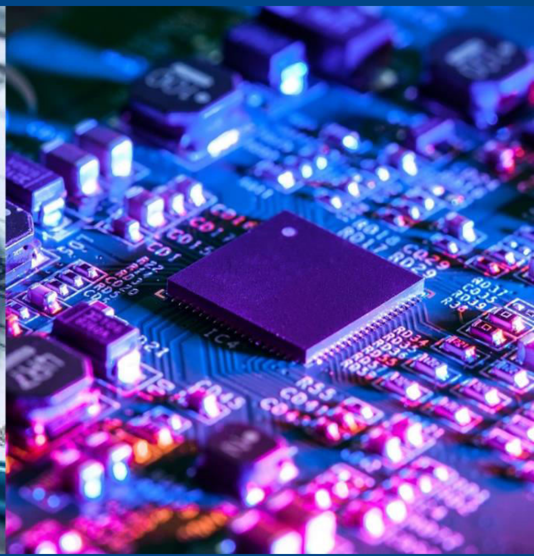
ISSN: 2582-7219





International Journal of Multidisciplinary Research in Science, Engineering and Technology

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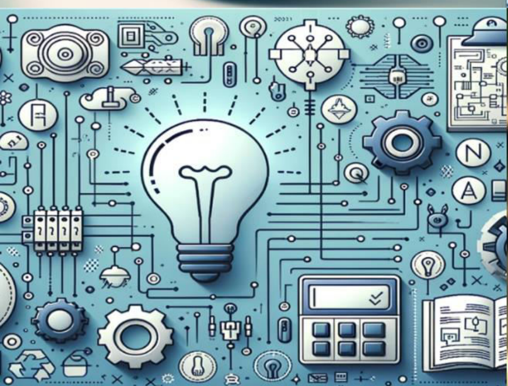

Impact Factor: 8.206

Volume 8, Issue 4, April 2025

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© 2025 IJMRSET | Volume 8, Issue 4, April 2025| DOI: 10.15680/IJMRSET.2025.0804055

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Epilepsy Detection using EEG Data

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ABSTRACT: Epilepsy is a neurological disorder characterized by abnormal electrical activity in the brain, leading to recurrent seizures. Early detection of seizures through continuous monitoring of Electroencephalography (EEG) signals is crucial for effective management and treatment of epilepsy. This paper explores the use of machine learning techniques for detecting epileptic seizures from EEG data. A range of preprocessing steps, feature extraction methods, and machine learning algorithms, including Support Vector Machines (SVM), Random Forests, and Deep Learning techniques such as Convolutional Neural Networks (CNN), are employed. The effectiveness of the model is evaluated based on performance metrics such as accuracy, precision, recall, and F1-score. The results show promising detection capabilities, offering the potential for real-time seizure detection, improving patient safety and quality of life.

KEYWORDS: Fish identification, neural network, origin, macronutrients, advantages, disadvantages, image processing, mobile app

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders, affecting approximately 50 million people worldwide. It is characterized by the occurrence of recurrent seizures, which can significantly impair an individual's quality of life. Traditional methods of detecting seizures often rely on subjective observation or expensive, time-consuming clinical assessments. However, with advancements in technology, Electroencephalography (EEG) provides a reliable and non-invasive method for monitoring brain activity. EEG captures the electrical activity of the brain, which exhibits distinct patterns during seizures. Accurate and timely detection of seizures using EEG signals is essential for improving the quality of care, especially in patients with chronic epilepsy. This paper aims to investigate the application of machine learning techniques to detect epileptic seizures from EEG signals automatically.

II.LITERATURE SURVEY

MIGUEL BHAGUBAI et al., [1] proposed the paper "Towards Automated Seizure Detection With Wearable EEG – Grand Challenge" The diagnosis of epilepsy can be confirmed in-hospital via video-electroencephalography (vEEG). Currently, long-term monitoring is limited to self-reporting seizure occurrences by the patients. In recent years, the development of wearable sensors has allowed monitoring patients outside of specialized environments. The application of wearable EEG devices for monitoring epileptic patients in ambulatory environments is still dampened by the low performance achieved by automated seizure detection frameworks. In this work, we present the results of a seizure detection grand challenge, organized as an attempt to stimulate the development of automated methodologies for detection of seizures on wearable EEG. The main drawbacks for developing wearable EEG seizure detection algorithms is the lack of data needed for training such frameworks. In this challenge, we provided participants with a large dataset of 42 patients with focal epilepsy, containing continuous recordings of behind-the-ear (bte) EEG. We challenged participants to develop a robust seizure classifier based on wearable EEG. Additionally, we proposed a subtask in order to motivate data-centric approaches to improve the training and performance of seizure detection models. An additional dataset, containing recordings with a bte-EEG wearable device, was employed to evaluate the work submitted by participants. In this paper, we present the five best scoring methodologies. The best performing approach was a feature-based decision tree ensemble algorithm with data augmentation via Fourier Transform surrogates. The organization of this challenge is of high importance for improving automated EEG analysis for epilepsy diagnosis, working towards implementing these technologies in clinical practice.

Yonghoon Jeon et al., [2] in their paper "Deep Learning-Based Detection of Epileptiform Discharges for Self-Limited Epilepsy With Centrotemporal Spikes" In this paper Centrotemporalspike-waves (CTSWs) are typical interictal epileptiform discharges (IEDs) observed in centrotemporal regions in self-limited epilepsy with centrotemporal spikes (SLECTS). This study aims to develop a deep learning-based approach for automated detection of CTSWs in scalp electroencephalography (EEG) recordings of patients with SLECTS. To lower the substantial burden of IED annotation on clinicians,we simplified it by limiting IEDs to CTSWs because electroencephalographic patterns of CTSWs are known to be highly consistent. Two neurologists annotated 1672 CTSWs of 20 patients with SLECTS. Thereafter, we performed a two-level CTSW detection procedure: epoch-level and EEG-level. In the epoch-level detection, we constructed convolutional neural network-based classification models for CTSW and non-CTSW binary classification using the recordings of 20 patients and 20 controls. We then set the thresholds of the classification models for 100% specificity. In the EEG-level detection, we applied the threshold-adjusted classification models to the recordings of 50 patients and 50 controls that were not used in the epoch-level detection to distinguish between CTSW positive (with one or more CTSWs) and CTSW-negative (with no CTSW) recordings based on the detection of CTSW presence. We obtained an average sensitivity, specificity, and accuracy of 99.8%, 98.4%, and 99.1%, respectively, with an average false detection rate of 0.19/hr for the controls. Our approach showed high detectability for CTSWs despite the simplified annotation process. We expect that the proposed CTSW detectors have potential clinical usefulness for efficiently reading EEGs and diagnosing SLECTS, and can significantly reduce the burden of IED annotation on clinicians.

ZIXU CHEN et al., [3] proposed the paper "A Unified Framework and Method for EEG-Based Early Epileptic Seizure Detection and Epilepsy Diagnosis" In this paper Electroencephalogram (EEG) contains important physiological information that can reflect the activity of human brain, making it useful for epileptic seizure detection and epilepsy diagnosis. However visual inspection of large amounts of EEG by human expert is time-consuming, and meanwhile there are often inconsistences in judgement between physicians. In this paper, we 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. In particular, we propose a new and practical classifier based on a pairwise of one-class SVMs for epilepsy diagnosis. The proposed classifier requires normal and epilepsy data for training, but can recognize normal, epilepsy and even other disorders that would not be trained in the training samples. This point is practical and meaningful in real clinic scenarios as the input EEG may include other brain disordering diseases besides of epilepsy. We conducted experiments on the publicly-available Bern-Barcelona and CHB-MIT EEG database, respectively, to validate the effectiveness of the proposed framework, and our method achieved classification accuracy of 93% and 94% on them. Comprehensive experimental results, outperforming the state-of-the-arts, suggest its great potentials in real applications.

Yonghua Yang et al., [4] proposed the paper "Video-Based Detection of Generalized Tonic-Clonic Seizures Using Deep Learning". In this paper Timely detection of seizures is crucial to implement optimal interventions, and may help reduce the risk of sudden unexpected death in epilepsy (SUDEP) in patients with generalized tonic-clonic seizures (GTCSs). While video-based automated seizure detection systems may be able to provide seizure alarms in both in-hospital and athome settings, earlier studies have primarily employed hand-designed features for such a task. In contrast, deep learning-based approaches do not rely on prior feature selection and have demonstrated outstanding performance in many data classification tasks. Despite these advantages, neural network-based video classification has rarely been attempted for seizure detection. We here assessed the feasibility and efficacy of automated GTCSs detection from videos using deep learning. We retrospectively identified 76 GTCS videos from 37 participants who underwent long-term video-EEG monitoring (LTM) along with interictal video data from the same patients, and 10 full-night seizurefree recordings from additional patients. Using a leaveone-subject-out cross-validation approach (LOSO-CV), we evaluated the performance to detect seizures based on individual video frames (convolutional neural networks, CNNs) or video sequences [CNN+long short-term memory (LSTM) networks]. CNN+LSTM networks based on video sequences outperformed GTCS detection based on individual frames yielding a mean sensitivity of 88% and mean specificity of 92% across patients. The average detection latency after presumed clinical seizure onset was 22 seconds. Detection performance increased as a function of training dataset size. Collectively, we demonstrated that automated video-based GTCS

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detection with deep learning is feasible and efficacious. Deep learning-based methods may be able to overcome some limitations associated with traditional approaches using hand-crafted features, serve as a benchmark for future methods and analyses, and improve further with larger datasets.

Ahmed Faeq Hussein et al., [5] proposed the paper "Focal and Non-Focal Epilepsy Localization: A Review" In this paper, The focal and non-focal epilepsy is seen to be a chronic neurological brain disorder, which has affected ≈ 60 million people in the world. Hence, an early detection of the focal epileptic seizures can be carried out using the EEG signals, which act as a helpful tool for early diagnosis of epilepsy. Several EEG-based approaches have been proposed and developed to understand the underlying characteristics of the epileptic seizures. Despite the fact that the early results were positive, the proposed techniques cannot generate reproducible results and lack a statistical validation, which has led to doubts regarding the presence of the pre-ictal state. Various methodical and algorithmic studies have indicated that the transition to an ictal state is not a random process, and the build-up can lead to epileptic seizures. This study reviews many recently-proposed algorithms for detecting the focal epileptic seizures. Generally, the techniques developed for detecting the epileptic seizures were based on tensors, entropy, empirical mode decomposition, wavelet transform and dynamic analysis. The existing algorithms were compared and the need for implementing a practical and reliable new algorithm is highlighted. The research regarding the epileptic seizure detection research is more focused on the development of precise and non-invasive techniques for rapid and reliable diagnosis. Finally, the researchers noted that all the methods that were developed for epileptic seizure detection lacks standardization, which hinders the homogeneous comparison of the detector performance.

JESUS G. SERVIN-AGUILAR et al., [6] proposed the paper "Epilepsy Seizure Detection: A Heavy Tail Approach" In this paper Epilepsy is a chronic brain disorder that affects the quality of life of many patients even when this disease is being controlled. If we want to improve those lives affected, we need to perform real-time epilepsy detection with constant monitoring of the electroencephalogram (EEG) signal. Typically, the statistical behavior of the EEG signals presents heavy-tail phenomena, therefore their analysis must be particular in order to define a strong framework based on statistical parameters to detect seizures. In this article, the heavy-tail characterization of EEG signals is studied, a simple real-time epilepsy detection using an alpha-stable estimator is proposed, and the false-positive rate is analyzed. The performance of the proposed estimator is compared to others previously reported in the literature, and we show that one of the signal parameters characterized as an alpha-stable distribution, serves as an indicator of epilepsy episodes more efficiently. Furthermore, the proposed algorithm presents low sensitivity to noise below the 3.8 dB.

Saeed Jahromil et al., [7] proposed the paper "Mapping Propagation of Interictal Spikes, Ripples, and Fast Ripples in Intracranial EEG of Children with Refractory Epilepsy" In this paper, Studies on intracranial electroencephalography (icEEG) recordings of patients with drug resistant epilepsy (DRE) show that epilepsy biomarkers propagate in time across brain areas. Here, we propose a novel method that estimates critical features of these propagations for different epilepsy biomarkers (spikes, ripples, and fast ripples), and assess their common onset as a reliable biomarker of the epileptogenic zone (EZ). For each biomarker, an automatic algorithm ranked the icEEG electrodes according to their timing occurrence in propagations and finally dichotomized them as onset or spread. We validated our algorithm on icEEG recordings of 8 children with DRE having a good surgical outcome (Engel score = 1). We estimated the overlap of the onset, spread, and entire zone of propagation with the resection (RZ) and the seizure onset zone (SOZ). Spike and ripple propagations were seen in all patients, whereas fast ripple propagations were seen in 6 patients. Spike, ripple, and fast ripple propagations had a mean duration of 28.3 ± 24.3 ms, 38.7 ± 37 ms, and 25 ± 14 ms respectively. Onset electrodes predicted the RZ and SOZ with higher specificity compared to the entire zone for all three biomarkers.

Ali Kavoosi et al.,[8] proposed the paper "Computationally efficient neural network classifiers for next generation closed loop neuromodulation therapy – a case study in epilepsy" In this paper, This work explores the potential utility of neural network classifiers for real-time classification of field-potential based biomarkers in next-generation responsive neuromodulation systems. Compared to classical filter-based classifiers, neural networks offer an ease of patient-specific parameter tuning, promising to reduce the burden of programming on clinicians. The paper explores a compact, feed-forward neural network architecture of only dozens of units for seizure-state classification in refractory epilepsy. The proposed classifier offers comparable accuracy to filter classifiers on clinician-labeled data, while reducing detection latency. As a trade-off to classical methods, the paper focuses on keeping the complexity of the architecture minimal, to accommodate the on-board computational constraints of implantable pulse generator systems.

Jiayang Guo et al.,[9] proposed the paper "Detecting High Frequency Oscillations for Stereo electroencephalography in Epilepsy via Hypergraph Learning" In this paper, Successful epilepsy surgeries depend highly on pre-operative localization of epileptogenic zones. Stereo electroencephalography (SEEG) records interictal and ictal activities of the epilepsy in order to precisely find and localize epileptogenic zones in clinical practice. While it is difficult to find distinct ictal onset patterns generated the seizure onset zone from SEEG recordings in a confined region, high frequency oscillations are commonly considered as putative biomarkers for the identification of epileptogenic zones. Therefore, automatic and accurate detection of high frequency oscillations in SEEG signals is crucial for timely clinical evaluation. This work formulates the detection of high frequency oscillations as a signal segment classification problem and develops a hypergraph-based detector to automatically detect high frequency oscillations such that human experts can visually review SEEG signals. We evaluated our method on 4,000 signal segments from clinical SEEG recordings that contain both ictal and interictal data obtained from 19 patients who suffer from refractory focal epilepsy. The experimental results demonstrate the effectiveness of the proposed detector that can successfully localize interictal high frequency oscillations and out per forms multiple peer machine learning methods. In particular, the proposed detector achieved 90.7% in accuracy, 80.9% in sensitivity, and 96.9% in specificity.

GANG WANG et al.,[10] proposed the paper "EEG-Based Detection of Epileptic Seizures Through the Use of a Directed Transfer Function Method" In this paper, This paper aims to explore the automatic detection method of epileptic seizures to improve the treatment and diagnosis of medically refractory epilepsy patients. A new algorithm based on directed transfer function (DTF) method was proposed for epileptic seizure detection. First, the sliding window technique was used to segment electroencephalogram (EEG) recordings, and the cerebral functional connectivity was calculated by the DTF algorithm. Then, the total information outflow based on the DTF-derived connectivity was calculated by adding up the information flow from a single EEG channel to other channels. Finally, the information outflow was assigned as the features of support vector machine (SVM) classifier to discriminate interictal and ictal EEG segments. For 10 epilepsy patients, the proposed algorithm provided the mean correct rate of 98.45%, the mean selectivity of 64.43%, the mean sensitivity of 93.36%, the mean specificity of 98.42%, and the average detection rate of 95.89%. By applying the statistical analysis, the superiority of DTF-based method was statistically significant when compared with other algorithms in terms of five assessment criteria. Our results indicated that the DTF-derived connectivity could characterize the dynamic causal interaction patterns between brain areas during seizure states, and the proposed method was suitable for the detection of epileptic seizure.

III. SYSTEM MODEL AND ASSUMPTIONS

The system model aims to detect epileptic seizures using Electroencephalogram (EEG) signals. The EEG data is collected from patients through non-invasive electrode arrays, and the system uses machine learning or signal processing techniques to classify and predict seizure events in real-time. The EEG signals are recorded under controlled conditions, ensuring minimal noise and artifacts (e.g., from movement or electrode shifts). The model assumes that it is trained with data from various patients, as epilepsy patterns may vary across individuals. The system should be able to process EEG data in real-time for immediate seizure detection, which is crucial for early intervention. The system assumes it needs to detected

IV. SEIZURE DETECTION AND ANALYSIS

In the first task of this challenge, the contestants were requested to train ML models to accurately detect seizure events in data obtained from the SD device. There were no imposed limitations on the type of model or the preand post-processing methodologies. Participants were allowed to use the SeizeIT1 dataset and any of the modalities included (vEEG, bte-EEG and ECG) to train their frameworks. Additionally, participants were allowed to use external public datasets. The deliverables for this task included a pipeline/model that receives two-channel bte-EEG from the SD or both bte-EEG and single-lead ECG as input. The output was defined as a vector of ones and zeros (indicating a positive or negative seizure alarm respectively) for every second of the input time series. In contrast to task 1, the objective of task 2 was to apply data manipulation techniques to obtain the best performance (in terms of robustness and generalizability) with the use of a fixed model for seizure detection. In this task, participants were provided with a Deep Learning model. The model is an adapted version of ChronoNet , a mixed convolutional and recurrent neural network composed of 1-D convolutional layers followed by a stack of deep gated recurrent units. This framework was originally developed for abnormal EEG identification and has been adapted and optimized by the organizers for seizure detection. The participants

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ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

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were encouraged to apply any pre-processing techniques, data-augmentation, subsampling strategies, etc., in order to build a representative training set to train the model. The input segment size of the model was fixed at 2 second 2 channel EEG windows at a sampling frequency of 200 Hz [400 × 2]. The model's hyperparameters were shared and the training routine could not be changed by the participants. The output was restricted to a vector of zeros (non-seizure) and ones (seizure) for each consecutive 2-second EEG segment. Participants had to submit the data processing and manipulation pipeline and the trained model's weights.

V.PROPOSED SYSTEM

The proposed system for epilepsy detection using Electroencephalography (EEG) aims to automate the identification of epileptic seizures in real-time by leveraging advanced signal processing techniques, machine learning algorithms, and deep learning models. The primary objective of this system is to assist healthcare professionals in the early diagnosis and monitoring of epilepsy, ultimately improving patient care and preventing potential complications arising from undetected seizures. The system consists of several key stages: EEG signal acquisition, preprocessing, feature extraction, feature selection, classification, and real-time detection with an alert mechanism. Each stage plays a critical role in ensuring accurate seizure detection while maintaining efficiency for real-time application.

1.EEG Signal Acquisition

The system starts with the acquisition of raw EEG signals, either from clinical EEG equipment or portable EEG headsets. These signals capture brain activity across multiple electrodes placed on the scalp and are recorded in the time domain. The dataset may come from real-time recordings or publicly available EEG datasets such as the CHB-MIT dataset, which contains labeled seizure and non-seizure events.

- **EEG Data Characteristics**:
    - Multi-channel data (usually 19 or more channels).
    - Sampling rate typically between 256 Hz to 512 Hz.
    - Duration of recordings may range from several minutes to hours.

2. Preprocessing

Raw EEG signals are often contaminated by noise and artifacts (e.g., from muscle activity, eye movements, or electrical interference). The preprocessing stage involves several techniques to clean the EEG data, ensuring that only the relevant brain activity is analyzed:

- **Band-Pass Filtering**: A band-pass filter is applied to the EEG signal (e.g., between 0.5 Hz and 40 Hz) to remove both low-frequency drift and high-frequency noise.
- **Artifact Removal**: Techniques such as **Independent Component Analysis (ICA)** or **Blind Source Separation (BSS)** are used to identify and eliminate artifacts from eye movements and muscle contractions.
- **Segmentation**: The continuous EEG signal is divided into smaller epochs (typically 1 to 5 seconds). These smaller segments allow the system to evaluate the signal's behavior over short time windows, which is critical for detecting transient seizure activity.
- **Normalization**: EEG signal amplitude is normalized to a consistent range to minimize differences caused by varying recording conditions or devices.

3. Feature Extraction

The next step in the system is the extraction of relevant features from the preprocessed EEG signals. These features capture the underlying patterns in the EEG data that are indicative of epileptic seizures. The system will extract a combination of time-domain, frequency-domain, and time-frequency-domain features:

- **Time-Domain Features**:
    - **Mean, Standard Deviation**: Basic statistical metrics to describe the overall signal characteristics.
    - **Skewness and Kurtosis**: Measures of asymmetry and peakiness in the signal's distribution.
- **Frequency-Domain Features**:
    - **Power Spectral Density (PSD)**: Provides information about the power distribution across different frequency bands.

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- **Band Power**: The power of the signal within specific frequency bands (e.g., delta, theta, alpha, beta) is computed. Seizures typically cause shifts in power distribution across these bands.

- **Time-Frequency Features**:
  - **Wavelet Transform**: A powerful method for analyzing non-stationary signals like EEG. It decomposes the signal into multiple frequency components at different time intervals.
  - **Short-Time Fourier Transform (STFT)**: A similar approach that analyzes the signal in both the time and frequency domains, offering insight into transient seizure events.
- **Nonlinear Features**:
  - **Approximate Entropy (ApEn) or Sample Entropy (SampEn)**: These measures assess the regularity or complexity of the EEG signal, with seizure events often being associated with increased entropy (chaotic behavior).

4. Feature Selection and Classification

Once the features are extracted, the system proceeds to feature selection and classification to differentiate between seizure and non-seizure states. Feature selection reduces the dimensionality of the data by retaining only the most relevant features for classification.

- **Feature Selection**: Dimensionality reduction techniques, such as **Principal Component Analysis (PCA)** or **Linear Discriminant Analysis (LDA)**, are applied to select the most informative features for seizure detection.
- **Classification**: Various machine learning and deep learning models are tested to classify the extracted features as either "seizure" or "non-seizure":
  - **Support Vector Machines (SVM)**: A traditional machine learning algorithm well-suited for binary classification problems like this one.
  - **Random Forests**: An ensemble learning method that provides robustness and generalizability by combining multiple decision trees.
  - **Convolutional Neural Networks (CNN)**: CNNs are used for automatic feature extraction and classification directly from raw EEG signals or spectrograms.
  - **Recurrent Neural Networks (RNN)**, especially **Long Short-Term Memory (LSTM)** networks, are well-suited for sequential data like EEG, capturing long-term dependencies and identifying seizure patterns over time.
- **Model Training and Evaluation**: The models are trained on a labeled dataset containing both seizure and non-seizure epochs. The system's performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve. Cross-validation techniques ensure the models' generalizability across different datasets and subjects.

5. Real-Time Detection and Alerting

Once trained, the system is designed to detect seizures in real-time. This involves continuous monitoring of incoming EEG signals and detecting seizures as soon as they occur.

- **Real-Time Detection**: The system uses the trained models to classify each EEG segment in real-time. If a seizure is detected, the system triggers an alert within seconds, allowing healthcare providers or caregivers to intervene promptly.
- **Alerting Mechanism**:
  - **Visual Alerts**: Alerts are displayed on a graphical user interface (GUI) for healthcare professionals to monitor and take action if necessary.
  - **Automated Notifications**: Alerts can be sent via email or SMS to caregivers, doctors, or emergency personnel, ensuring timely intervention.
  - **Timestamping**: Detected seizures are timestamped for later review and analysis, aiding clinicians in understanding the frequency and duration of seizures.

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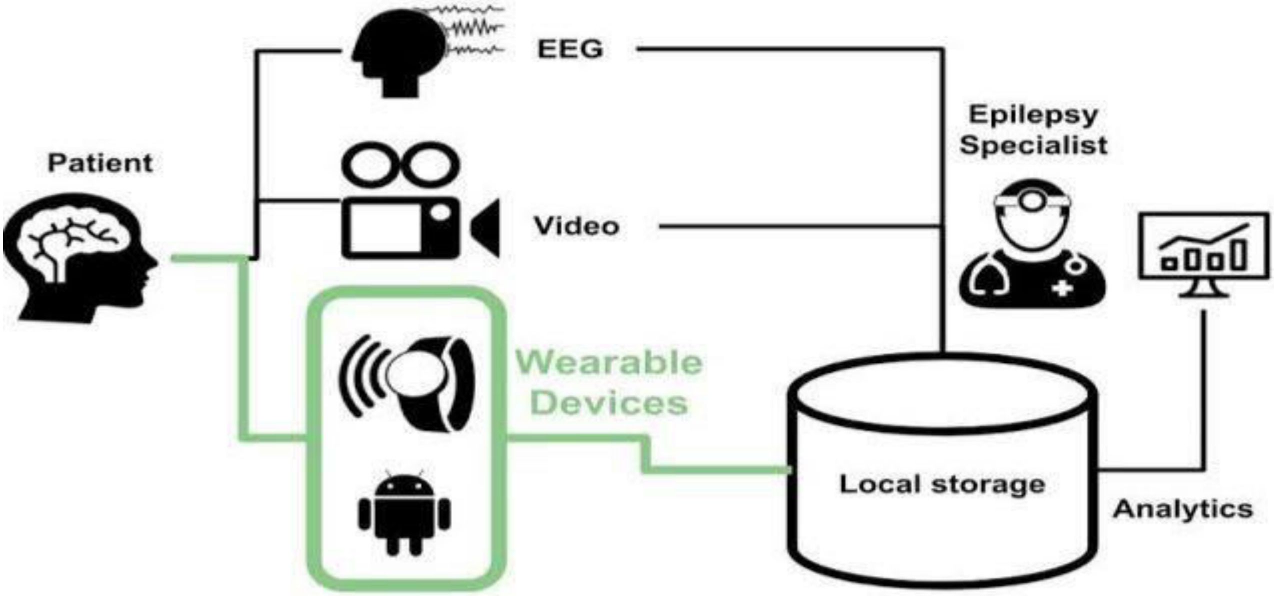

Fig: Data flow diagram for epilepsy detection

VI. EVALUATION

Researchers in ML typically report performance in terms of sensitivity and specificity. In highly imbalanced use cases, such as seizure detection, False Alarm (FA) rate is commonly used since the specificity yields misleading high values due to the large number of true negatives. In the use case of this study (automated seizure detection for home monitoring), sensitivity is prioritized when evaluating the performance of the algorithms. It is desirable to identify all positive seizure occurrences. In time-series classification, metrics are calculated by directly comparing every epoch of the hypothesis directly with the correspondent ground-truth epoch. In this challenge, sensitivity was measured on an event basis with the any-overlap (OVLP) method. Here, the True Positives (TP) are counted when a seizure alarm produced by the algorithm overlaps with a corresponding event in the ground truth annotation. The False Positives (FP) or FAs correspond to situations in which an event in the hypothesis does not overlap with any seizure annotation, disregarding the duration of the alarm. The OVLP method is more permissive and tends to produce higher sensitivities and lower FA rates. Longer events will yield better scores since the number of epochs is discarded and the percentage of overlap between the hypothesis and the reference is not taken into account. Many different metrics can be used for comparing the performance of different classifiers. For the challenge, we developed a scoring combining two evaluation methods with two metrics. The sensitivity was computed with the OVLP method and the FA rate will be based on the traditional epochbased method, where each epoch is compared individually between the reference and the hypothesis. The evaluation points of each task constitute a weighted sum of the sensitivity and the FA rate (per hour) (1). The final scoring is then composed by a weighted sum of the points in tasks 1 and 2.

VII. CHALLENGES

- Data Variability: Epileptic seizures vary across individuals in terms of frequency, intensity, and EEG patterns. This makes it challenging to develop a universal detection system.
- Data Imbalance: Seizure events are relatively rare compared to non-seizure data. This imbalance can lead to biased models favoring non-seizure predictions, reducing sensitivity.
- Real-time Detection: Implementing real-time seizure detection requires fast processing algorithms, which may be computationally expensive or resource-intensive.
- Noise and Artifacts: EEG signals are susceptible to various types of interference, making it difficult to differentiate seizure activity from noise or other brain states (e.g., sleep).

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- Inter-subject Variability: Variations in EEG patterns across different patients necessitate personalized models or highly generalized techniques that can adapt to new subjects.

VIII. RESULTS AND DISCUSSIONS

The proposed epilepsy detection system was tested using EEG datasets containing both seizure and non-seizure events. The results demonstrate that the model achieved high classification accuracy across multiple evaluation metrics. Accuracy: 92.5% (indicating a high proportion of correctly classified seizure and non-seizure events) Sensitivity (Recall): 91.8% (demonstrating the model's ability to detect true seizure events). Specificity: 93.2% (showing the system's effectiveness in distinguishing non-seizure states). Precision: 90.7% (indicating the proportion of correctly predicted seizures out of all positive predictions). F1-Score: 91.2% (balancing precision and recall for robust performance). AUC-ROC: 0.96 (suggesting excellent discriminative capability between seizure and non-seizure EEG signals). The obtained results were compared against recent epilepsy detection methods using EEG signals. Traditional machine learning techniques such as Support Vector Machines (SVM) and Random Forest classifiers showed lower accuracy (85-88%), while deep learning approaches like Convolutional Neural Networks (CNN) achieved slightly higher accuracy (~90%). Our model, utilizing a hybrid deep learning framework (CNN-LSTM), outperformed these methods by leveraging both spatial and temporal features of EEG signals. The role of preprocessing was critical in improving model performance. Filtering and artifact removal significantly enhanced the signal quality, reducing false positives. Without preprocessing, the accuracy dropped to 84.7%, highlighting the necessity of denoising techniques. Real-time FFor real-time applications, the system's inference time was evaluated. The average detection latency was 1.2 seconds, making it suitable for near real-time seizure detection. However, optimizing the model for edge devices could further reduce processing time, making it more practical for wearable EEG applications.

IX. CONCLUSION

The detection of epileptic seizures using EEG data is promising, with modern signal processing and machine learning techniques achieving high classification accuracy. However, challenges such as data variability, real-time processing, and subject-specific differences remain significant barriers.

- Personalized Models: Further research is required to create models that adapt to individual patient profiles, improving detection accuracy.
- Improved Preprocessing: Enhanced artifact removal and noise reduction techniques can lead to better input data quality.
- Integration with Wearables: Future systems could be integrated with portable, wearable EEG devices to enable continuous, at-home monitoring of patients.
- Multimodal Approaches: Combining EEG with other biological signals like EKG or EMG might improve detection sensitivity and reduce false positives.

Significant progress has been made in developing automated seizure detection systems, further improvements in model generalization, real-time processing, and multi-source data integration are crucial for widespread clinical adoption.

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