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Automated Machine Learning-Based Epilepsy Detection

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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.

Key Words: 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 behaviour 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 behaviours 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

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

The study concentrated on the Signal Transformation methodologies and the Bracket Algorithms applied and estimated which is prevailing during the rearmost times. This review concluded on the following compliances 1) the future on automatic epilepsy discovery lies on methodologies that employ a combination of Time- frequence metamorphoses 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 Discovery and Healthy- Interictal problems. 2) the most popular database is Bonn DB, still more databases similar as Neurology and Sleep Centre DB, Freiburg DB, Temple DB give more applicable EEG recordings (meaning no combination of crown EEG and intracranial EEG) for bracket tasks and are decreasingly employed in combination with the most well- established Bonn and CHB- MIT databases. 3) limitations regarding each DB live.

B. Energy-Effective Tree- Grounded EEG Artifact Discovery

This work presented the analysis and perpetration of an artifact discovery frame with minimum EEG setups (4 temporal channels), considering different bracket approaches (binary, Ulti-label, Ulti-classmate-output). We used a combination of FFT and DWT for signal pre- processing and an automated machine literacy frame (TPOT) to search for the optimal model for each script.

C. Machine Learning and Deep Learning Approaches for Brain Disease opinion Principles and Recent Advances

The use of mongrel algorithms and a combination of supervised with unsupervised and ML with DL styles are promising to give better results. Indeed, colourful fine tunings can occasionally offer promising advancements, 3D- CNN is used first to prize primary features, and next, rather of the general FC subcaste, the FSBi- LSTM is used. This slight change in a part of the system ultimately redounded in superior performances.

D. Simple Discovery of Epilepsy from EEG Signal Using Original Binary Pattern Transition Histogram

The work presents, the machine learning bracket of epilepsy from EEG signals. Grounded on Discrete Wavelet transfigure combined with two recently proposed features Original double Pattern Transition Histogram (LBPTH) and Original Binary Pattern Mean Absolute divagation (LBPMAD), our proposed system allows effective point birth from a time series signal similar as EEG signals, achieving high bracket delicacy with fairly small point vector size of only 18.

E. Enhanced Discovery of Epileptic Seizure Using EEG Signals in Combination with Machine Learning Classifiers

In this work, authors propose a new approach to opinion the EEG signals using multi-DWT, and inheritable algorithm coupled with four classifiers similar as SVM, ANN, KNN, and Naive Bayes. The experimental results showed that the DWT features coupled with some machine learning algorithms had handed conspicuous results, and the ANN classifier outperforms all tested classifiers. F.

F. A Unified Framework and Method for EEG-Grounded Early Epileptic Seizure Discovery and Epilepsy opinion

In this paper, authors develop a unified frame for early epileptic seizure discovery and epilepsy opinion, 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 normal (ARMA) model to characterize the dynamic gets of the EEG time series. The residual error between the prognosticated value of learned ARMA model and the actually observed value is used as the anomaly score to support a null thesis testing for making epileptic seizure decision. The epileptic seizure discovery phase can give a quick discovery for anomaly EEG patterns, but the performing suspicious member may include epilepsy or other disordering EEG conditioning therefore needed to be linked. thus, in the alternate phase, we use pattern recognition fashion to classify the suspicious EEG parts.

III. METHODOLOGY

• The proposed system uses 54- DWT mama ripples, inheritable algorithm, and four classifiers to classify the EEG signals for epilepsy seizure discovery. Figure 1 shows the inflow of the proposed methodology.

• We acquire intimately 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 parts with a slice rate of 171.4 HZ. The EEG signals were filtered using a Bandpass sludge and smoothing system. The first two sets (A, B) represent healthy people, whose signals were taken with open and unrestricted 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 discovery, set (E) was only treated as an epileptic seizure.

A. Algorithm

Naïve Bayes Algorithm

Naïve bayes training completed and we got its delicacy as 95 and in confusion matrix X-axis represents prognosticated classes and y- axis represents True class markers and in below graph, we can see total 1916 records rightly prognosticated as NORMAL and only 48 records are incorrectly identified.

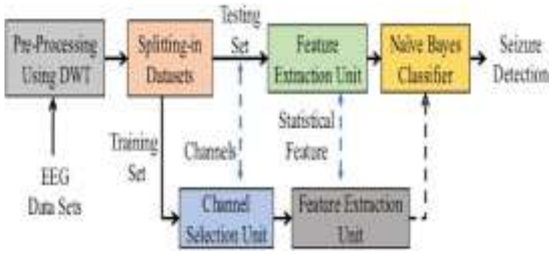


Fig 1 Naïve Bayes Algorithm Flow

B. Modules

• Upload Epilepsy Dataset

• Using this module, we will upload dataset to operation

• Dataset Preprocessing

• Dataset frequently contains missing values and non- numeric data similar as patient ID so we need to reuse dataset to remove patient ID and missing values. Process data will be resolve 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

• Prognosticate Epilepsy from Test Data

• Using this module, we will upload new test data and also apply trained Naïve Bayes model to prognosticate whether test data is normal or contains Epilepsy complaint

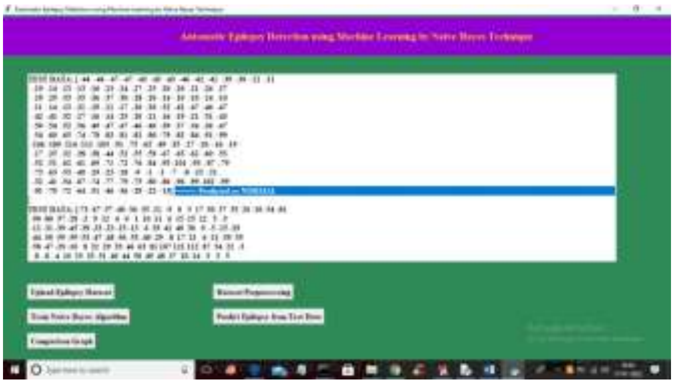
• Comparison Graph

• Using this module, we will compass Naïve Bayes performance graph in terms of perfection, recall, delicacy and FSCORE.

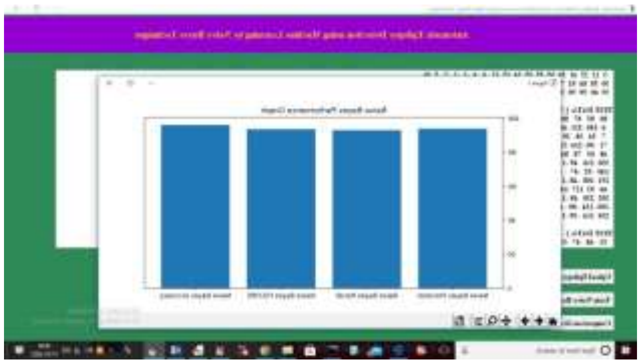
IV. EXPERIMENTAL RESULTS

In above screen click on 'Upload Epilepsy Dataset' button to upload 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 in square bracket displaying TEST DATA values and after =□ arrow symbol displaying predicted value as NORMAL or EPILEPSY



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 opinion is critical, challenging an effective and precise approach. In our exploration, we introduce a new system exercising multi-DWT and inheritable Algorithm in confluence with four classifiers SVM, ANN, KNN, and Naive Bayes for EEG signal opinion. The experimental issues displayed promising results, with the ANN classifier displaying

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superior performance among all classifiers tested. The developed automated system demonstrates a high delicacy in epilepsy discovery.

The process for epilepsy seizure discovery involves distinct stages. originally, preprocessing of EEG signals is conducted, which is pivotal for enhancing system performance by noise elimination. The posterior stage involves point birth. While colorful styles have been preliminarily employed for this purpose, our study utilizes multiple DWT to putrefy signals into sub-bands and cipher different features for each sub-band.

The inheritable algorithm is employed to reduce the multitudinous features attained and elect the most applicable bones. This results in a features matrix used in EEG signal bracket. The bracket stage involves decision- timber and system performance evaluation. Our approach was tested across 13 dataset combinations, using criteria similar as Accuracy, Sensitivity, and particularity. The issues demonstrate promising results across these criteria, indicating the efficacy of DWT analysis compared to former studies. specially, the artificial neural network (ANN) outperformed other classifiers in utmost cases, emphasizing its superior performance in the evaluation criteria for the 13 dataset combinations.

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