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Article

Artificial Intelligence and Deep Learning in Seizure Detection for Alzheimer's Disease: A Review

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Abstract: Alzheimer's disease (AD) is a neurodegenerative disorder that leads to seizures, failure to manage the disease and stimulates cognitive decline. The comprehensive development of the dataset for the early detection of the predicted model involves intricate steps. In this article, we explore the various approaches for the detection of seizure from the AD patients with the collection of datasets and annotation by focusing on multi-modal data sources, including neuroimaging, Electroencephalography, physiological signals, and cognitive evaluations. The detection models are included in this study with the integration of deep learning, machine learning approaches along with wearable sensor technology, EEG monitoring, and neuro-imaging analysis with the usage of large-scale datasets. The challenges in developing the datasets and detection of seizures are analysed to provide better detection of AD. The application of artificial intelligence techniques for identifying AD using various datasets is analyzed. This study provides the way for the generation of standardized publicly available datasets and therein significantly helps in detecting AD from the patients earlier.
Keywords: Alzheimer's disease, Dataset development, Artificial intelligence, Cognitive evaluation

1. Introduction:

AD is a neurological illness that worsens with time and is typified by psychological abnormalities, diminished recall, and cognitive impairment [1]. Seizures are one of the least well-studied side effects of AD, although they have recently drawn greater recognition because of their effects on the course of the illness and the health of the patient. According to research, people with Alzheimer's disease are more likely than the wider community to experience seizures, which can hasten cognitive decline. Despite its diagnostic importance, little is known about the identification of seizures in Alzheimer's patients. This is mainly because there aren't any effectively organized databases particularly designed for this group [2].

The best method for identifying seizures is still electroencephalography (EEG), which captures neural activity with an elevated time sensitivity [3]. EEG data by itself, nevertheless, might not be enough to detect seizures in Alzheimer's patients fully. A more comprehensive understanding of seizure events can be obtained by combining multimodal information, such as wearable sensor measurements (heart levels, function variations), brain scanning (MRI, CT), and patient medical information [4]. To increase the reliability of identifying seizures and create individualized intervention plans, a strong database that includes these different approaches is necessary.

Current seizure recognition databases, such as the CHB-MIT Scalp EEG Database and the Temple University Hospital EEG Corpus (TUH-EEG), mostly concentrate on epileptic seizures and the absence of neurodegenerative conditions like AD. Studies trying to create machine-learning algorithms for estimating and categorization seizures in Alzheimer's patients face difficulties because of this shortage of information. Additionally, seizures associated with Alzheimer's disease have unique features, frequently manifesting as non-convulsive occurrences that need particular recognition methods. AI-driven diagnostic devices customized for this particular patient population might be developed with the help of a specialized database [5].

EEG scans from Alzheimer's patients who are having seizures must be recorded, and supplementary records must be integrated, to create a trustworthy database. The dataset's usefulness for studies and therapeutic purposes can be increased by adding demographic data, seizure episode labels (preictal, ictal, and postictal phases), and clinical comments from neurologists. Preprocessing methods including detection of features, artifact disposal, and noise reduction should also be used to enhance the integrity of data and guarantee precise seizure categorization [6].

By utilizing deep learning frameworks such as Transformer-based simulations, Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs), an organized effective database can propel improvements in seizure recognition systems [7]. These algorithms can determine seizure episodes unique to Alzheimer's patients by analyzing the spatial and temporal properties of EEG data. Furthermore, hybrid AI methods that combine neuroimaging and EEG data might succeed better in anticipating the onset and intensity of seizures.

In summary, expanding studies on neurodegenerative diseases requires the creation of a comprehensive data set for Alzheimer's seizure identification. Experts can improve Alzheimer's patients' early recognition of seizures and intervention tactics by utilizing cutting-edge AI algorithms, merging multimodal information, and increasing annotation reliability [8]. In addition to advancing scientific understanding, such a dataset would open the door for real-time monitoring capabilities in intelligent healthcare facilities, which would eventually improve the treatment of patients.

The rest of the work is organized as the relevant works are analyzed and presented in section 2. The proposed approach for the development of Seizure detection AD is presented in section 3. The dataset models and benchmark are presented in section 4. The technological integration details are presented in section 5. Challenges of the seizure detection are presented in section 6. Future scope of the work is stated in section 7. Finally, the work is concluded in Section 8.

2. Literature survey:

Clinical Alzheimer's diagnostic techniques are costly and susceptible to human mistakes. Effective AD identification remained difficult to achieve despite several computer-aided techniques that use artificial intelligence and EEG data. Puri et al. [9] suggested low-complexity EEG-based AD detection CNN (LEADNet) to provide disease-specific characteristics. It consists of spatiotemporal EEG data such as a softmax layer, two convolutional layers, two fully connected layers, and one max-pooling layer. The framework may have more potential uses than AD because of its outstanding success in detecting the disease; it may also be useful in diagnosing additional brain diseases including epilepsy and sleep issues. Hence, it was difficult in computation.

A common neurodegenerative illness and the main reason for dementia can be AD. Miltiadous et al. [10] developed a Dual-Input Convolution Encoder Network (DICE-net) to develop the classification of EEG data for the automated identification of AD. Following denoising, characteristics related to band voltage and cohesion were retrieved and sent to the suggested method, which was composed of feed-through, transformer encoder, and convolution levels. It demonstrated strong generalization efficiency, obtaining a precision of 83.28% in the AD-CN issue using Leave-One-Subject-Out evaluation. This strategy may increase the precision of early detection and result in the creation of more potent AD treatments. Other less expensive and quicker diagnostic methods must be investigated.

A progressive brain disorder, Alzheimer's disease (AZD) results in cognitive and brain shrinkage. It was useful to diagnose EEGs. Khare et al. [11] determined an automated and explainable Alzheimer's disease detection model (Adazd-Net) for diagnosing AZD using EEGs. The functionality of the system was efficient for an ideal number of features. The method for analyzing the classifier algorithm's particular and aggregate forecasts was addressed in the examination. Using a ten-fold cross-validation approach, it could recognize AZD EEG data with a detection rate of 99.85%. It was dependable and precise to identify AZD in medical settings. However, it was difficult to handle challenging scenarios.

Early discovery, still, helps lessen the disease's devastating symptoms. To facilitate early diagnosis of the various phases of AD Siuly et al. [12] created a computer-aided diagnostic (CAD) architecture that incorporates a LSTM network using enormous multi-channel EEG data. It determines the ideal EEG pathways and patterns needed for the detection of AD. A current AD EEG database was used to evaluate the suggested architecture. The suggested method was also tested on a different moderate cognitive impairment (MCI) EEG database, with outstanding outcomes (precision>99%). The suggested structure would help develop a CAD program that can diagnose AD automatically. Hence, the method's inability was to be examined.

To identify and categorize AD and other types of brain disease advanced computer-aided detection methods utilizing artificial intelligence (AI) have proliferated in the last few years. Nour et al. [13] determined Deep Ensemble Learning (DEL) and 2-dimensional Convolutional Neural Networks (2D-CNN) to find the appropriate characteristics from the complex spectral-temporal EEG signals that can yield appropriate data for an evaluation. Consequently, the first-ever EEG-based DEL algorithm offered good diagnostic precision for AD. Five cross-fold learning helped the suggested DEL system achieve a standard precision of 97.9% in AD identification. Therefore, it was insufficient to use in a massive database.

AD can be a progressive, indestructible illness that can be delayed or prevented from progressing, even if considered terminal. Highly efficient AD identification chips were few, even though there exist multiple neural network-based techniques for recognizing AD. Chen et al. [14] developed a recurrent computational approach for the effective identification of AD methodology. The platform does advanced EEG processing by utilizing an Artificial Neural Network (ANN) integrated into a System on Chip (SoC). Additionally, structured and Processing Element (PE) methods were employed to carry out the multiply-accumulate activities of the ANN, while data remapping approaches were employed to guarantee consistency of the input information examination addresses. It achieves 98.53 % of precision. Nevertheless, there has still not been much investigation into identifying AD using hardware.

Mild Cognitive Impairment (MCI) frequently precedes AD, an accelerated neurological disease marked by decreased memory, psychological abnormalities, and poor self-care. Kumar et al. [15] established the Adaptive Moving Self-Organizing Map-Fuzzy K-Means (AMSOM-FKM) technique for enhancing cell area segmentation, which can be crucial for AD early detection. Adequate tissue segmentation can be guaranteed by the approach's exact cluster location identification, a feature essential for proper evaluation. Additionally, the technique's remarkable 99.8% precision highlights its dependability for diagnostic applications. Nevertheless, because it requires a lot of information methods for prediction.

One of the leading causes of dementia globally is AD, which impairs a person's capacity to carry out everyday tasks on their own as it progresses from moderate to extreme. Mahim et al. [16] modified a Vision Transformer and a Gated Recurrent Unit (ViT-GRU) can precisely and consistently identify AD traits using Magnetic Resonance Imaging (MRI) images. It creates distinct connections among the important elements that the ViT extracts from the source image. The suggested approach outperforms current techniques in terms of precision and efficacy while resolving the group imbalance problem in the MRI image database. The suggested paradigm has the potential to diagnose AD quickly and accurately, allowing for prompt treatment and better patient care. Thus, the method could be costly.

3. Alzheimer's Seizure Detection

The seizure detection of AD patients can be achieved with various approaches like clinical approaches, machine learning, deep learning, and wearable technologies. It is illustrated in **Figure 1**.

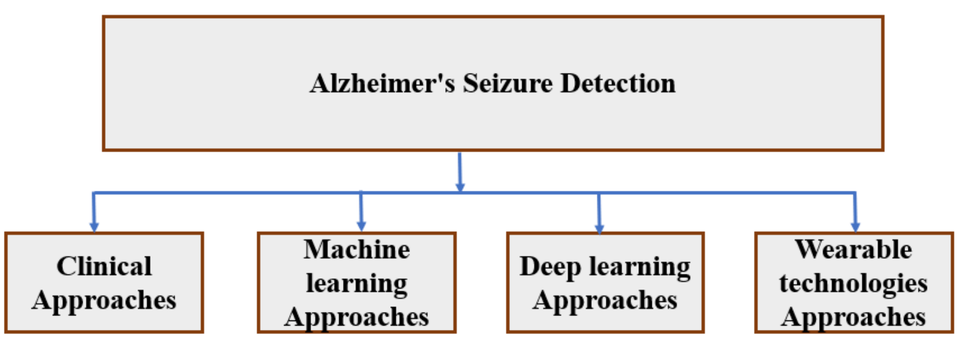

Figure 1. Alzheimer’s seizure detection approaches.

3.1. Clinical Approaches:

The comprehensive dataset for Alzheimer's seizure disease can be developed from multimodal data to improve robustness, accuracy, and reliability. Some of the data types required are Electroencephalography signals, Neuroimaging Data, Physiological and Biosignal Data, and Clinical and Cognitive Assessment Data. Jasphin et al. [17] stated that the possibility of occurrence of seizure is maximum for patients with Alzheimer's disease and cognitive impairment. To measure Alzheimer's disease, EEG signal was taken by the authors. The authors used particle swarm optimization for the extraction of features from the EEG signals and for the reduction of dimensionality, kernel PCA is used. The authors utilized benchmark datasets known as Dementia and Bon datasets and stated that the EEG signals can be used for the detection of Alzheimer's disease with higher recall, F1-score, and accuracy.

Oltu et al. [18] demonstrated an approach for the detection of AD using EEG signals. The work has utilized 35 subjects and analyzed the AD using the 2 phase algorithm namely, discrete wavelet transform (DWT), Coherence, and Power Spectral Density (PSD). The major sub-bands of the EEG signals were assessed using the DWT and Burg's approach is used to estimate the PSD of each sub-band. Following this, the interhemispheric coherence values were evaluated. The features were determined by the amplitude and variance summation of each subband. With high accuracy, specificity, and sensitivity this work provided better AD detection using the EEG signals.

For easy detection of AD Al-Nuaimi et al. [19] presented a novel EEG biomarker. This used the clinically acceptable performance with integrated strengths of key biomarkers. The authors investigated a higher number of biomarkers with the mitigation of complexity, pacing of the EEG, and reduction in EEG connectivity. For analyzing the best combination support vector and linear discriminate analysis approaches were used. The authors analyzed 325,568 EEG biomarkers and scrutinized 6 for better diagnosis.

EEG-based AD detection was performed by Ohal et al. [20] with the utilization of EEG signals from patients with mild cognitive impairment, healthy controls, and AD. The median filter and Savitzky Golay technique are used for the preprocessing of the signals and extracted all three domain features such as time domain, statistical, and frequency domain. The authors stated that with the proposed approach over the EEG signal, the detection accuracy is higher and can be used for the detection of AD. Dogan et al. [21] stated that for the early detection of AD EEG signals can be used. Based on the directed graph technique the local textures of EEG signals were extracted. The graph was designed with the topological mapping of the macroscopic connectome. With the available EEG signals the primate brain pattern was tested. The dataset contains 12 patients' EEG signal recordings with the health controllers of 11. The generation of features per signal input is performed with the q-factor wavelet transform and 1D EEG signal. The K-Nearest Neighbor classifier is used for the detection of AD and attained accuracy of 100% accuracy and ensures the usage of EEG signal for the detection of AD.

3.2. Machine Learning Approaches:

Based on the Hjorth parameters and other features, Safi et al. [22] suggested early AD detection from the EEG signals. For the analysis, various approaches, including DWT, empirical mode decomposition (EMD), and classification algorithms, including KNN, SVM, and regularized linear discriminant analysis, were estimated. The dataset includes 35 healthy, 20 moderate, and 31 mild Ads. The analysis was conducted by adding the Hjorth parameters using various classifiers. Amini et al. [23] suggested time time-dependent power spectrum for the diagnosis of the AD from the EEG signals. For that, the patients with mild cognitive impairment, healthy control test samples, and AD. The classification techniques such as KNN, SVM, and Linear Discriminant analysis (LDA). Apart from this, a convolutional neural network (CNN) is utilized. The CNN produces higher accuracy than the SVM and the LDA.

Pang et al. [24] demonstrated a work for detecting AD with the collection of data modality images, including MRI and PET images, to predict the cognitive assessments, genetics, and cerebrospinal fluid and blood biomarkers. The authors utilized a multi-task algorithm based on the multimodal datasets. The progression of the disease is predicted based on the assessments of cognitive trends of the patient's future. This ensures the usage of the multimodal dataset for the prediction of AD in patients. Zhu et al. [25] use a multimodal dataset for diagnosing AD with multimodality data fusion. The low-rank determinations are completely designed with the objective function using the correlation between the various modalities. Moreover, an alternative direction approach for the multipliers was used to optimize the model.

The identification of AD using multimodal data is presented by Zhang et al. [26]. The authors utilized an end-to-end mapping function for the conversion of input MRI scans with the underlying PET scans. The synthetic outcomes quality was enhanced with the designed 3D convolutional U-Net generator for preserving the diverse framework of various subjects. The maximized similarity ground truth of the PET can be identified with the 3D gradient profile and ground truth structural similarity index measures.

3.3. Deep Learning Methods

While developing the dataset for the AD detection the factors considered are dataset types and how the deep learning or AI techniques are integrated with the dataset for attaining higher detection accuracy. For that, this section analyses the various research articles related to the application of AI or deep learning techniques to the available dataset for accurate detection of AD. Chang et al. [27] delineated the application of datasets for the detection of AD using AI and deep learning techniques. For that, the authors utilized CNN and appliedit to the T1-weighted MRI images. For the differentiation feature visualization techniques have been adopted.

Sadegh-Zadeh et al. [28] utilized a Support Vector Machine for the classification of AD along with the EEG signals. The feature extraction techniques used by the work are PSD and temporal data. Variational autoencoders were used for the augmentation. The authors stated that unbalanced and insufficient data were the common issues in the detection of AD. With the integration of deep ensemble learning and 2D CNN, the detection of AD was analyzed by Nour et al. [29]. This effectively diagnoses the AD from the EEG signals and the HC subjects. The authors cleaned the noises and artifacts and directly applied the developed model without including the feature extraction technique. The internal classifier used for the classification was 5 various models of CNN and attained an accuracy of 97.8%.

Pandya et al. [30] suggested an AI model for the K-complex detection with the EEG Cz strip. The dataset used by the authors is EEG signals. This showed better identification of AD from the sick person. Images of the 18F-FDG PET brain were utilized by Ding et al. [31] for the detection of AD and were collected from the Alzheimer's Disease Neuroimaging Initiative (ADNI). The images taken were 2108 and collected from the years 2005 to 2017. The number of patients involved during the collection duration was 1003. The authors utilized CNN and Inception V3 architecture and attained a result of 90%.

Qiu et al. [32] deliberately explained the interpretable deep learning techniques for the detection of AD from multimodal inputs such as mini-mental state examination, age, and gender. The fully connected CNN is constructed with high-resolution maps and generates precise results with the utilization of a multilayer perceptron. The authors took the ADNI dataset and attained higher results of accuracy. With the integration of feature selection with the deep learning classification techniques Mahendran et al. [33] have stated novel AD detection techniques. For the dataset, the DNA Methylation dataset has been utilized. The dataset was normalized, quality controlled, and downstream and forwarded to the feature extraction techniques. The CpG sites were incorporated into the datasets for the classification model.

3.4. Wearable Technologies

For epileptic seizure detection, an automatic annotation correction was suggested by Zhang et al. [34] based on wearable EEG. Because of ictal activity absence, recorded wearable EEG with the seizure activity delineated gold-standard 25-channel. For visual annotation correction and the training set, the seizure annotations were corrected with its effectiveness corrected. From wearable EEG, non-seizure data were automatically removed and the trained seizure detection models were compared to evaluate the correction of automatic annotation. Compared with the approach trained, fewer false-positive detections and more sensitivity were automatically corrected seizure annotations and trained automated seizure uncovering model. From gold-standard vEEG, an original seizure annotations with the trained approach. For the correction of automatic seizure annotation, better performances are provided by the approach of wearable EEG seizure detection.

The multiple convolutional neural networks were presented by Carmo et al. [35] for the segmentation of Alzheimer's disease. The neuropsychiatric disorders investigation and key importance was magnetic resonance imaging-based segmentation. Deep learning with several recent models was utilized in an active research field for automatic segmentation. From public datasets, Alzheimer's disease patients and train the segmentation of state-of-the-art hippocampus. In different domains, the hippocampus is recognized with these methods. The hippocampus segmentation method is based on ready-to-use, open-source, and state-of-the-art presented. The orientation alignment and automatic pre-processing with the approach of 2D-multi-orientation were utilized. The hippocampus resections in-house epilepsy dataset and HarP test set. Separately reported the testing and training results of HCUnicamp volumes.

Fathima et al. [36] suggested epileptic seizure with modern analysis and dataset review. The non-communicable and brain chronic disease Epilepsy. The brain neurological disorder occurs with most commonly epileptic seizures. The study of brain anatomy utilized an efficient diagnostic tool by using EEG. The decision-making and validation scope was improved by analytical tools of modernization and technological advancements. To avoid complications and risk, the initial stages of epilepsy are evaluated and predicted. From various sources, utilized the dataset, techniques, and methodologies focused. For decision-making and futuristic learning, an understanding of epileptic seizures was forwarded and the dataset sources detailed review included. Different datasets utilize deep learning methodology and machine learning that concentrate.

For automatic epileptic seizure detection, Ayodele et al. [37] presented supervised domain generalization to integrate the disparate scalp EEG datasets integration. From epilepsy and canines, intracranial electroencephalography with seizure development detection algorithms. From the contest, continuous ambulatory human and standard clinical data were included with out-of-sample patient data validated from the top three models. Over the world participated, in the kaggle.com competition and 200 teams of data scientists presented. According to the out-of-sample validation study, the consistent performance and more accurate algorithms were submitted by the top-performing teams. For the detection of personalized seizure, freely available data code was achieved and the seizure detection performance was obtained. To impact patient care, the significant potential and powerful translational tools creation results in high-quality data shared.

In Alzheimer's disease and epilepsy, similar brain proteomic signatures were presented by Leitner et al. [38]. The published proteomics datasets and epilepsy with the protein variations associated were detected. An advanced AD significantly altered the epilepsy patient's hippocampus, altered in protein differences. The tau expression regulates and interacts with several proteins altered in epilepsy. In AD and epilepsy, common protein changes are mediated with the tau. For increased intraneuronal pTau231 and pTau217, shown the multiple phosphorylated tau species and immunohistochemistry. For mediating common pathological protein variations, the potential role of tau is highlighted with the common mechanisms insights provided. For early AD detection, Nagarajan et al. [39] presented deep learning techniques with a comprehensive review. The significantly reduced or prevented early stages of AD were identified. The approach of deep learning's most recent work is examined with the current review. Employed the pre-processing methods and the modalities of various neuroimaging with the early diagnosis of AD purpose. Performed DL techniques with various classification methods along with the comparative analysis.

Bhagubai et al. [39] suggested a wearable EEG grand challenge and the detection of automated seizures. The automated seizure detection models achieved low performance and are still dampened in an ambulatory environment to monitor epileptic patients. For training, the lack of data needed with wearable EEG seizure detection is the major drawback. The behind-the-ear had continuous recordings and 42 patients' large datasets with participants provided. Based on wearable EEG, a robust seizure classifier was developed with the challenged participants. The seizure detection models' performance and training were enhanced with the data-centric approaches that motivated.

4. Datasets and Benchmarking

For the detection of seizures from the AD patients, high quality dataset is needed. However, a limited number of datasets are available, and some of the commonly used datasets are the CHB-MIT Scalp EEG dataset [40], EPILEPSIAE dataset [41], Temple University Hospital (TUH) EEG corpus dataset [42], and DEAP datasets [43]. These are EEG-based datasets used for the detection of seizures. The Alzheimer specific datasets are Alzheimer's Disease neuroimaging initiative [44], Open Access Series of Imaging Studies [45]. Some works are taking to combine both the EEG, clinical data, and imaging system to provide multimodal datasets.

4.1. Challenges in Dataset Collection

The comprehensive datasets for the AD can be developed under various challenges related to data acquisition, pre-processing, annotation, and standardization. Meanwhile, the labeling of AD by the experts, including the multimodal data sources, and the heterogeneity of AD seizure occurrences are the intricate nature of the dataset development. Hence, it is necessary to address these challenges to develop the standardized datasets with a high quality of data. While considering the data acquisition, the main disadvantage is the non-availability of patient data. There are restrictions for accessing the data from the patients based on the medical privacy regulations, including the HIPAA and GDPR. This prevents the collection of large-scale data. For instance, the recording of seizure events is not possible in most of the cases due to the sporadic and unpredictability. The EEG recordings need the monitoring of long term and hence it is expensive. The other techniques, such as neuroimaging techniques, are not even possible for long-term tracking.

The pre-processing of datasets is to be a concern when considering the quality of EEG signals and others. The EEG signals included more susceptibility to noise and artifacts, and hence pre-processing is expensive. The availability of artifacts can make feature extraction a more intricate task. The EEG recording settings also required a complicated process with the electrode placements and file formatting. This might lead to the constraints of the application of machine learning techniques for AD classification.

Moreover, the challenges in labeling and annotation of data seizure also lead to complications. It consumes more time while performing manual seizure labeling with the assistance of EEG technicians and neurologists. The cost is high with the pruning of inter-rater variability. There are standardized seizure event definitions and hence the labeling will affect the generalization and performance. The temporal resolutions of varying modalities are also challenging with the multi-modal annotations. Nowadays AI assistance annotation can be used to provide the labeling, however, the reliability is low and is dependent on the expert leading to consensus-driven approaches and cross-validation.

Universally, there is no standardized format for developing the datasets and it remains challenging. The format of storing the EEG signals varies with MATLAB, EDF, and CSV. The effort of combining the complicated data is high with the varying neuroimaging data formats such as NIfTI, and DICOM. There is no availability of benchmarked datasets and hence comparing various deep learning techniques remains challenging. The generalized demographics of patients are also concerned with the available age, disease severity, and ethnicity. Meanwhile, computational efficiency also remains challenging with the dimensionality of EEG signals and computational resources of neuroimaging systems. For storing the dataset cloud cloud-based system might be utilized with higher GPUs. Processing real-time AD seizure with wearable devices needs optimized accuracy and processing latency. Researchers should consider designing the system to overcome these barriers to predicting AD earlier for better personalized treatment for the patients.

5. Technological Integration

Different technologies are integrated to detect the AD using the dataset. Real-time AD is one among them, which provides a time-to-time analysis framework, and if it senses abnormalities in brain activity, it will provide alert warnings. For this, EEG signals are monitored continuously with the integration of deep learning techniques for the detection of brain signal patterns. The key elements of the system include low-latency data processing units, wearable headsets, and integration with mobile. This provides significant proactive care among the neurodegenerative situations.

The integration of telemedicine's revolutionized access to healthcare with chronic neurological conditions. With this integration, the detections are made continuously over remote areas and help in assisting the patients. The data are often sent to the physicians and also provide alerts about the seizure without visiting the patients. This significantly mitigates healthcare costs and ensures safety. Moreover, AI and IoT-based approaches are used for the detection of AD. IoT devices, including smart watches, wearable EEG headsets, etc, are used for collecting the data in real time. The inclusion of AI in this will help in identifying the anomalies or malicious signals and there in significantly protect the patients. This will change with time for effective learning of the patient's profile. Meanwhile, faster response time can be obtained with the integration of edge computing.

Apparently, Clinical Decision Support Systems (CDSS) incorporated with AI has been developed for the seizure detection of AD patients. The EEG signals are synthesised with the help of this system and analyse the medical history, medication profiles, and patterns of behavioural and provide insightful actions. Based on this, the dosage also adjusted and mitigates the response time, increases the clinical accuracy and avoids intricates.

6. Challenges

Some of the challenges in detecting the seizures from the AD patients are listed as follows,

- Limited availability of dataset and there is no specific EEG pattern dataset for the AD. Moreover, labeling of seizure events is difficult or needs annotation by experts and is time-consuming and costly. Noise is available in the EEG recordings due to the wearable settings and non-clinical data performance.
- The manifesting or non-convulsive nature of the AD seizures makes them difficult for the detection and varying the AD symptoms. This will make the performance of AD-specific contexts challenging tasks.
- The usage of deep learning is also challenging with the black box nature and so it is challenging to trust the prediction values with the lack of explainability.
- Since the datasets are limited, the models that are validated using these datasets might not provide valuable outcomes for patients with various demographics, recording environments, and EEG devices.

7. Future Scope

In the future, some developments are deployed for the better predictions of seizures and some of them are listed below.

- Multimodal models are deployed with the combination of PET, cognitive assessments, behavioral data, and MRI.
- The deployment of multimodal fusion might enhance the prediction accuracy and provide better details about the early detection of seizures.
- Moreover, large-scale datasets can be developed with the collaboration of AI institutions, research labs, and hospitals. Longitudinal EEG monitoring should be implemented for the capturing of seizure events across varying time.
- With sharing the data of individuals, the accuracy and security are enhanced with the implementation of transfer learning and federated learning. With the development of personalized or customized models can increase the sensitivity of the detection model.

8. Conclusion

For the early prediction of AD, it is necessary to develop a comprehensive dataset for training the models. Meanwhile, there are enormous challenges related to data acquisition, pre-processing, annotation, and standardization when considering factors such as reliability and usability. More challenges related to the availability of datasets are often limited for this type of data with the requirement of high cost for monitoring the patients continuously. The protocols of neuroimaging and EEG variability also limit the availability of the data. The imbalanced seizure-to-non-seizure data ratios, contamination of EEG signals by the artifacts, and time consumed by the manual annotation are the main challenges in developing the datasets. These can be overcome with the collaboration of multi-institutional, AI-optimized annotation techniques and standardized data collection. The analysis of including the deep learning techniques for the noise mitigation and fusion of multimodal features provides the way for the enhancement of the quality of the dataset and usage. These key points are used for the establishment of the structure of the benchmark and to develop unbiased AD detection models. Moreover, the challenges related to seizure detection were presented with the future scope. The work analysed various seizure detection models and presented the relevant details.

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Ethics approval and consent to participate

Not Applicable

Consent for publication

Not Applicable

Competing interests

The authors declare that we have no competing interest.

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Data availability

All data generated or analyzed during this study are included in this article.

Authors' contributions

Author 1: Performed the Analysis of overall concept, writing and editing

Author 2: participated in the methodology, Conceptualization, Data collection and writing the study

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