification.

Fig 1: System Architecture

The proposed method uses 54-DWT mother wavelets, Genetic algorithm, and four classifiers to classify the EEG signals for epilepsy seizure detection. Figure 1 shows the flow of the proposed methodology.

We acquire publicly accessible EEG data from Bonn University, wherein the data include five sets (A, B, C, D, and E). Each set consists of 100 single EEG segments with a sampling rate of 173.6 HZ. The EEG signals were filtered using a Bandpass filter and smoothing method. The first two sets (A, B) represent healthy people, whose signals were takenwith open and closed eyes. The other three sets represent epileptic persons. Sets (C, D) were treated as non-seizure because the signals are captured in duration without seizures. For seizure detection, set

(E) was only treated as an epileptic seizure

B. Algorithm

• Naïve Bayes Algorithm:

• Naïve bayes training completed and we got its accuracy as 95% and in confusion matrix X-axis represents predicted classes and y-axis represents True class labels and in above graph we can see total 1817 records correctly predicted as NORMAL and only 52 records are incorrectly predicted.

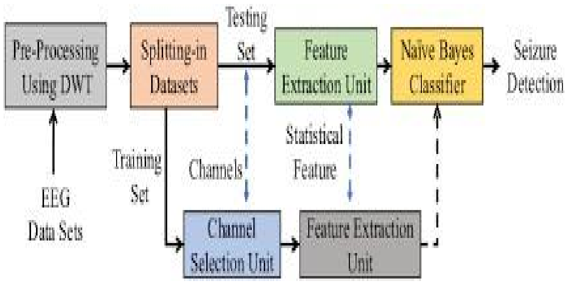


Fig2:Naïve Bayes Algorithm Flow

C. Modules

• Upload Epilepsy Dataset

• Using this module we will upload dataset to application

• Dataset Preprocessing:

• Dataset often contains missing values and non- numeric data such as patient ID so we need to process dataset to remove patient ID and missing values. Process data will be split into 80% training data and 20% testing data

• Train Naive Bayes Algorithm:

• Process data will be input to Naive Bayes algorithm to train a model

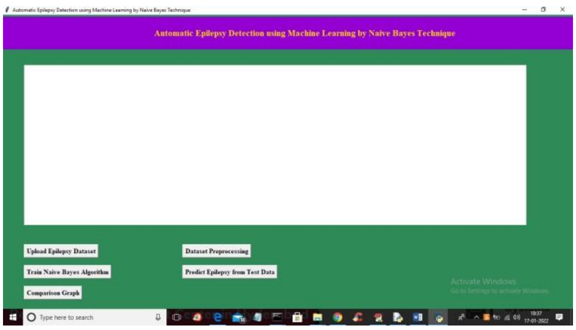
• Predict Epilepsy from Test Data:

• Using this module we will upload new test data and then apply trained Naïve Bayes model to predict whether test data is normal or contains Epilepsy disease

• Comparison Graph:

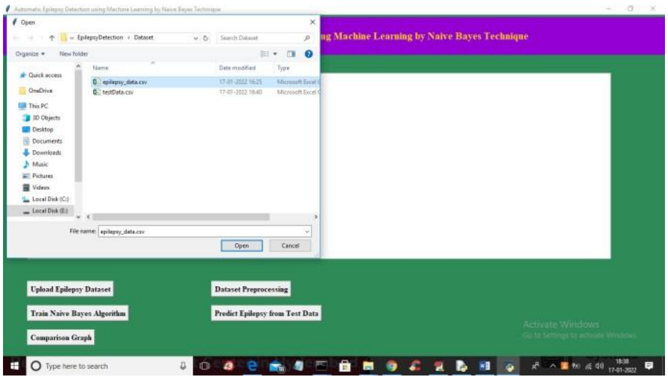
• Using this module we will plot Naïve Bayes performance graph in terms of precision, recall, accuracy and FSCORE

IV. EXPERIMENTAL RESULTS

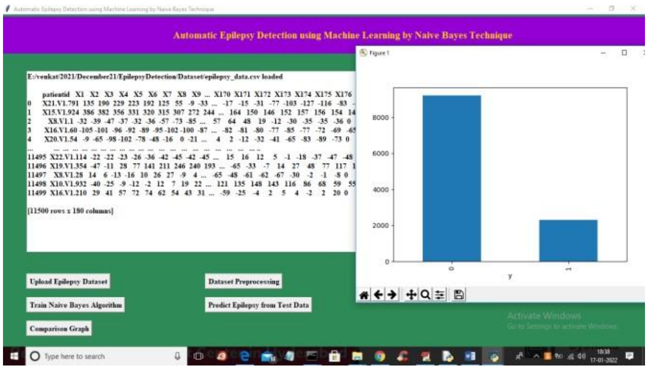


In above screen click on 'Upload Epilepsy Dataset' button to upload dataset and to get below screen

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 2, October 2023

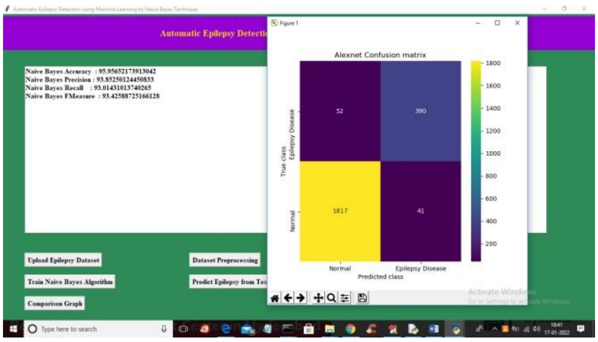


In above screen selecting and uploading ‘epilepsy_data.csv’ file and then click on ‘Open’ button to load dataset and to get below screen



In above screen text area we can see dataset values loaded and in graph x-axis represent 0 (normal) and 1 (epilepsy disease) and y-axis represents number of records in that category. In above values patient id contains non-numeric data so we need to preprocess data so close above graph and then click on ‘Dataset Preprocessing’ button

In above screen we can see after processing non-numeric data is removed and then split dataset into train and test and now dataset is ready and now click on ‘Run Naïve Bayes Algorithm’ button to train naïve bayes with process dataset and to get below output



IJARSCT

ISSN (Online) 2581-9429

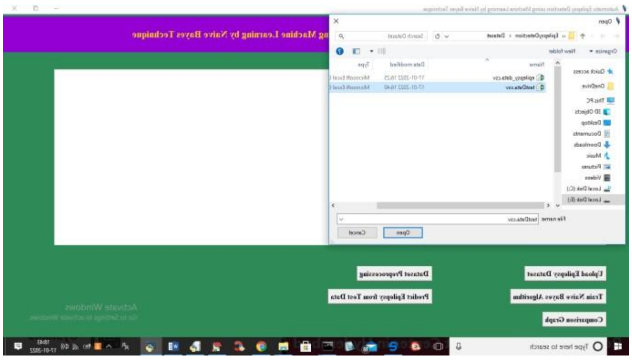
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

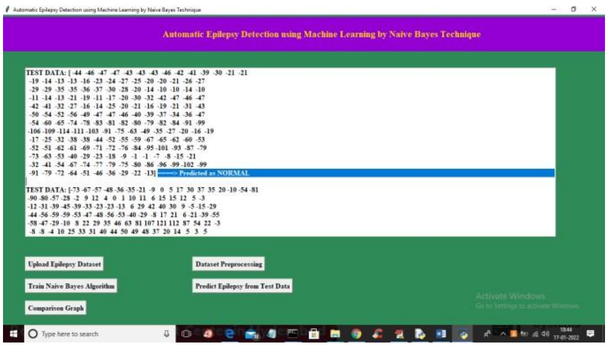
Impact Factor: 7.301

Volume 3, Issue 2, October 2023

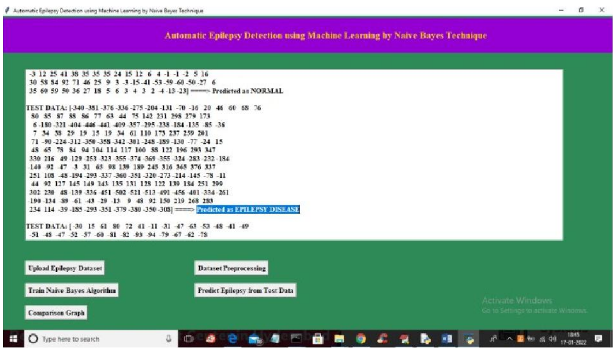
In above screen Naïve bayes training completed and we got its accuracy as 95% and in confusion matrix X-axis represents predicted classes and y-axis represents True class labels and in above graph we can see total 1817 records correctly predicted as NORMAL and only 52 records are incorrectly predicted. Now close above graph and then click on 'Predict Epilepsy from Test data' button to upload test data and get below output



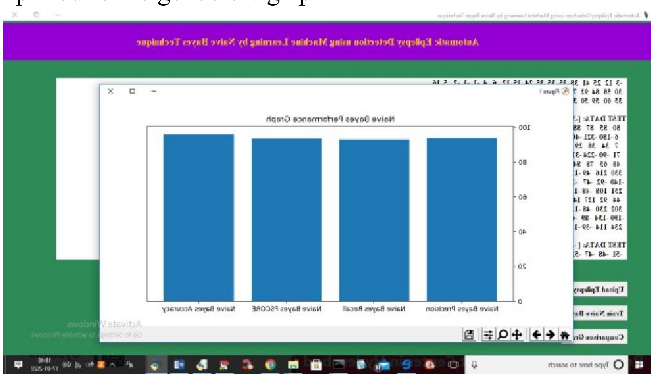
In above screen selecting and uploading 'testData.csv' file and then click on 'Open' button to load test data and to get below result



In above screen in square bracket displaying TEST DATA values and after =➔ arrow symbol displaying predicted value as NORMAL or EPILEPSY



Now click on 'Comparison Graph' button to get below graph



In above graph x-axis represents precision, recall, FSCORE And accuracy and in y-axis represents values and in above graph we can see all metrics got values closer to 100% so Naïve Bayes is good at predicting epilepsy disease

V. CONCLUSION

Epilepsy diagnosis is critical, necessitating an effective and precise approach. In our research, we introduce a novel method utilizing Multi-DWT and Genetic Algorithm in conjunction with four classifiers: SVM, ANN, KNN, and Naive Bayes for EEG signal diagnosis. The experimental outcomes exhibited promising results, with the ANN classifier displaying superior performance among all classifiers tested. The developed automated system demonstrates a high accuracy in epilepsy detection.

The process for epilepsy seizure detection involves distinct stages. Initially, preprocessing of EEG signals is conducted, which is crucial for enhancing system performance by noise elimination. The subsequent stage involves feature extraction. While various methods have been previously employed for this purpose, our study utilizes multiple DWT to decompose signals into sub-bands and compute diverse features for each sub-band. The genetic algorithm is utilized to reduce the numerous features obtained and select the most relevant ones. This results in a features matrix used in EEG signal classification.

The classification stage involves decision-making and system performance evaluation. Our approach was tested across 14 dataset combinations, using metrics such as Accuracy, Sensitivity, and Specificity. The outcomes demonstrate promising results across these metrics, indicating the efficacy of DWT analysis compared to previous studies. Notably, the artificial neural network (ANN) outperformed other classifiers in most cases, emphasizing its superior performance in the evaluation metrics for the 14 dataset combinations

REFERENCES

[1] L. Hussain, W. Aziz, A. S. Khan, A. Q. Abbasi, and S. Z. Hassan, ''Classification of electroencephlography (EEG) alcoholic and control subjects using machine learning ensemble methods,'' J. Multidiscip. Eng. Sci. Technol., vol. 2, no. 1, pp. 126–131, Jan. 2015.

[2] A. Hamad, E. H. Houssein, A. E. Hassanien, and A. A. Fahmy, ''Feature extraction of epilepsy EEG using discrete wavelet transform,'' in Proc. 12th Int. Comput. Eng. Conf. (ICENCO), Dec. 2016, pp. 190–195.

[3] U. R. Acharya, S. Vinitha Sree, G. Swapna, R. J. Martis, and J. S. Suri, ''Automated EEG analysis of epilepsy: A review,'' Knowl.-Based Syst., vol. 45, pp. 147–165, Jun. 2013.

[4] P. Sarma, P. Tripathi, M. P. Sarma, and K. K. Sarma, ''Pre-processing and feature extraction techniques for EEGBCI applications-a review of recent research,'' ADBU J. Eng. Technol., vol. 5, no. 1, pp. 1–8, 2016.

[5] C. Umale, A. Vaidya, S. Shirude, and A. Raut, ''Feature extraction techniques and classification algorithms for EEG signals to detect human stress-a review,'' Int. J. Comput. Appl. Technol. Res., vol. 5, no. 1, pp. 8–14, Jan. 2016.

[6] K. Polat and S. Güneş, ''Artificial immune recognition system with fuzzy resource allocation mechanism classifier, principal component analysis and FFT method based new hybrid automated identification system for classification of EEG signals,'' Expert Syst. Appl., vol. 34, no. 3, pp. 2039–2048, Apr. 2008.

[7] O. Salem, A. Naseem, and A. Mehaoua, ''Epileptic seizure detection from eeg signal using discrete wavelet transform and ant colony classifier,'' in Proc. IEEE Int. Conf. Commun. (ICC), Jun. 2014, pp. 3529–3534.

[8] S. A. Aljawarneh, V. Radhakrishna, and A. Cheruvu, ''VRKSHA: A novel tree structure for time-profiled temporal association mining,'' in Neural Computing and Applications. Cham, Switzerland: Springer, 2017, pp. 1–29. [Online]. Available: https://link.springer.com/article/ 10.1007%2Fs00521-018-3776-7

[9] S. A. Aljawarneh, R. Vangipuram, V. K. Puligadda, and J. Vinjamuri, ''G-SPAMINE: An approach to discover temporal association patterns and trends in Internet of Things,'' Future Gener. Comput. Syst., vol. 74, pp. 430–443, Sep. 2017.

[10] V. Radhakrishna, S. A. Aljawarneh, P. Veereswara Kumar, and V. Janaki, ''ASTRA—A novel interest measure for unearthing latent temporal associations and trends through extending basic Gaussian membership function,'' Multimedia Tools Appl., vol. 78, no. 4, pp. 4217–4265, Feb. 2019.

[11] V. Radhakrishna, S. A. Aljawarneh, V. Janaki, and P. Kumar, ‘‘Looking into the possibility for designing normal distribution based dissimilarity measure to discover time profiled association patterns,’’ in Proc. Int. Conf. Eng. MIS (ICEMIS), May 2017, pp. 1–5.
[12] S. M. Akareddy and P. K. Kulkarni, ‘‘EEG signal classification for epilepsy seizure detection using improved approximate entropy,’’ Int. J. Public Health Sci., vol. 2, no. 1, pp. 23–32, Feb. 2013.
[13] A. Baldominos and C. Ramon-Lozano, ‘‘Optimizing EEG energy- based seizure detection using genetic algorithms,’’ in Proc. IEEE Congr. Evol. Comput. (CEC), Jun. 2017, pp. 2338–2345.
[14] N. Williams, S. Zander, and G. Armitage, ‘‘A preliminary performance comparison of five machine learning algorithms for practical IP traffic flow classification,’’ ACM SIGCOMM Comput. Commun. Rev., vol. 36, no. 5, pp. 5–16, 2006.
[15] L. Guo, D. Rivero, and A. Pazos, ‘‘Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks,’’ J. Neurosci. Methods, vol. 193, no. 1, pp. 156–163, 2010.
[16] R. Moshrefi, M. G. Mahjani, and M. Jafarian, ‘‘Application of wavelet entropy in analysis of electrochemical noise for corrosion type identification,’’ Electrochem. Commun., vol. 48, pp. 49–51, Nov. 2014.
[17] D. Chen, S. Wan, J. Xiang, and F. S. Bao, ‘‘A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG,’’ PLoS ONE, vol. 12, no. 3, Mar. 2017, Art. no. e0173138.
[18] A. Sharmila and P. Geethanjali, ‘‘DWT based detection of epileptic seizure from eeg signals using naive Bayes and k-NN classifiers,’’ IEEE Access, vol. 4, pp. 7716–7727, 2016.
[19] S. Madan, K. Srivastava, A. Sharmila, and P. Mahalakshmi, ‘‘A case study on discrete wavelet transform based hurst exponent for epilepsy detection,’’ J. Med. Eng. Technol., vol. 42, no. 1, pp. 9–17, Jan. 2018.
[20] D. Selvathi and V. K. Meera, ‘‘Realization of epileptic seizure detection in EEG signal using wavelet transform and SVM classifier,’’ in Proc. Int. Conf. Signal Process. Commun. (ICSPC), Coimbatore, India, Jul. 2017, pp. 18–22, doi: 10.1109/cspc.2017.8305848.
[21] B. Harender and R. K. Sharma, ‘‘DWT based epileptic seizure detection from EEG signal using k-NN classifier,’’ in Proc. Int. Conf. Trends Electron. Informat. (ICEI), Tirunelveli, India, May 2017, pp. 762–765, doi: 10.1109/icoei.2017.8300806.
[22] S. Lahmiri and A. Shmuel, ‘‘Accurate classification of seizure and seizurefree intervals of intracranial EEG signals from epileptic patients,’’ IEEE Trans. Instrum. Meas., vol. 68, no. 3, pp. 791–796, Mar. 2019, doi: 10. 1109/tim.2018.2855518.
[23] G. Wang, D. Ren, K. Li, D. Wang, M. Wang, and X. Yan, ‘‘EEG- based detection of epileptic seizures through the use of a directed transfer function method,’’ IEEE Access, vol. 6, pp. 47189–47198, 2018, doi: 10. 1109/access.2018.2867008.
[24] Z. Zakeri, S. Assecondi, A. P. Bagshaw, and T. N. Arvanitis, ‘‘Influence of signal preprocessing on ICA-based EEG decomposition,’’ in Proc. 13th Medit. Conf. Med. Biol. Eng. Comput. Cham, Switzerland: Springer, 2013, pp. 734–737.
[25] A. Hamad, E. H. Houssein, A. E. Hassanien, and A. A. Fahmy, ‘‘A hybrid EEG signals classification approach based on grey wolf optimizer enhanced SVMs for epileptic detection,’’ in Proc. Int. Conf. Adv. Intell. Syst. Inform. Cham, Switzerland: Springer, Sep. 2017, pp. 108–117.
[26] A. Hamad, E. H. Houssein, A. E. Hassanien, and A. A. Fahmy, ‘‘Hybrid grasshopper optimization algorithm and support vector machines for automatic seizure detection in EEG signals,’’ in Proc. Int. Conf. Adv. Mach. Learn. Technol. Appl. Cham, Switzerland: Springer, Feb. 2018, pp. 82–91.
[27] M. Kołodziej, A. Majkowski, and R. J. Rak, ‘‘A new method of EEG classification for BCI with feature extraction based on higher order statistics of wavelet components and selection with genetic algorithms,’’ in Proc. Int. Conf. Adapt. Natural Comput. Algorithms. Berlin, Germany: Springer, Apr. 2011, pp. 280–289.
[28] J. A. Nasiri, M. Sabzekar, H. S. Yazdi, M. Naghibzadeh, and B. Naghibzadeh, ‘‘Intelligent arrhythmia detection using genetic algorithm and emphatic SVM (ESVM),’’ in Proc. 3rd UKSim Eur. Symp. Comput. Modeling Simulation, Nov. 2009, pp. 112–117.
[29] Y. Kaya, M. Uyar, R. Tekin, and S. Yıldırım, ‘‘1D-local binary pattern based feature extraction for classification of epileptic EEG signals,’’ Appl. Math. Comput., vol. 243, pp. 209–219, Sep. 2014.

[30] D. Torse, V. Desai, and R. Khanai, ''A review on seizure detection systems with emphasis on multi-domain feature extraction and classification using machine learning,'' BRAIN. Broad Res. Artif. Intell. Neurosci., vol. 8, no. 4, pp. 109–129, 2017.

[31] A. S. Al-Fahoum and A. A. Al-Fraihat, ''Methods of EEG signal features extraction using linear analysis in frequency and time- frequency domains,'' ISRN Neurosci., vol. 2014, pp. 1–7, Feb. 2014.

[32] U. R. Acharya, C. K. Chua, T.-C. Lim, Dorithy, and J. S. Suri, ''Automatic identification of epileptic EEG signals using nonlinear parameters,'' J. Mech. Med. Biol., vol. 9, no. 4, pp. 539–553, Dec. 2009, doi: 10.1142/S0219519409003152.

[33] P. Jahankhani, J. A. Lara, A. Pérez, and J. P. Valente, ''Two different approaches of feature extraction for classifying the EEG signals,'' in Engineering Applications of Neural Networks, vol. 363. L. Iliadis and C. Jayne. Berlin, Germany: Springer, 2011.

[34] P. Jahankhani, V. Kodogiannis, and K. Revett, ''EEG signal classification using wavelet feature extraction and neural networks,'' in Proc. IEEE John Vincent Atanasoff Int. Symp. Mod. Comput. (JVA), Sofia, Bulgaria, Oct. 2006, pp. 120–124, doi: 10.1109/jva.2006.17.

[35] A. Miltiadous et al., "Machine Learning Algorithms for Epilepsy Detection Based on Published EEG Databases: A Systematic Review," in IEEE Access, vol. 11, pp. 564-594, 2023, doi: 10.1109/ACCESS.2022.3232563.

[36] T. M. Ingolfsson, A. Cossettini, S. Benatti and L. Benini, "Energy- Efficient Tree-Based EEG Artifact Detection," 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Glasgow, Scotland, United Kingdom, 2022, pp. 3723-3728, doi: 10.1109/EMBC48229.2022.9871413.

[37] P. Khan et al., "Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances," in IEEE Access, vol. 9, pp. 37622-37655, 2021, doi: 10.1109/ACCESS.2021.3062484.

[38] M. Yazid et al., "Simple Detection of Epilepsy From EEG Signal Using Local Binary Pattern Transition Histogram," in IEEE Access, vol. 9, pp. 150252-150267, 2021, doi: 10.1109/ACCESS.2021.3126065.

[39]W. Mardini, M. M. Bani Yassein, R. Al-Rawashdeh, S. Aljawarneh, Y. Khamayseh and O. Meqdadi, "Enhnced Detection of Epileptic Seizure Using EEG Signals in Combination With Machine Learning Classifiers," in IEEE Access, vol. 8, pp. 24046-24055, 2020, doi: 10.1109/ACCESS.2020.2970012.

[40] Z. Chen, G. Lu, Z. Xie and W. Shang, "A Unified Framework and Method for EEG-Based Early Epileptic Seizure Detection and Epilepsy Diagnosis," in IEEE Access, vol. 8, pp. 20080-20092, 2020, doi: 10.1109/ACCESS.2020.2969055