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Automatic Epilepsy Detection using Machine Learning

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Abstract
Epilepsy is a brain disorder which causes seizures. Nerve cell activity of brain is disturbed which repeated seizures and disrupts the normal life of human. The nerve cells are connected with each other in complex way to communicate with each other. Epilepsy is neurological disorder where these nerve cells function in different way. This can be evaluated with help of Electroencephalogram (EEG) and Electrocorticography (ECoG) monitoring. Electroencephalogram help to check the signals of brain through images. These when monitored through machine learning system can help to evaluate whether the person has epilepsy disorder. The high-volume data is used to classify the disorder with machine learning classifier and statistical features The system is implemented with convolutional neural network for high dataset of image of signals of Electroencephalogram to classify the disorder. The research is ongoing where the performance is evaluated with different classifier and features.

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

I. Introduction

Brain is main part of our body which is operated through complex network of nerves. When this network is disturbed, it causes other normal activities of brain to dysfunction or conquers the other activities of brain, in other words it can be said that “it seizes upon,” same name is given to disorder which has been originated from Greek word “epilepsies” which means “to seize upon.” Epilepsy is a brain disorder which causes normal activities of brain to be subdued by abnormal behavior which can cause serious injury in small time. It is a serious neurological disorder with unique characteristics, tending of recurrent seizures [1]. The ancient scripts of Babylon also mention context of epilepsy with medicines which can be used to curb it.[2, 3]. This disease is not limited to human beings, but extends to cover all species of mammals such as dogs, cats, and rats.
The complex nerve network in brain operates through electric signal when this is disturbed the disorder arises and several reasons are listed for this disturbance such as shortage of oxygen during childbirth or low sugar level being some of them. One of 100 million people are affected by epilepsy once in lifetime and approximately 50 million are affected globally[5, 10]. Overall, it accounts for 1% of the world’s burden of diseases, and the prevalence rate is reported at 0.5– 1% . Having seizure once can be listed as main symptom for disorder. Seizure is disturbed activity in brain cells which causes unusual behavior of individual and sudden breakdown, which gives rise to momentary unconsciousness by person. This behavior of unconsciousness can be caused at any time of day for few seconds to few minutes which may lead to small injuries, burns or even serious injures such fractures or sudden death.
Through medical exploration over times, depending on symptoms, neuro experts have astronomically

distributed epilepsy in two orders videlicet partial and generalized. Partial seizure, also called 'focal seizure, causes only a section of the cerebral semicircle to be affected. There are two types of Partial seizure simple-partial and complex- partial. In the simple-partial, a case does not lose knowledge but cannot communicate duly. In the complex-partial, a person gets confused about the surroundings and starts carrying abnormally like chewing and mumbling; this is known as 'focal disabled mindfulness seizure' On the negative, in the generalized seizures, all regions of the brain suffer and entire brain networks get affected snappily (14). Generalized seizures are of numerous types, but they are astronomically divided into two orders convulsive and on- convulsive. clearly, in the history, multitudinous reviews have been carried out on seizure discovery along with applied features, classifiers, and claimed delicacy without fastening on the challenges faced by the data scientists whilst doing exploration on datasets of neurological diseases. thus, this composition provides a detailed study of machine literacy operations on epileptic seizure discovery and other affiliated knowledge discovery tasks. In this review, the collected papers are from well- known journals of their applicable field. These references are moreover listed by SCOPUS or Web of Science (WOS). either, we also considered some good ranked conference papers. expansive literature is available covering the deep analysis of different features and classifiers applied on EEG datasets for seizure discovery. Both, point birth and applying bracket ways are grueling tasks. former literature reveals that for the once many times, interest has been increased in the operation of machine literacy classifiers for

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rooting meaningful patterns from EEG signals, which helps for detecting seizures, its position in the brain, and other emotional affiliated knowledge discoveries. Three decades ago, Jean Gottman, anatomized and proposed the model for effective operation of EEG signals by applying different computational and statistical ways for automatic seizure discovery. likewise, the exploration has been carried out by different signal processing styles and data wisdom styles to give better issues.

The paper is organized with presenting the implementation of epilepsy detection while giving the analysis for earlier used systems. Section I gives detail introduction while section II gives the overall systems survey. The section III gives architecture for detection with discussion for methodology in section III. The section IV gives results and analysis for the implementation.

II. Literature survey

A. 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.

B. *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.

C. *Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent*

	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

D. *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.

E. *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 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.

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

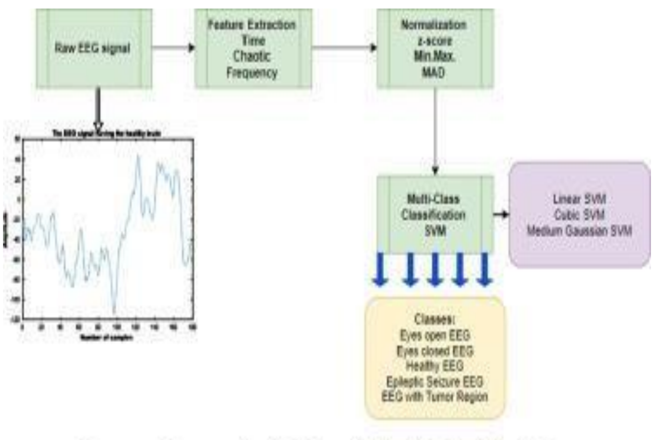
In this work, authors propose a novel approach to diagnosis the EEG signals using Multi-DWT, and Genetic algorithm coupled with four classifiers such as SVM, ANN, KNN, and Naive Bayes. The experimental results showed that the DWT features coupled with some machine learning algorithms had provided noticeable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

G. 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.
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

METHODOLOGY

A. *System Architecture*



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

Fig1: 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 kenwith 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.

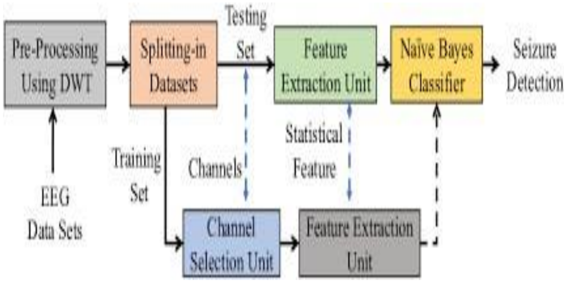
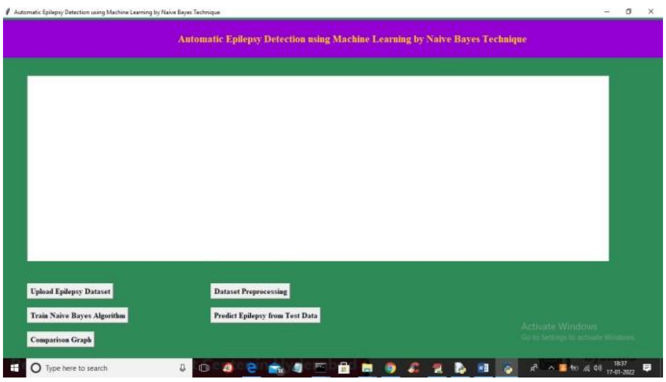


Fig2:Naïve Bayes Algorithm Flow

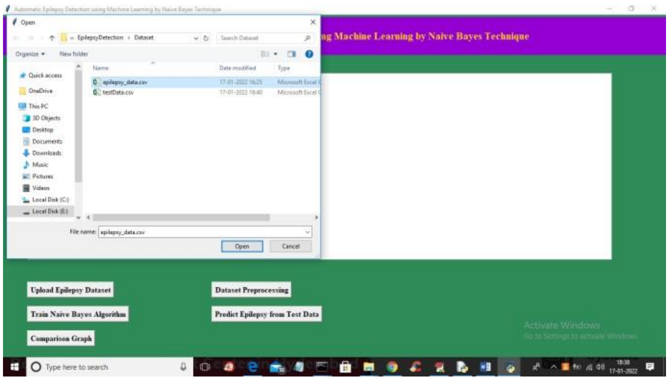
C. Modules

- 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

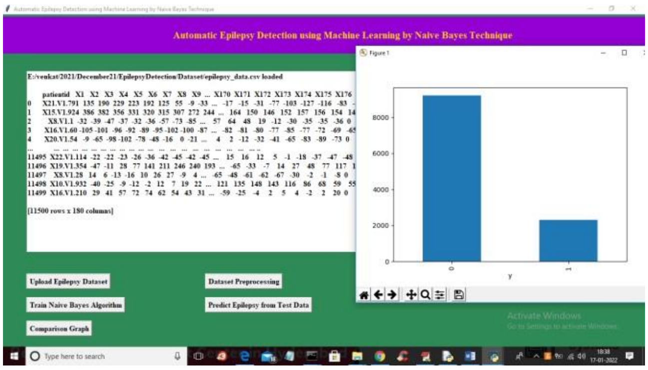
III.EXPERIMENTAL RESULTS



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

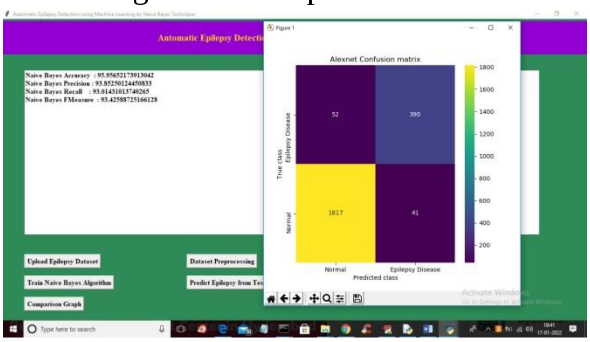


In above screen selecting and uploading ‘epilepsy_data.csv’ file and then click on ‘Open’ button to load dataset and to get below screen

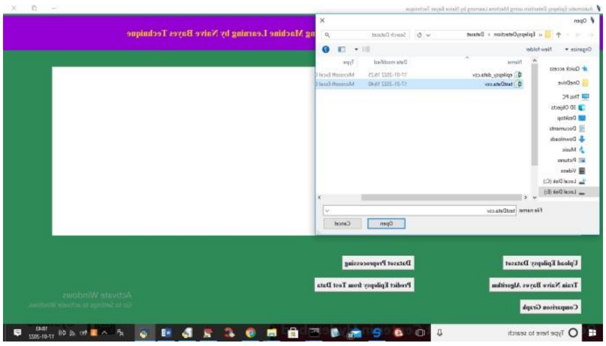


In above screen text area we can see dataset values loaded and in graph x-axis represent 0 (normal) and 1 (epilepsy disease) and y-axis represents number of records in that category. In above values patient id contains non-numeric data so we need to preprocess data so close above graph and then click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

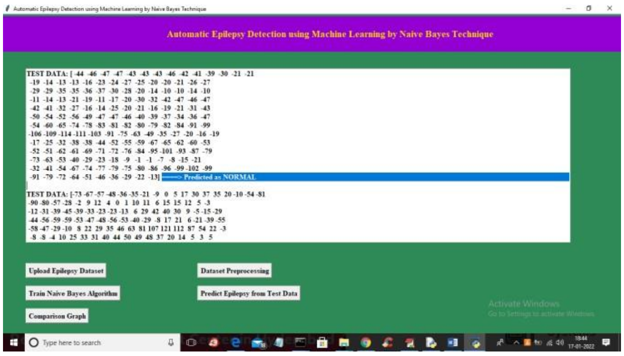
In above screen we can see after processing non-numeric data is removed and then split dataset into train and test and now dataset is ready and now click on ‘Run Naïve Bayes Algorithm’ button to train naïve bayes with process dataset and to get below output



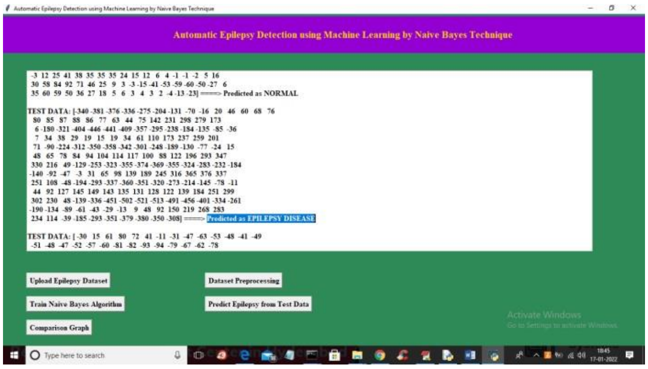
In above screen Naïve bayes training completed and we got its accuracy as 95% and in confusion matrix X-axis represents predicted classes and y-axis represents True class labels and in above graph we can see total 1817 records correctly predicted as NORMAL and only 52 records are incorrectly predicted.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



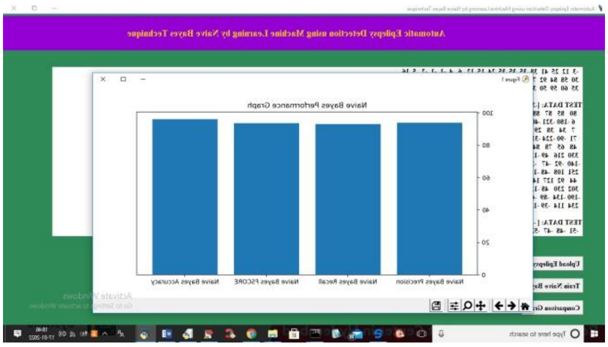
In above screen selecting and uploading 'testData.csv' file and then click on 'Open' button to load test data and to get below result



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

IV. CONCLUSION

Epilepsy is one of the most diseases that affect human lives, so they need to diagnose; it is one of the lives needed. The diagnosis process is not a simple task. In this work, we 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. The new automated system can detect epilepsy with high accuracy. The detection process of epilepsy seizure passes through different stages. The first step is the preprocessing of the EEG signals that are considered the primary step, which will increase the system performance. This step aims to remove the noises. The second step features extraction. This step is previously implemented with different methods; in this work, we apply multiple DWT. The main aim of this step is to decompose the signals into sub-bands, then compute different features functions on each sub-band. In our work, we use multiple DWT to extract various features, and then these features are reduced by the genetic algorithm to select the best features from a vast number of features. The output of this stage is a features matrix that will be used later in EEG signals classification. In EEG signals classification, the decision is made, and the system performance will be evaluated. The success of the suggested approach is verified by implementing the same procedure for 14 combinations of datasets. The proposed system was tested under different measurement metrics such as Accuracy, Sensitivity, and Specificity.

The results showed that our approach achieved good results in terms of these metrics, and it can be concluded that DWT analysis give satisfactory results compared with the previous studies, and the best performance was gained by artificial neural network classifier. The ANN was compared with the different classifiers, and it performs better in terms of the evaluation metrics in most cases of 14 dataset combinations.

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