JOURNAL OF THE ROYAL LAUREATES ACADEMY

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INTELLIGENT COMPUTER AIDED DIAGNOSIS OF EPILEPTIC SEIZURES USING EEG SIGNALS

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ABSTRACT

Electroencephalography (EEG) readings may identify epileptic seizures, which are triggered by aberrant brain electrical activity. But medical professionals have a hard and time-consuming job manually interpreting EEG recordings that last for lengthy periods of time. This research details a pipeline for computer-assisted seizure identification using electroencephalogram (EEG) recordings that uses machine learning. Seizure and non-seizure activity are classified using machine learning approaches after EEG data is preprocessed and relevant characteristics are extracted. The goal of the technology is to make seizure detection more efficient and accurate while also making healthcare workers' jobs easier. Early diagnosis, continuous monitoring, and improved care of epilepsy patients may be facilitated by such an automated method.

Keywords: Electroencephalography, Disorder, Machine learning, Seizure, Convolutional neural networks

I. INTRODUCTION

Seizures that happen repeatedly and without apparent cause are the hallmark of epilepsy, a long-term neurological disorder caused by an overactive and abnormal brain electrical activity. The condition has a profound impact on individuals's physical and mental health, as well as their educational opportunities, occupational status, and quality of life in general; it may strike at any age and affect millions of people globally. Therefore, a significant challenge in clinical neurology is the rapid and accurate diagnosis of epileptic seizures. A crucial tool for the diagnosis and assessment of epilepsy, electroencephalography (EEG) is one of the most used non-invasive methods for measuring brain activity. Seizure activity is commonly accompanied by noticeable alterations in electroencephalogram (EEG) recordings, which provide important insight into the brain's electrical dynamics. It usually takes highly qualified neurologists or clinical specialists a lot of time and effort to decipher EEG data. Reliable computer-aided solutions that may help in seizure identification are necessary due to the growing number of EEG recordings and the length of time they take. This puts additional strain on medical personnel.

Visual examination of electroencephalogram (EEG) recordings or manually constructed signal-processing algorithms are typical components of traditional seizure detection approaches. Even while seasoned doctors can see a lot of patterns associated with seizures, human error, subjectivity, and inter-observer variability may all impact manual analysis. Furthermore, seizures may happen at any time, which makes continuous monitoring challenging, especially with long-term EEG recordings. Researchers have been motivated to create automated seizure detection systems that can effectively analyse EEG data and offer timely alarms due to these obstacles. Faster clinical intervention, better continuous patient monitoring, less diagnostic effort, and professional assistance are all possible outcomes of such systems.A new and exciting direction in the development of intelligent and automated seizure detection systems based on electroencephalograms (EEGs) is machine learning (ML). By analysing massive amounts of EEG data, machine learning algorithms can detect abnormalities and learn meaningful patterns.

Acquiring EEG data, preprocessing, segmenting, feature extraction or representation learning, classification, and performance assessment are the usual phases of a pipeline based on machine learning. In order to enhance the quality of the signal, preprocessing involves reducing noise and artefacts that are generated by things like eye movements, muscle activity, electrode impedance, and ambient interference. In order to extract useful characteristics from the time, frequency, or time-frequency domains, the continuous EEG data is first split into appropriate time intervals. Wavelet coefficients, entropy measurements, statistical features, and spectral qualities are all examples of features that may be used to describe signals. A variety of machine learning classifiers may be developed to distinguish between seizure and non-seizure EEG patterns. These include support vector machines, random forests, decision trees, k-nearest neighbours, and artificial neural networks.

The capacity of automated seizure detection has been considerably enhanced by recent deep learning advancements. There is less need for manually engineered features when complex representations can be automatically learned from raw or transformed EEG signals using convolutional neural networks, recurrent neural networks, long short-term memory networks, and hybrid architectures. Problems like as computational complexity, class imbalance, signal artefacts, limited labelled datasets, inter-patient variability, and the need for strong real-time performance continue to be significant concerns in the field.

II. COMPUTER AIDED SEIZURE DETECTION

There has been a recent movement in healthcare away from a focus on the physician and toward one on the patient, with the latter increasingly playing an active role in her own care management. The author's important work for the identification of absence seizures over a decade ago enhanced automated computer-aided diagnosis of epilepsy, a much more difficult task than computer-aided seizure detection. Summarising the studies presented since then is the goal of this review. Neurologists may benefit from a CAD system as it allows for a more precise and efficient diagnosis. An automated system for the detection and diagnosis of epilepsy and seizures is shown in Figure 1 as a block diagram. There is both an online and an offline component to it. The design processes required to develop and evaluate the CAD algorithm structure make up the offline system.

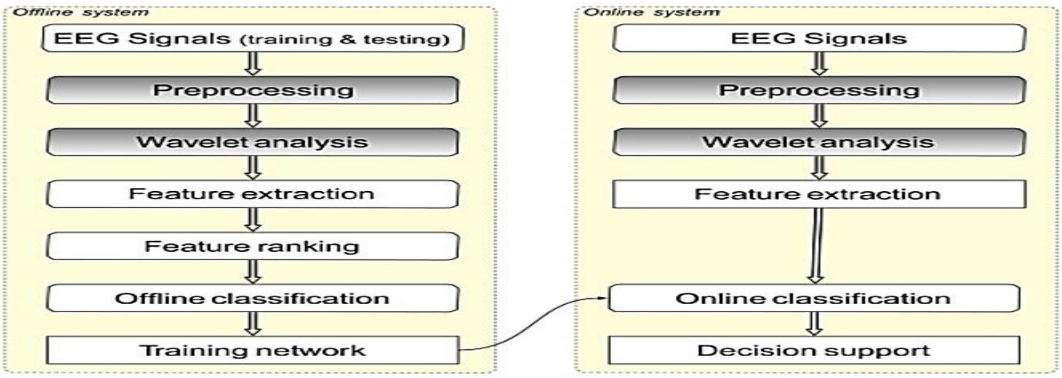

Figure 1. Block diagram of the EEG-based seizure detection system.

Signal preprocessing, denoising, and feature extraction are all tasks that make use of WT. In order to address the limitations of previous approaches, including the Fourier transform, WT was created in the 1980s as a robust tool for signal processing. Many signal processing applications have made use of it since then. While the short time Fourier transform uses a windowed representation, WT gives a smoother one. Consequently, it is possible to record intricate details, rapid shifts, and shared patterns in the EEG data. WT simulates a mathematical microscope by analysing EEG signals at various scales. Novel wavelets have been suggested by researchers. You can see some examples of mother wavelets used for EEG processing in Figure 2. These include (a) Morlet, (b) Biorthogonal, (d) Orthogonal Cubic Spline, (e) Mexican Hat, (f) Haar, (g) Complex Gaussian, and (h) Coiflet. The two sections that follow provide an overview of how WT is used in computer-assisted seizure detection.

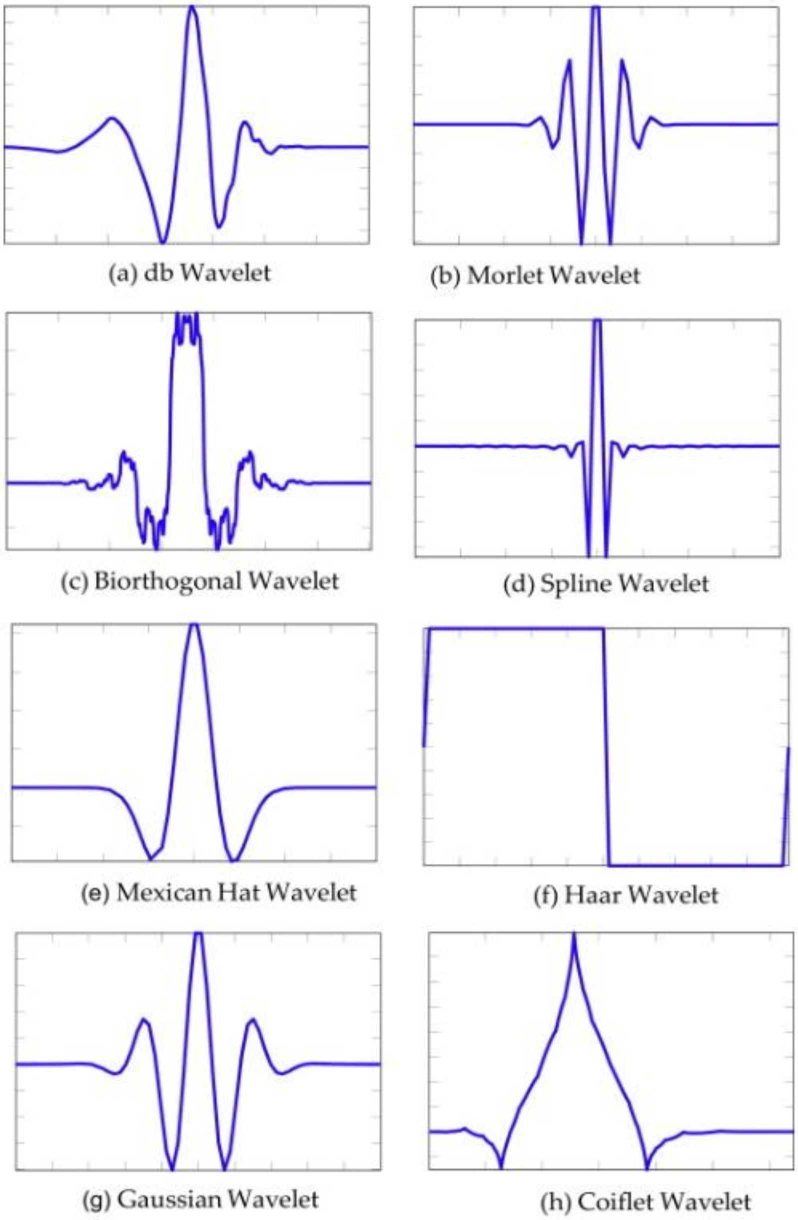

Figure 2: Examples of wavelets used for EEG processing

III. PROCESS FOR EEG SIGNAL ANALYSIS

Figure 3 shows the approach of EEG signal analysis, which is the main emphasis of this section. The pipeline is associated with EEG signal categorisation. An outline of the procedure for equipment-based EEG signal capture is provided to kick off the discussion. Next, we have a look at the denoising EEG signal technique, which may filter out false positives and glean useful information. The process of feature engineering, which entails deleting unimportant functionality, is next covered. At last, we take a look at classification algorithms that use deep learning and machine learning.

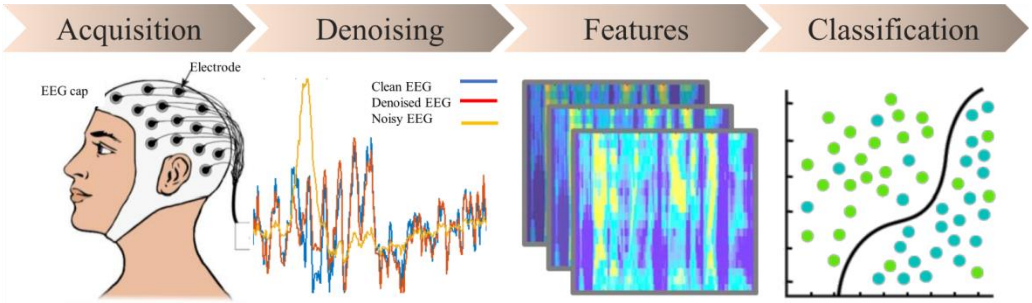

Figure 3. EEG signal analysis process

Acquisition

A neurophysiological method, electroencephalography (EEG) measures and quantifies neural activity in different parts of the brain. Different levels of awareness, responses to environmental stimuli, and other elements are represented by diverse scalp potentials, which are generated by the actions of the many neurones that make up the brain. The right acquisition gear is crucial for gathering EEG signal data for a variety of uses and studies. There are two main ways EEG signals may be acquired: invasively and non-invasively. Electrodes are surgically implanted into specific areas of the brain, such as the cerebral cortex, in order to get signals by invasive acquisition. In contrast, non-invasive methods do not use implanted electrodes but rather EEG sensors placed on the surface of the scalp. There are already a number of non-invasive ways to get EEG signals. German scientist Hans Berger used a galvanometer to detect electrical impulses in the brain's cortex in 1924, during the early phases of electroencephalogram (EEG) data collection. Scientists started taking detailed EEG readings by implanting metal electrodes into the brain cortex after first tests. A better resolution of recorded EEG signals has been made possible by vast improvements in EEG signal collecting methods brought about by developments in computing technology. Modern electroencephalogram (EEG) signal collecting devices often use personal computer screens, connected data transfer, and external power supplies. Strong data processing capabilities, positive results, and reliable performance are all displayed by these devices. On the other hand, they are bulky, dangerous, and electrically demanding. Because of this, there is a growing demand for portable EEG recording devices.

The Emotiv EPOC and similar portable EEG recorders have become increasingly popular in the last several years. The Emotiv EPOC has 14 channels for electrical data acquisition, 2 reference electrodes, and uses nonimplantable electrodes. The Emotiv EPOC can really record authentic EEG data, as the author discovered. Another option for monitoring brain activity is the Emotiv EPOC neural headphones. Even though they may collect EEG data, the Emotiv EPOC headset devices don't function as well as bigger ones. Martins suggested a wearable EEG capture device and a data processing platform for sleep inertia identification in an additional investigation. The system is an all-in-one, low-power EEG acquisition system with a low-noise analogue front end. The method has shown to be very accurate, very reliable, and very adaptable. It was also suggested to record and analyse dolphin EEG data using a novel, lightweight, portable, and waterproof equipment. Generally unfettered EEG acquisition was the goal of the device's design. The suction cups that come with their acquisition equipment are specifically designed to hold electrodes. A Bluetooth module is also included in for communication with the base station. The portable Muse brain wave sensor gadget was also used for stroke detection. The gadget uses one reference electrode (Fpz) and four recording electrodes (AF7, AF8, TP9, TP10) in accordance with the worldwide 10-20 system. To solve the problems with expensive and inaccurate current EEG acquisition systems, they developed a high-precision portable EEG acquisition system based on the Compact PCI platform in. The aforementioned techniques are only a few of many available for gathering EEG signals. Neural electrodes inserted into particular brain areas allowed for deep brain stimulation, for instance. An implantable pulse generator is used by these electrodes to generate current or voltage. In addition, cerebral blood flow and oxygen saturation may be reflected by the MR signal. It may be used for functional imaging and to reflect neuronal activity.

Denoising

Several electrodes are affixed to the scalp in order to get EEG data, as previously stated. Nevertheless, a variety of artefacts might occur as a result of outside interference, lowering the signal quality. Involuntary eye movements, blinking, heart activity, and muscular movement are examples of physiological artefacts that may degrade the quality of EEG readings. As a result, there is a lot of interest and focus in the field of denoising EEG data. Features retrieved from EEG signals must be free of artefacts if they are to be trusted. A number of denoising methods are now available.

Evaluation Criteria for Denoising

It is usual practice to evaluate EEG signal denoising using a number of measures, including mean squared error (MSE), root mean squared error (RMSE), signal-to-noise ratio (SNR), and percentage root mean square difference (PRD). When comparing the original EEG signal with the noise-reduced signal, MSE is a common metric to use. Metrically, root-mean-squared error (RMSE) is just the mean squared error (MSE) squared. One way to compare the strengths of the signal and the noise is via the signal-to-noise ratio, or SNR. To find out how similar the original and noise-reduced signals are to one another, we utilise the PRD. A lower PRD means that the two signals are more similar. One way to describe these measures is as:

MSE $= (1/n) \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$,

RMSE $= \sqrt{[(1/n) \sum_{i=1}^{n} (y_i - \hat{y}_i)^2]}$

SNR $= 10 \log_{10} [(\sum_{i=1}^{n} y_i^2) / (\sum_{i=1}^{n} (y_i - \hat{y}_i)^2)]$,

PRD $= (100\%/n) \sum_{i=1}^{n} |y_i - \hat{y}_i| / |y_i|$

where$\mathbf{y_i}$ typically refers to the true EEG signal value at time point *i*, $\hat{\mathbf{y}}_\mathbf{i}$ represents the denoised value of the EEG signal at time point *i*, and **n** is the total number of values.

Feature Engineering

Through the process of improving feature engineering, raw data can be transformed into more expressive features, which in turn can improve the accuracy of predictions. As a result of the complexity of EEG signal processing, extracting usable characteristics usually calls for a team of human specialists. It is now possible to automatically extract characteristics from EEG data using machine learning methods like adversarial generative networks and deep neural networks. Nevertheless, deep learning is often criticised for its interpretability issue. Deep learning model interpretability has been a focus of recent explainable AI (XAI) approach advancements. Some examples of XAI-based applications are Smooth Grad, which is utilised for EEG-based emotion identification and seizure detection. It enables the removal of the need for human specialists to manually pick using XAI approaches.

EEG Based Classifications

Classifying electroencephalogram (EEG) signals is an essential part of studying brain activity; this is essentially one-dimensional biomedical signal processing. Statistical analysis, machine learning (deep learning), and other processing methods may be used to categorise EEG readings. With an emphasis on techniques based on machine learning, this section will go into the classification methods used in different EEG application domains.

- **Traditional Classification Method**

In order to classify brain signals using ML approaches, supervised and unsupervised learning methods are primarily used. Naive Bayesian (NB), decision tree (DT), K-nearest neighbour (KNN), support vector machine (SVM), and random forest (RF) are just a few of the algorithms that fall into this category. Building predictive models for classification and regression with the help of input and expected output data is the domain of supervised learning. In contrast, unsupervised learning entails reducing dimensions and clustering input data to propose a prediction model.

When utilising classifiers like SVM or KNN, supervised learning produces better results than unsupervised learning. An individual classification method can only be as accurate as the use cases it is designed for. Researchers often use multimodal integration algorithms in their research to boost classification accuracy. Algorithm accuracy and bias could be compromised by their ever-increasing complexity. A number of disorders and rehabilitation techniques have been studied by analysing EEG data using machine learning algorithms. These include epilepsy, depression, and stroke. One such intervention is motion imagining.

- **Deep Learning**

Deep learning models provide better benefits in EEG signal classification and prediction than classical ML, despite the complexity of their structure. In order to diagnose and forecast the development of disorders like Alzheimer's, epilepsy, ischaemic stroke, etc., a number of researchers have used deep learning models to examine EEG data.

IV. CONCLUSION

The automatic identification of seizures using electroencephalogram (EEG) data is a promising area for machine learning. The most effective way to analyse EEG recordings for aberrant seizure patterns is to combine signal preprocessing, feature extraction, and classification algorithms. To better support medical personnel in patient monitoring, a trustworthy computer-aided detection system may shorten the time needed for manual EEG analysis. While there are still obstacles to overcome, such as patient variability, data scarcity, and background noise, future seizure detection systems may be more accurate and reliable thanks to advancements in deep learning and machine learning.

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