Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024

EPILEPTIC SEIZURE DETECTION IN EEG SIGNALS USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

Dr. Abdul Khadeer, Associate Professor, Department of CSE, Deccan College of Engineering and Technology, Osmania University, Hyderabad, Telangana : abdulkhadeer@deccancollege.ac.in
Sulemaan Saleem Mohammed, PG Scholar, Department of CSE, Deccan College of Engineering and Technology, Osmania University, Hyderabad, Telangana : sulemaansm123@gmail.com

***Abstract*— This research presents a novel approach to detecting epileptic seizures leveraging the strengths of Machine Learning (ML) and Deep Learning (DL) algorithms in EEG signals. Epileptic seizures are neurological events with distinctive features found in Electroencephalography (EEG) that lend considerable credibility to researchers. Machine Learning (ML) and Deep learning (DL) algorithms have emerged as powerful feature extraction and classification tools in EEG signal analysis. Many studies have converted the EEG signals into either images and /or calculated time-frequency domain features and performed classification. This study focuses on classifying time-series data representation of EEG signals with machine learning-based classifiers by tuning parameters and deep learning-based One-Dimensional Neural Network (ANN) methods. The primary objective is not only to determine the optimal classifier but also to emphasize critical metrics such as sensitivity, precision, and accuracy, which are critical in medical investigations, particularly for the early detection of diseases and patient care optimization. The UCI Epileptic Seizure Recognition dataset used in this study consists of time-series data points extracted from the EEG signals. The dataset has been preprocessed and fed to the classifiers, namely Extreme SVM, ANN, Navie Bayes, KNN, Logistic regression, and achieved encouraging accuracies of 98%, 97%, 95.2%, and 94%, respectively.**

.

***Index Terms*— Deep Learning (DL), Machine Learning (ML), SVM , Epileptic Seizures**

I. INTRODUCTION

Epilepsy, a neurological disorder affecting approximately 50 million individuals globally, stands as one of the most prevalent neurological diseases worldwide, as reported by the World Health Organization. It is characterized by recurrent and unpredictable seizures. Epileptic seizures pose a significant challenge to the quality of life for affected individuals [1]. It is marked by a tendency for recurrent episodes across one's lifespan. Epileptic seizures can manifest under diverse circumstances, encompassing factors such as skull fractures, genetic predisposition, tumors, and other contributing factors [2]. It is found that anyone can be affected at any age, but it is most initiated in childhood or over the age of 65 [3]. An epileptic seizure is a sudden and temporary disturbance in the normal functioning of the brain, characterized by abnormal and excessive electrical activity. This electrical activity can result in various physical and mental manifestations, ranging from subtle sensations to convulsions and loss of consciousness, and sometimes leads to sudden, unexpected death [4]. Accurate detection of seizures in epilepsy patients is vital for diagnosing the condition correctly and devising personalized treatment strategies. A better quality of life and reduced life risks can be ensured through early diagnosis and continuous monitoring of seizures. The purpose of analyzing the electroencephalogram (EEG) signals, which record electrical activity in the brain, is to evaluate patients with known seizures to detect the accurate seizure type [5]. Epileptic EEG signals provide a dynamic representation of neural activity, capturing the intricate patterns associated with seizures. EEG signals are recorded using electrodes attached to the scalp. These electrodes detect the electrical impulses generated by neurons in the brain. Raw EEG signal data often contains noise and irrelevant information. Preprocessing steps, such as filtering, artifact removal, and baseline correction, are applied to clean the signals and enhance their quality. Once preprocessing is done, feature selection and extraction play a crucial role in epileptic seizure detection using EEG signal classification [6]. Extracting relevant features from the signal data provides more discriminative information than the raw signal alone. Machine learning and Deep learning techniques have shown remarkable potential in extracting relevant features and classifying them in various medical applications, including epilepsy diagnosis. Epileptic seizures can vary widely in their presentation, severity, and duration. The brain's regular activity results from intricate communication between neurons through electrical signals. In individuals with epilepsy, there is a tendency for the brain's neurons to fire excessively and abnormally, leading to a seizure. Seizures can be classified into different types based on their characteristics and the brain regions from which they originate. In Figure 1, we observe the diverse patterns of EEG signals recorded from different brain regions: the healthy brain area, the region affected by a tumor, and during a seizure event. In healthy brain areas, we typically observe regular, rhythmic patterns characterized by consistent frequency and amplitude, which reflect normal electrical activity. At the tumor site, the EEG signals exhibit alterations compared to those from the healthy brain area. These can manifest in various ways depending on the nature and location of the tumor. However, during a seizure event, the EEG signals exhibit distinctive patterns that reflect abnormal neuronal activity with high frequency and amplitude. This study employs various ML classifiers and a ANN network to classify EEG time-series data. This approach allows for a comprehensive comparison of different classification techniques, enabling insights into which methods are most effective for seizure detection. The aim of this study is not only to acquire the best accuracy but also to demonstrate a commitment to addressing the real-world needs of healthcare practitioners and patients. The focus is on the critical metrics relevant to medical diagnosis and decision-making, such as sensitivity, the ability to identify seizures and specificity correctly, and the ability to correctly identify non-seizures to classify EEG time-series data, explicitly targeting the accurate prediction of epileptic seizures. The dataset used in this study consists of time series data points that represent the value of the EEG signal at a particular time. Further, the data was preprocessed and classified using Machine learning methods. The parameters of the classifiers are tuned according to the nature of the dataset to acquire qualitative results and high-performance evaluations.

II. LITERATURE REVIEW

The paper "Seizures and Epilepsy in the Elderly: Diagnostic and Treatment Considerations "is to highlight important clinical aspects in diagnosis and management of epilepsy in the elderly and to highlight recent literature and its relevance to current practice. Recent studies have shown that elderly patients are under referred for evaluation to epilepsy monitoring units and for epilepsy surgery, which has been demonstrated to be safe and effective in this population. The elderly are at increased risk for acute symptomatic seizures and epilepsy. Accurate diagnosis can be challenging in older patients due to limitations in history, atypical symptoms, and medical comorbidities. Inpatient video-EEG monitoring is a valuable tool for the clinician when diagnosis is unclear or patients are unresponsive to medication. Drug resistance rates in the elderly are like younger adults with epilepsy, but elderly patients are less likely to be referred for epilepsy monitoring unit admissions and epilepsy surgery, despite evidence of safety and effectiveness.

This paper "Epilepsy Seizure Detection Using Optimized KNN Algorithm Based on EEG" Modern artificial intelligence relies heavily on the concept of machine learning. It has rapidly developed and been used widely in numerous sectors during the past 20 years. The epileptoid cortex can be identified most precisely by electroencephalography (EEG). Age and recording techniques, such as sleep records and activation processes, have an impact on the sensitivity and specificity of the device (hyperventilation, photic stimulation). Several epilepsy disorders have distinctive EEG characteristics. In recent years, it has been noted that machine learning is widely being used in medicine. The literature review presents different machine learning methods for EEG signal processing in epilepsy research, with particular emphasis on applications for automated seizure identification, prediction, and orientation. Because an EEG signal is non-stationary and has a significant degree of time variation, it can be analyzed using non-linear methods. Therefore, we have used the discrete wavelet transform (DWT) which is used to extract the frequency components of the EEG. And we have proposed a better hybrid algorithm for detection.

This paper "1D-local binary pattern-based feature extraction for classification of epileptic EEG signals" an effective approach for the feature extraction of raw Electroencephalogram (EEG) signals by means of one-dimensional local binary pattern (1D-LBP) was presented. For the importance of making the right decision, the proposed method was performed to be able to get better features of the EEG signals. The proposed method was consisted of two stages: feature extraction by 1D-LBP and classification by classifier algorithms with features extracted. On the classification stage, the several machine learning methods were employed to uniform and non-uniform 1D-LBP features. The proposed method was also compared with other existing techniques in the literature to find out benchmark for an epileptic data set. The implementation results showed that the proposed technique could acquire high accuracy in classification of epileptic EEG signals. Also, the present paper is an attempt to develop a general-purpose feature extraction scheme, which can be utilized to extract features from different categories of EEG signals.

In this paper "Pilot study of a single-channel EEG seizure detection algorithm using machine learning" The dataset applied in our algorithm contains EEG recordings from human neonates. A 19-channel EEG system recorded the brain waves of 79 term neonates admitted to the NICU at the Helsinki University Hospital. From these datasets, we selected six patients with conformational seizure annotations for the pilot study and allocated four and two patients for our training and testing datasets, respectively. The presence of seizures in the EEGs was annotated independently by three experts through visual interpretation. We divided the data into epochs of 5 s each and further defined a seizure block to label the annotations from each expert recorded every second. Subsequently, to create a balanced dataset, any data point with a non-seizure label was moved to the training and test dataset.

In this paper "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier" Analysis of electroencephalogram (EEG) signal is crucial due to its non-stationary characteristics, which could lead the way to proper detection method for the treatment of patients with neurological abnormalities, especially for epilepsy. The performance of EEG-based epileptic seizure detection relies largely on the quality of selected features from an EEG data that characterize seizure activity. This paper presents a novel analysis method for detecting epileptic seizure from EEG signal using Improved Correlation-based Feature Selection method (ICFS) with Random Forest classifier (RF). The analysis involves, first applying ICFS to select the most prominent features from the time domain, frequency domain, and entropy-based features. An ensemble of Random Forest (RF) classifiers is then learned on the selected set of features. The experimental results demonstrate that the proposed method shows better performance compared to the conventional Correlation-based method and also outperforms some other state-of-the-art methods of epileptic seizure detection using the same benchmark EEG dataset.

The EEG signal, characterized by non-stationary behaviour and notable time variations, necessitates applying non-linear analytical methods. To address this, [7] employed the discrete wavelet transform (DWT) to extract the intricate frequency components inherent in EEG signals. Their proposed approach utilizes an optimized k-nearest neighbours (KNN) algorithm for enhanced detection accuracy.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024
The quantitative features have been extracted from the EEG data using a one-dimensional local binary pattern (IDLBP) in [8], and these features were fed to various classifiers, which include logistic regression, Bayes Net, SVM, ANN, and functional tree. The authors in [9] introduced a novel seizure detection algorithm that employs principal component analysis (PCA) for feature extraction. The algorithm compares these features with other machine learning (ML) algorithms, incorporating four prediction models: logistic regression (LR), dense trees, 2D-support vector machine (2D-SVM), and cosine k-nearest neighbour (cos-KNN). The algorithm enhanced training and test dataset's performance by leveraging PCA to reduce data dimensions.

Furthermore, The authors in [10] introduce an innovative approach to identifying epileptic seizures in EEG signals through the application of the Improved Correlation-based Feature Selection method (ICFS) in conjunction with the Random Forest classifier (RF). The methodology entails an initial step of employing ICFS to extract key features from the time domain, frequency domain, and entropy-based features. Subsequently, the Random Forest ensemble is trained on a refined set of selected features. Furthermore, the authors in [11] chose fourteen highly correlated features using the Chi-square tests. They applied classifiers such as random forest, decision tree, support vector machine, k-nearest neighbour, and Tab Net. Extraction of meaningful features from EEG signals will directly impact the classification of the model's performance [12].

The Convolutional Neural Network (CNN) employs various filters in its convolutional layers to extract a distinctive and rich set of meaningful features. However, one-dimensional CNNs are suitable for tasks where the input data is structured in a sequence, time-series data. In [13], the author proposed a 1D-CNN approach by converting EEG signals into 2D/3D images and achieved an accuracy of 96.30%.

In [14], nineteen EEG data channels were selected, and then the signals were resampled at a frequency of 256Hz. Subsequently, these signals were partitioned into time frames of 3 seconds each. Further, we feed the data into the Comvest model for epileptic seizure identification. Another study [15] proposed an innovative method capable of autonomously extracting features from deep within a CNN and generating easily interpretable rules for classifying seizures in EEG signals. Their objective is to elucidate the internal logic, providing neurologists with valuable insights for decision-making, whereas [16] proposed a 13-layer deep CNN algorithm to detect normal, preictal, and seizure classes. Their proposed method achieved accuracy, sensitivity, and specificity of 88.67%, 95.00%, and 90.00%, respectively

In this paper "Machine learning applications to differentiate comorbid functional seizures and epilepsy from pure functional seizures This was a retrospective study of an electronic database of patients with seizures. All patients with a diagnosis of FS (with or without comorbid epilepsy) were studied at the outpatient epilepsy clinic at Shiraz University of Medical Sciences, Shiraz, Iran, from 2008 until 2021. We arbitrarily selected 14 features that are important in making the diagnosis of patients with seizures and also are easily obtainable during history taking. Pytorch and Scikit-learn packages were used to construct various models including random forest classifier, decision tree classifier, support vector classifier, k-nearest neighbor, and TabNet classifier.

III. EXISTING METHODS:

- In existing methos EEG data channels were selected, and then the signals were resampled at a frequency of 256Hz. Subsequently, these signals were partitioned into time frames of 3 seconds each.
- Further, it feed the data into the ConvLSTM model for epileptic seizure identification. Another study proposed an innovative method capable of autonomously extracting features from deep within a CNN and generating easily interpretable rules for classifying seizures in EEG signals.
- Their objective is to elucidate the internal logic, providing neurologists with valuable insights for

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024
decision-making, whereas proposed a 13-layer deep CNN algorithm to detect normal, preictal, and seizure classes. Their existing method achieved accuracy, sensitivity, and specificity of

88.67%, 91.00%, and 90.00%, respectively.

IV. PROPOSED SYSTEM

The proposed system for epileptic seizure detection utilizes multiple algorithms, including SVM, Logistic Regression, Naive Bayes, kNN, and ANN, to analyze EEG signals. SVM and ANN are found to deliver the highest accuracy, with SVM achieving 98% and ANN 95.6%, making them the most effective in this setup. The comparison highlights SVM and ANN as superior choices for accurate seizure detection, balancing performance and computational efficiency. Multiple machine learning Deep learning algorithms are trained and best algorithm is used for

METHODOLOGY:

- **User module:**

  User need to collect data set from kaggle website. This dataset has features and labels which are used for prediction. User can load data using flask web framework and enter all EEG data related to Epileptic Seizure disease and predict if patient has Epileptic Seizure disease or not.
- **Preprocessing Module:**

  This is preprocessing module where datasets are converted to training data and then converted to single combined dataset. This dataset is used as input for application in the next for creating model.
- **Split dataset:**
- In this step dataset is split in to training and testing phase and training data is used to input to model and test set is used for calculating accuracy of the model.
- **Model Evaluation and Predictions:**

  In this step, in which we assess how well our model has performed on testing data using certain scoring metrics, I have used 'accuracy score' to evaluate my model. First, we create a model instance, this is followed by fitting the training data on the model using a fit method and then we will use the predict method to make predictions on x_test or the testing data, these predictions will be stored in a variable called y_test_hat. For model evaluation, we will feed the y_test and y_test_hat into the accuracy_score function and store it in a variable called test_accuracy, a variable that will hold the testing accuracy of our model. We followed these steps for a variety of classification algorithm models and obtained corresponding test accuracy scores.

- **Model training Module:**

  In this stage final dataset is taken as in put and model is created using Multiple machine learning and DL (SVM, Navie Bayes, Logistic Regression, ANN) algorithms are used and process is in three steps.

  First data is dividing in to testing and training set and features and labels are extracted from these datasets and then data is trained and fitting is done. Then a pkl file is created which is

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024
model for this application.
This pkl file is used as model for predicting results.

- **Flask web app:**
  Flask webapp with MySQL database is used to develop a website. User can register with application, login and upload EEG data of patients which is in csv file and predict to get if respective patient has Epileptic Seizure or not.

ARCHITECTURE:

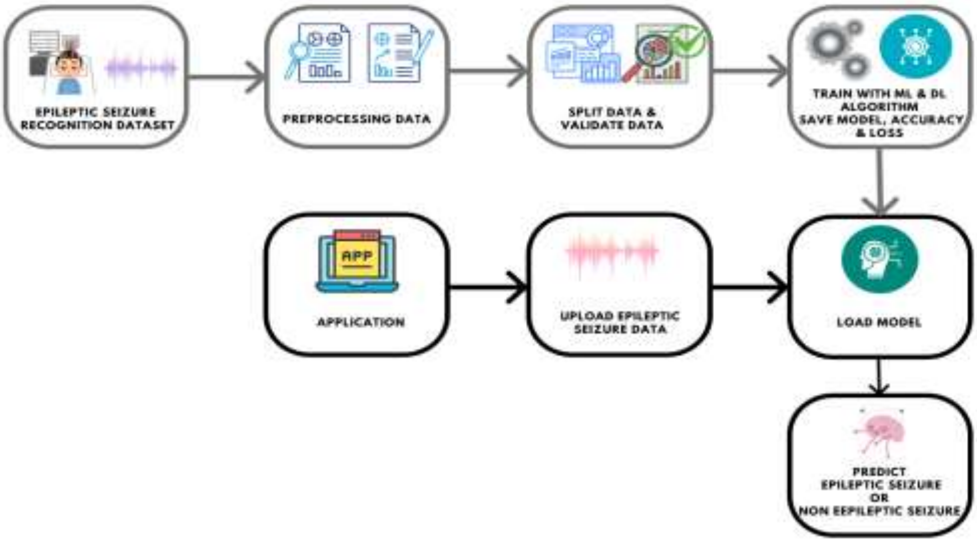


Figure 1. System Architecture

Figure 1 illustrates the framework of the proposed method ology representing data processing, classifiers, and a set of evaluation metrics employed in the approach. In the feature extraction process, the authors in [18] extracted data points from the EEG signals. In our study, we considered those extracted datapoints as features and further preprocessed and normalized to ensure all the features are on a consistent scale, preventing certain features from dominating others in the learning process. Further, the data was fed to the classifiers and evaluated with the following metrics.

SVM:

Support Vector Machine (SVM) is a supervised learning model that excels in classification tasks by finding the optimal hyperplane to separate different classes, particularly effective in high-dimensional spaces.

ANN:

Artificial Neural Networks (ANN) mimic the human brain's structure, capable of learning complex patterns and features from data, making them highly effective in tasks requiring deep learning.

Logistic Regression:

A statistical model that estimates the probability of a binary outcome based on input features, often used for classification tasks.

Navie Bayes:

A probabilistic classifier based on Bayes' theorem, assuming independence between features, which works well with small datasets and for text classification.

KNN:

k-Nearest Neighbors (kNN) is a simple, non-parametric algorithm that classifies a data point based on the majority class among its k nearest neighbors, effective in pattern recognition but computationally intensive.

FLOW DIAGRAM:

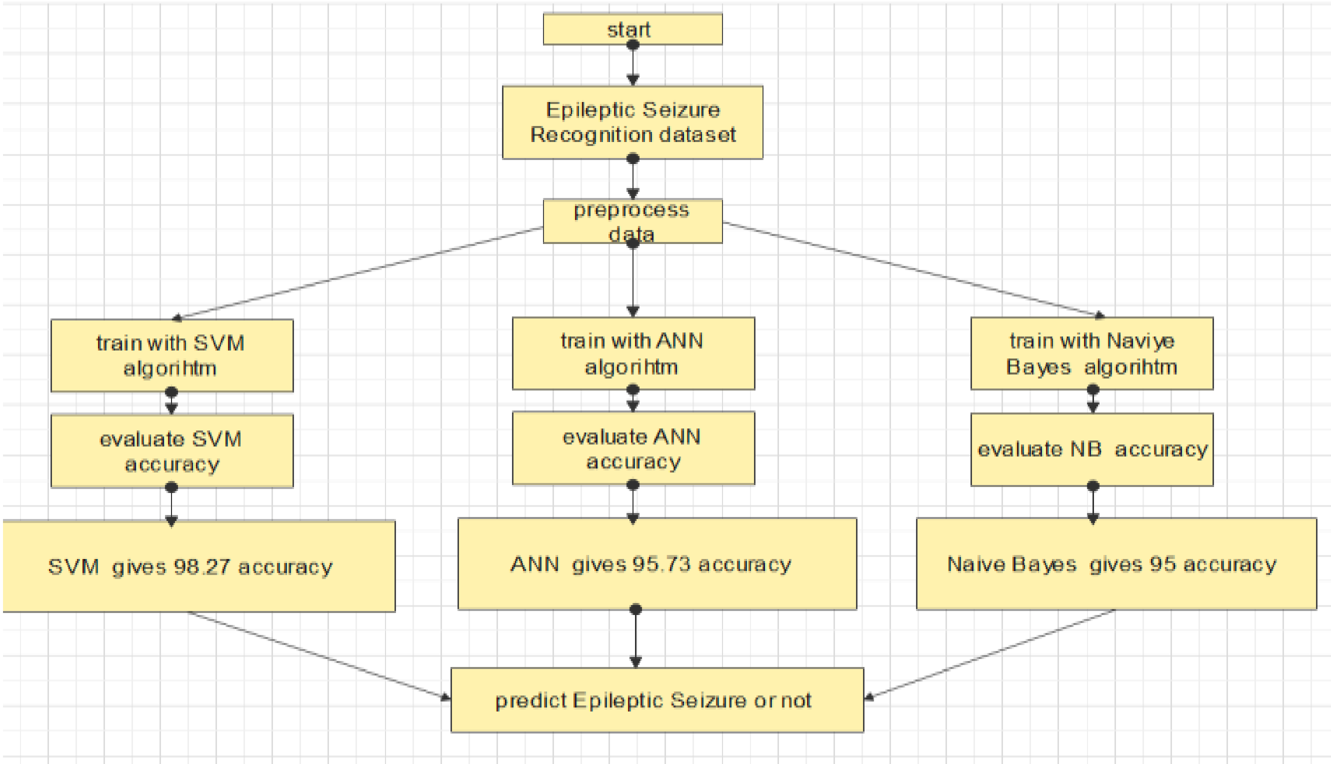


Figure 2. Model Flow Diagram

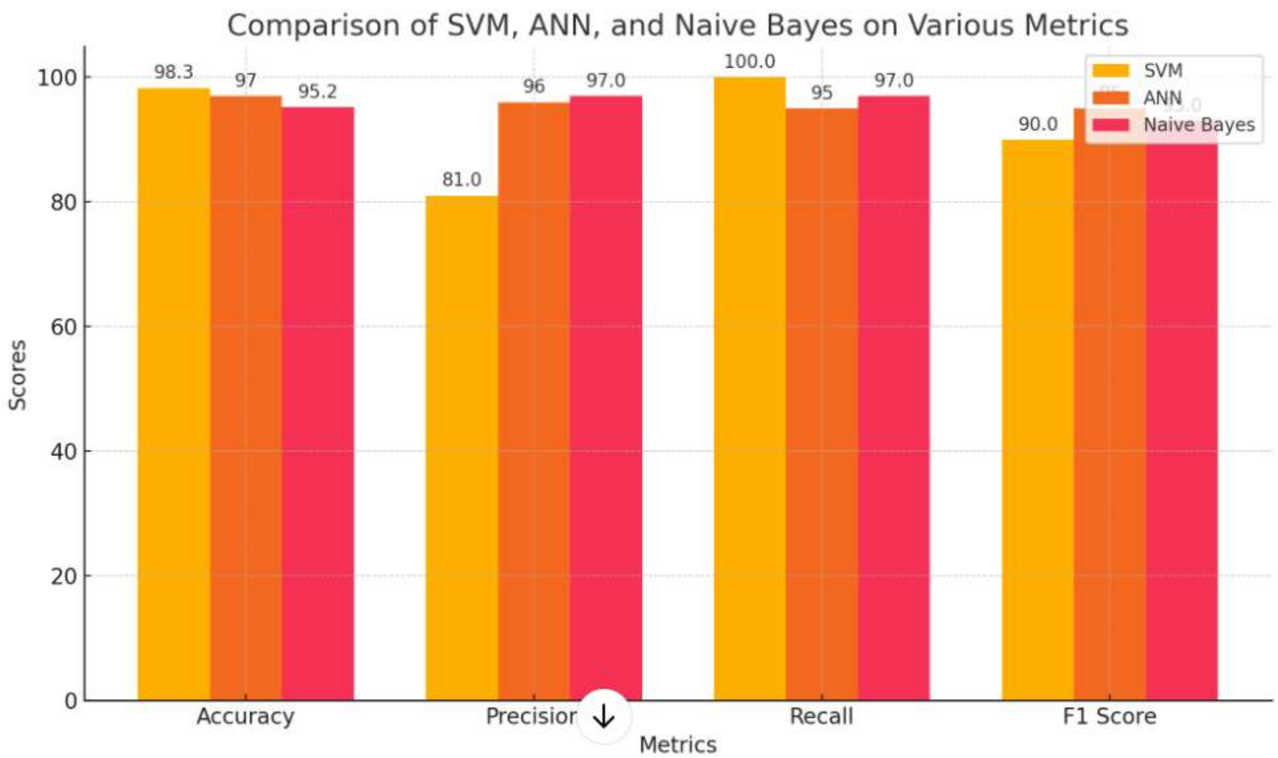
V. EVALUATION METRICS

Comparative analysis on different machine learning

Algorithm	Accuracy	Precision	Recall	F1 Score
SVM	98.3	81	100	90
ANN	97	96	95	95
Navie Bayes	95.2	97	97	93

Above table shows comparison table for various algorithms showing accuracy, precision, recall and F1 score for (SVM, ANN AND NAVIE BAYES) from above table svm gives more accuracy compare to other algorithms.

COMPARISION GRAPH:



Abo ve graph shows comparison graph comparing various parameters accuracy, precison and recall values for three algorithms.

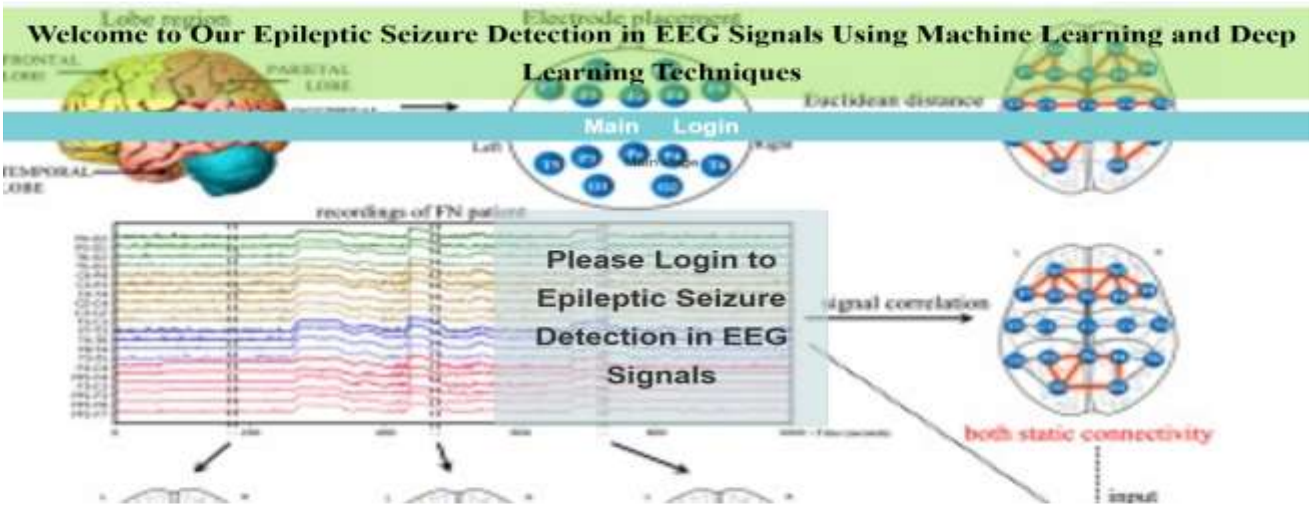
Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024

.
RESULTS:

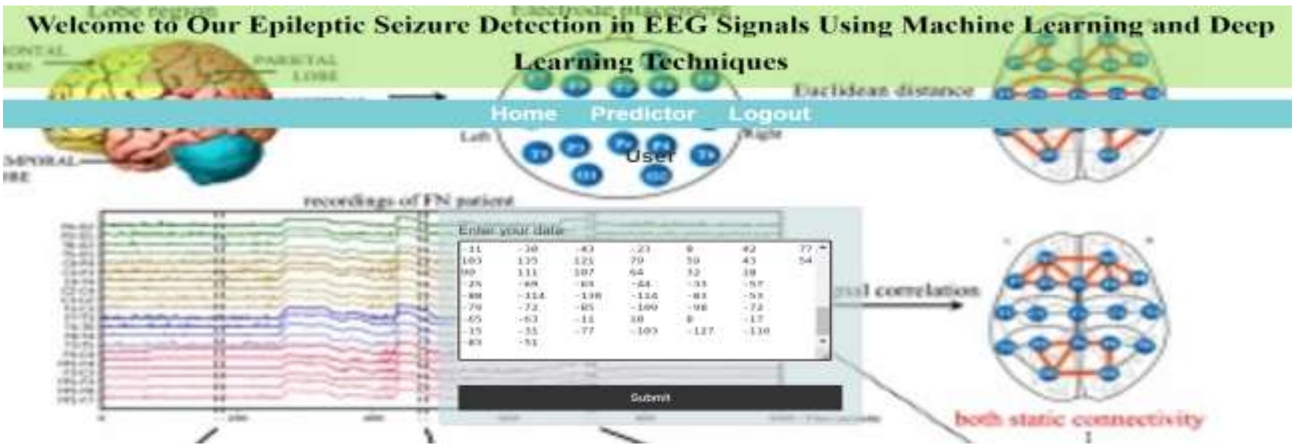
DATASET:

1	Unnamed	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18
2	X21.V1.79	135	190	229	223	192	125	55	-9	-33	-38	-10	35	64	113	152	164	127	50
3	X15.V1.92	386	382	356	331	320	315	307	272	244	232	237	258	212	2	-267	-605	-850	-1001
4	X8.V1.1	-32	-39	-47	-37	-32	-36	-57	-73	-85	-94	-99	-94	-96	-104	-103	-92	-75	-69
5	X16.V1.60	-105	-101	-96	-92	-89	-95	-102	-100	-87	-79	-72	-68	-74	-80	-83	-73	-68	-61
6	X20.V1.54	-9	-65	-98	-102	-78	-48	-16	0	-21	-59	-90	-103	-84	-43	-9	3	-21	-60
7	X14.V1.56	55	28	18	16	16	19	25	40	52	66	81	98	111	122	105	85	66	51
8	X3.V1.191	-55	-9	52	111	135	129	103	72	37	0	-38	-77	-113	-128	-121	-105	-71	-27
9	X11.V1.27	1	-2	-8	-11	-12	-17	-15	-16	-18	-17	-19	-18	-16	-15	-14	-21	-19	-24
10	X19.V1.87	-278	-246	-215	-191	-177	-167	-157	-139	-118	-92	-63	-39	-11	14	36	60	70	78
11	X3.V1.491	8	15	13	3	-6	-8	-5	4	25	41	48	44	34	16	-2	-11	-24	11
12	X3.V1.6	-5	15	28	28	9	-29	-41	-19	14	30	22	-6	-30	-40	-42	-48	-50	-55
13	X21.V1.72	-167	-230	-280	-315	-338	-369	-405	-392	-298	-140	27	146	211	223	214	187	167	166
14	X7.V1.162	92	49	0	-32	-51	-65	-37	-19	-25	-29	-52	-62	-85	-107	-97	-69	-46	-37
15	X1.V1.211	15	12	0	-17	-28	-31	-39	-51	-44	-35	-20	1	16	24	22	26	27	22
16	X1.V1.615	-24	-15	-5	-1	4	3	6	10	11	7	8	12	10	10	5	-1	-11	-13
17	X22.V1.24	-135	-133	-125	-118	-111	-105	-102	-93	-94	-90	-82	-75	-71	-69	-69	-69	-61	-59
18	X1.V1.863	39	41	41	42	43	43	46	47	49	50	52	52	53	59	58	63	62	64
19	X9.V1.302	9	4	-5	-10	-22	-30	-33	-43	-41	-40	-42	-46	-47	-52	-50	-51	-43	-34
20	X7.V1.541	-21	-5	1	7	19	20	13	2	-1	-3	-3	-14	-18	-21	-2	17	39	56
21	X9.V1.915	4	24	51	76	92	102	104	101	90	80	53	32	9	5	17	42	72	94
22	X23.V1.96	410	451	491	541	581	641	736	757	692	435	61	-387	-823	-1107	-1188	-1110	-947	-765
23	X1.V1.614	-24	-27	-23	-28	-34	-40	-47	-43	-38	-23	-1	7	18	7	11	-1	-18	-22
24	X11.V1.13	-264	-189	-117	-45	20	70	111	143	161	179	194	200	193	164	128	92	67	57

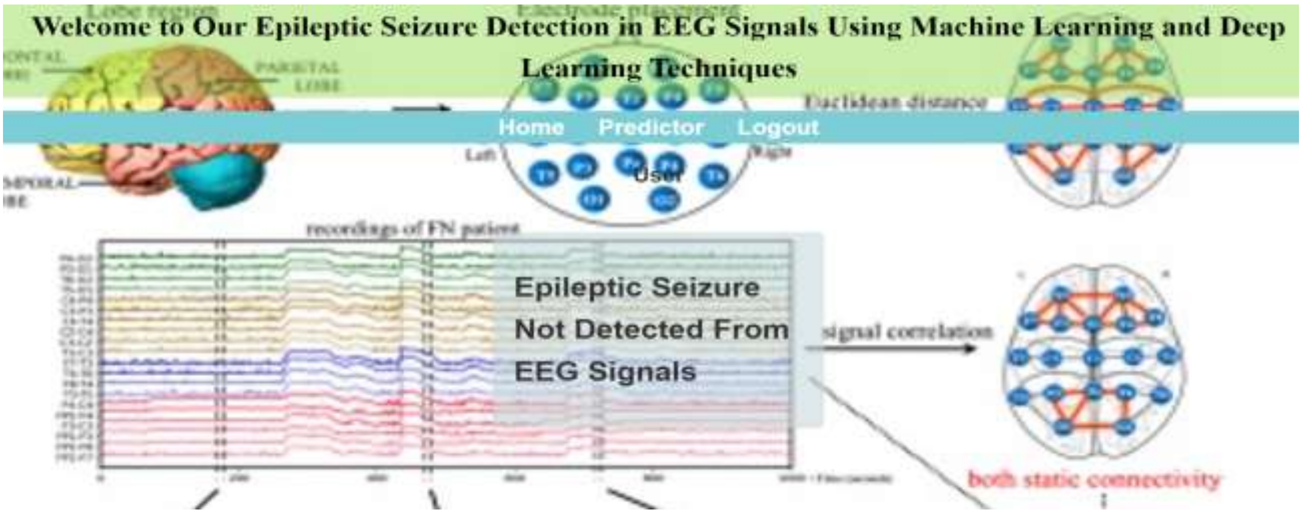
Home Page:



Input Form:



Prediction Result:



VI. CONCLUSION

The project demonstrates that Support Vector Machines (SVM) are highly effective in detecting epileptic seizures from EEG signals, achieving an accuracy of 98.3%, which surpasses both Artificial Neural Networks (ANN) at 97% and Naive Bayes (NB) at 95%. The superior performance of SVM underscores its capability to handle high-dimensional and complex datasets like EEG signals, making it a robust choice for seizure detection. While ANN also provides competitive results, SVM's marginally better accuracy suggests its suitability for clinical applications where precision is critical. Overall, the study validates the effectiveness of machine learning techniques in automating the detection of epileptic seizures.

VII. FUTURE SCOPE

Future work can focus on enhancing the model's generalizability by incorporating a larger and more diverse dataset, including EEG signals from various sources and different patient demographics. Additionally, integrating deep learning techniques like Convolutional Neural Networks (CNNs) could further improve accuracy by capturing spatial features in EEG data. Real-time deployment in clinical settings could also be explored, ensuring that the models perform efficiently in dynamic environments. Moreover, developing a hybrid model that combines the strengths of SVM, ANN, and other algorithms could lead to even higher detection accuracy. Lastly, user-friendly interfaces for non-expert clinicians could be designed to make the technology more accessible in medical practice.

VIII. REFERENCES

[1] L. DeClerck, A. Nica, and A. Biraben, ‘‘Clinical aspects of seizures in the elderly,’’ Geriatr Psychol. Neuropsychiatr Vieil., vol. 17, no. 1, pp. 7–12, Mar. 2019.
[2] S.NallaandS.Khetavath,‘‘Areviewonepilepticseizuredetectionandpre diction,’’ in Intelligent Manufacturing and Energy Sustainability. Cham, Switzerland: Springer, 2023, pp. 225–232.
[3] A. S. Daoud, A. Batieha, M. Bashtawi, and H. El-Shanti, ‘‘Risk factors for childhood epilepsy: A case-control study from Irbid, Jordan,’’ Seizure, vol. 12, no. 3, pp. 171–174, Apr. 2003.
[4] K. You Harris. Need (2018). Immediate The Dangers Treatment. of Seizures: [Online]. Why
[5] J. W. Britton, L. C. Frey, and J. L. Hopp, An Introductory Text and Atlas of

NormalandAbnormalFindingsinAdults,Children,andInfants[Internet]. Chicago, IL, USA: American Epilepsy Society, 2016.
[6] L.-L. Chen, J. Zhang, J.-Z. Zou, C.-J. Zhao, and G.-S. Wang, ‘‘A framework on wavelet-based nonlinear features and extreme learn ing machine for epileptic seizure detection,’’ Biomed. Signal Process. Control, vol. 10, pp. 1–10, Mar. 2014, doi: 10.1016/j.bspc.2013.11. 010.
[7] A. Dogra, S. A. Dhondiyal, and D. S. Rana, ‘‘Epilepsy seizure detection using optimised KNN algorithm based on EEG,’’ in Proc. Int. Conf. Advancement Technol. (ICONAT), Jan. 2023, pp. 1–6, doi: 10.1109/ICONAT57137.2023.10080847.
[8] 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.
[9] S. Ryu, S. Back, S. Lee, H. Seo, C. Park, K. Lee, and D.-S. Kim, ‘‘Pilot study of a single-channel EEG seizure detection algorithm using machine learning,’’ Child’s Nervous Syst., vol. 37, pp. 2239–2244, May 2021, doi: 10.1007/s00381-020-05011-9.
[10] M. Mursalin, Y. Zhang, Y. Chen, and N. V. Chawla, ‘‘Automated epilep tic seizure detection using improved correlation-based feature selection with random forest classifier,’’ Neurocomputing, vol. 241, pp. 204–214, Jun. 2017, doi: 10.1016/j.neucom.2017.02.053.
[11] A. A. Asadi-Pooya, M. Kashkooli, A. Asadi-Pooya, M. Malekpour, and A. Jafari, ‘‘Machine learning applications to differentiate comor bid functional seizures and epilepsy from pure functional seizures,’’ J. Psychosomatic Res., vol. 153, Feb. 2022, Art. no. 110703, doi: 10.1016/j.jpsychores.2021.110703.
[12] T. Wadhera, ‘‘Brain network topology unraveling epilepsy and ASD association: Automated EEG-based diagnostic model,’’ Expert Syst. Appl., vol. 186, Dec. 2021, Art. no. 115762, doi: 10.1016/j.eswa.2021. 115762.
[13] N. K. C. Pratiwi, I. Wijayanto, and Y. N. Fu’adah, ‘‘Performance analysis of an automated epilepsy seizure detection using EEG signals based on 1D-CNNapproach,’’ in Proc. 2nd Int. Conf. Electron., 2022, pp. 265–277.
[14] Md. N. A. Tawhid, S. Siuly, and T. Li, ‘‘A convolutional long short-term memory-based neural network for epilepsy detection from EEG,’’ IEEE Trans. Instrum. Meas., vol. 71, pp. 1–11, 2022, doi: 10.1109/TIM.2022.3217515.
[15] M. Woodbright, B. Verma, and A. Haidar, ‘‘Autonomous deep fea ture extraction based method for epileptic EEG brain seizure clas sification,’’ Neurocomputing, vol. 444, pp. 30–37, Jul. 2021, doi: 10.1016/j.neucom.2021.02.052.