A project report on

# DETECTION AND LATERALIZATION OF EPILEPTIC SEIZURES

Submitted in partial fulfillment for the award of the degree of

## Bachelor of Technology in Computer Science and Engineering with Specialization in Artificial Intelligence and Machine Learning

by

**ROCHANI KRISHNA PRADEEP (21BAI1255)**

**PRIYAM CHOWDHURY (21BAI1267)**

**SHUVADIPTA BISWAS (21BAI1294)**


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Vellore Institute of Technology

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CHENNAI

**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

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I hereby declare that the thesis entitled "Detection and Localization of Epileptic Seizures" submitted by Priyam Chowdhury (21BAI1267), for the award of the degree of Bachelor of Technology in Computer Science and Engineering, Vellore Institute of Technology, Chennai is a record of Bonafide work carried out by me under the supervision of Dr. Nayeemulla Khan.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Chennai

Date: 16/04/25

Priyam Chowdhury

Signature of the Candidate

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This is to certify that the report entitled "Detection and Localization of Epileptic Seizures" is prepared and submitted by Priyam Chowdhury (21BAI1267) to Vellore Institute of Technology, Chennai, in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Artificial Intelligence and Machine Learning is a bonafide record carried out under my guidance. The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

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# ABSTRACT

Epilepsy is a chronic neurological disorder marked by recurrent, unprovoked seizures that affect millions globally, posing significant challenges for diagnosis and treatment. One of the most critical aspects in clinical epilepsy care is not only the accurate detection of seizures but also the determination of seizure lateralization—the identification of which hemisphere of the brain is primarily involved during a seizure. This is especially important for patients being considered for surgical treatment, where knowing the lateralized origin of seizures can inform surgical planning. However, the manual analysis of EEG data to detect and lateralize seizures is often time-consuming, subject to expert variability, and difficult due to the subtle and diverse patterns seizures can exhibit across patients and seizure types.

To address these challenges, this work presents an automated, data-driven framework designed to assist in seizure detection and the analysis of seizure lateralization using EEG data. The system is built around a deep learning approach that is first trained on structured EEG datasets and then extended to operate on multichannel real-world EEG recordings. It incorporates data preparation methods to manage class imbalance, robust model validation techniques to ensure consistent performance, and tailored processing pipelines that adapt the model for use on more complex multichannel datasets. Once trained, the model evaluates EEG recordings second-by-second across multiple brain regions, producing a detailed temporal and spatial profile of seizure activity.

The predictions from all EEG channels are combined into a comprehensive format, which is then visualized through montage plots that illustrate the presence or absence of seizures over time across the scalp. These visual tools make it possible to observe asymmetries in seizure activity between the hemispheres, thus offering insight into lateralization. In addition, spectral maps focusing on the alpha frequency range are used to further validate the findings. These maps, generated over short segments during the seizure, help highlight hemispheric differences in frequency-based activity that may correspond with the model's classification results. By integrating time-domain predictions with spatial and frequency-based visualizations, the system provides a multifaceted approach to understanding seizure behavior. Overall, this framework offers a promising step toward automated assistance in the lateralization of epileptic seizures, contributing to faster, more objective, and potentially more reliable analysis in clinical environments.

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## CONTENTS PAGE NO


**CONTENTS** 7

**LIST OF FIGURES** 9

**LIST OF ACRONYMS** 10

**CHAPTER 1**

INTRODUCTION 11

1.1 EPILEPSY 11

1.2 ELECTROENCEPHALOGRAM 14

1.3 SEIZURE DETECTION 18

1.4 SEIZURE LOCALIZATION AND LATERALIZATION 21

**CHAPTER 2**

BACK GROUND 26

2.1 THE RESEARCH PROBLEM 26

2.2 LITERATURE SURVEY 27

**CHAPTER 3**

PROPOSED SOLUTION 30

3.1 THE APPROACH TO THE PROBLEM 30

3.2 DATASET USED 30

3.3 PREPROCESSING 33

3.4 SYSTEM ARCHITECTURE 36

3.5 THE BENEFITS OF THIS SOLUTION 46

**CHAPTER 4**

RESULTS 49

4.1 DETECTION RESULTS 49

4.2 MONTAGE PLOTS 50

4.3 TOPOGRAPHIC EEG MAPS 52

**CHAPTER 5**

CONCLUSION AND FUTURE WORK 54

**APPENDICES** 57

**REFERENCES** 59

**LIST OF FIGURES** **PAGE NO.**

Figure 1: Seizure types 13

Figure 2: Brain waves 16

Figure 3: EEG Procedure 17

Figure 4: Seizure Localization 22

Figure 5: SMOTE 35

Figure 6: Wavelet denoising 36

Figure 7: Accuracy and Loss curve for Seizure Detection using 1D CNN 39

Figure 8: Seizure Visualization 43

Figure 9: Seizure Visualization on Montage 50

Figure 10: Seizure Signal on single channel for 1 second 51

Figure 11: Topographic EEG Maps 53

## LIST OF ACRONYMS

| | |
|---|---|
| EEG | Electroencephalogram |
| CNN | Convolutional Neural Network |
| SMOTE | Synthetic Minority Over-sampling Technique |
| SOZ | Seizure Onset Zone |
| IoT | Internet of Things |
| XAI | Explainable Artificial Intelligence |
| TP | True Positive |
| TN | True Negative |
| FP | False Positive |
| FN | False Negative |
| ESI | Electrical Source Imaging |
| EDF | European Data Format |
| SNR | Signal-to-Noise Ratio |
| MRI | Magnetic Resonance Imaging |
| PET | Positron Emission Tomography |
| ECG | Electrocardiogram |
| EOG | Electrooculogram |
| EMG | Electromyogram |
| Fp1, Fp2, F3, etc. | Standard 10-20 EEG Electrode Positions |
| TPR | True Positive Rate (Sensitivity) |
| TNR | True Negative Rate (Specificity) |

# Chapter 1

# Introduction

## 1.1 EPILEPSY

Epilepsy is a long-term, non infectious brain condition that occurs in individuals of any age, and with about 50 million affected globally, it represents one of the most prevalent neurological conditions on earth. Of the people afflicted, almost 80% live in low- and middle-income countries, where effective diagnosis and management are typically restricted. Indeed, as many as 70% of individuals with epilepsy might be able to live without seizures if they had proper care, but three quarters of them in developing countries receive no treatment at all. The risk of premature mortality in individuals with epilepsy is as much as three times greater than in the general population. In most parts of the world, patients with epilepsy and their families also encounter considerable stigma and discrimination, making their situation worse.

### 1.1.1 SEIZURES

Pronounced "see-zhr," a seizure is characterized by a sudden surge of abnormal electrical activity in the brain. One of the most frequently recognized signs is a brief loss of consciousness and automatic movements such as convulsions.

All seizures, however, are not exhibited similarly. One could experience tiny twitching of their muscles, isolate muscle jerking, or be interrupted from the activity they're doing and staring blankly for a couple seconds. Seizures happen sometimes and in variable forms; whereas some people would experience one time in their entire lifetime, while others have dozens per day. Thus, seizures' experience tends to be individualized.

Most diseases have the ability to disrupt the brain's normal electrical activity, so a broad range of variables can cause seizures. Some of the possible causes include changes in blood glucose levels, infections, traumatic injuries, and underlying medical conditions.

An expert physician is able to decide on the appropriate therapy based on the specific needs and medical history of the individual.

### 1.1.2 EPILEPTIC SEIZURES

An epileptic seizure is a brief, unexpected rush of brain activity that interferes with regular neuronal communication. All aspects of an individual's behavior, movement, feelings, and consciousness can temporarily be influenced by this abnormal activity spike. Approximately 50 million people worldwide suffer from epilepsy, a long-term neurological disorder that is characterized by epileptic seizures, according to the World Health Organization. Usually lasting

anywhere from a few seconds to a few minutes, the severity and duration of such seizures can vary widely, thereby being frequently unpredictable. Although the precise cause of an epileptic seizure is not always determinable, it may be caused by numerous different factors, such as tumors, infections, brain injury, genetic disorders, or developmental abnormalities. Depending on where within the brain the seizure occurs, a person will experience jerking of the muscles, loss of consciousness, confusion, or abnormal sensations like déjà vu or tingling during a seizure that disrupts the brain's normal electrical signal pattern. In contrast to seizures due to outside causes like fever or drug withdrawal, epileptic seizures are usually repetitive and unprovoked, i.e., they happen without cause. In addition to the seizures themselves, epileptic seizures can have a tremendous negative impact on quality of life by inducing social stigma, psychological and emotional distress, and impairment in cognitive functioning. Although medication does not work in all patients, control of epilepsy usually requires extended treatment, usually with anti-seizure medication that stabilizes brain electrical activity. In such a situation, neurostimulation or surgery might be an available solution that would be worth considering. Significantly, epileptic seizures are not contagious; under correct care and treatment, the majority of patients suffering from epilepsy are able to enjoy active, useful lives.

### 1.1.3 TYPES OF SEIZURES

Seizures can manifest in different ways, each having a different impact on the brain and resulting in different symptoms. Focal aware seizures involve retained consciousness, where the person is completely aware of their environment despite feeling unusual sensations or movements. These can be such things as sudden jerking of a limb, unusual tastes or odors, or emotional shifts such as fear or déjà vu. Although short and not necessarily apparent to others, these experiences can be disturbing and disruptive to the individual undergoing them.

On the other hand, focal impaired awareness seizures have a change or loss of consciousness. A person will seem confused, dazed, or unresponsive to others during these attacks and will also produce automatic behavior like lip smacking, hand rubbing, or purposeless walking. The seizure lasts from 30 seconds to a few minutes, and the person usually has no or little memory of the episode.

Absence seizures, which are most common in children, consist of a sudden brief loss of consciousness. The individual will stare off into space for a few seconds, perhaps with slight movements such as eye blinking or lip smacking. The seizures are very short—usually less than 10 seconds—but may occur many times a day, possibly disrupting learning and activities of daily living if not detected and treated.

Myoclonic seizures are characterized by abrupt, fleeting jerks of the muscles, most frequently of the upper body, arms, or legs. These jerks can be alone or occur in clusters and are not associated with loss of consciousness. Individuals having these seizures often have the feeling

that they've been shocked or startled and often drop objects or fall as a result of the jerks, depending on their localization and intensity.

Tonic seizures are an instantaneous stiffening of muscles, usually in the arms, legs, and back, that may result in someone's falling while standing. They typically don't last longer than 20 seconds and most often happen while one is sleeping. Atonic seizures, or drop attacks, are an instantaneous loss of muscle tone that results in sudden falling or head dropping. Because they don't warn the person beforehand, they are likely to cause injury.

Lastly, tonic-clonic seizures are the most well-known form and typically involve two stages: tonic stage in which the body stiffens, then clonic stage with rhythmic jerking of the limbs. Seizures can last up to a few minutes and sometimes have a preceding cry, incontinence, tongue biting, and postictal confusion or tiredness. The recovery period may differ a lot from person to person.

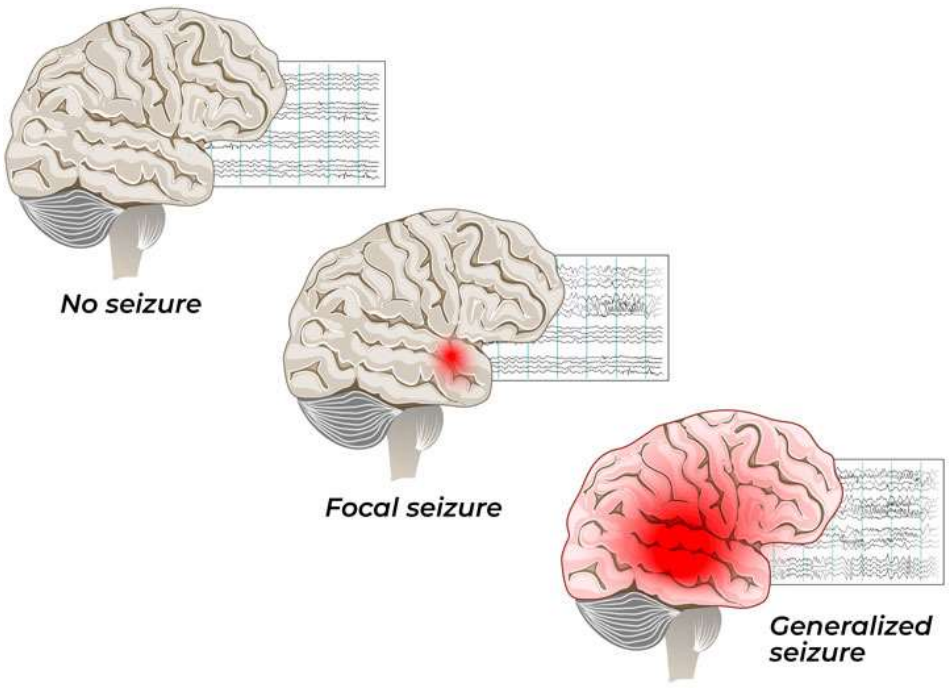



Fig 1: Seizure Types

The illustration illustrates normal brain activity, focal seizures, and generalized seizures. For no seizure, the brain shows normal electrical activity, as reflected by a normal EEG tracing. For focal seizure, abnormal electrical discharges arise from one specific localized location in one cerebral hemisphere. This is illustrated as a red-hatched area within the brain and as a corresponding localized disturbance in the EEG. In contrast, there is generalized, simultaneous widespread abnormal electrical activity from the onset all over both hemispheres in a generalized seizure, as is seen with the diffuse red shading everywhere on the brain and an even

more disorganized EEG. This makes the key difference really stand out: focal seizures originate in one region, but generalized seizures are simultaneous throughout the entire brain.

## 1.2 ELECTROENCEPHALOGRAM (EEG)

An electroencephalogram (EEG) is an outpatient procedure that quantifies electrical brain activity using electrodes on the scalp. The electrodes detect voltage changes from ionic current flows within the neurons, namely the synchronised firing of cortical pyramidal cells. The signals are amplified and displayed as waveforms, typically banded into frequency bands—delta, theta, alpha, beta, and gamma—each of which is associated with different states of the brain such as sleep, relaxation, or active thinking. EEG is used widely in clinical and research settings to monitor brain activity, diagnose neurological diseases such as epilepsy, and study mental processes.

### 1.2.1 ELECTRICAL ACTIVITY IN THE BRAIN

The electrical operation of the brain is an accurate and tightly regulated system, relying upon the timing and ratio of the firing of the neurons to enable normal function. Information is passed from neuron to neuron using electrochemical transmission, and activity needs to be accurately controlled to prevent abnormal excitability. In the normal situation, inhibition and excitation mechanisms in combination ensure that the neurons fire appropriately and with proper intensity. This equilibrium is preserved through ion channel activity, synaptic transmission, and neuromodulation governing the passage of ions like sodium, potassium, calcium, and chloride. However, if the regulation fails, some brain areas become hyperexcitable and then develop instantaneous fits of coordinated electric activity diverging from usual neuronal processing. These seizures can lead to transient disruptions in sensation, behavior, awareness, or movement, depending on the affected brain region.

There are a number of underlying causes that can lead to this abnormal electrical activity. Genetic differences can lead to mutations in ion channels or receptor proteins, changing their function and predisposing neurons to hyperexcitability. Structural brain disease, congenital or secondary to trauma, stroke, or derangements of development, may produce fields of abnormal connectivity or scar that provide a location for deranged electrical activity. Inflammatory and metabolic derangements affect excitability of neurons as well, because these can alter levels of neurotransmitters, shift pH balance, or derange energy delivery to neurons. Hormonal changes, especially in the situation of increased sensitivity of a person to endocrine fluctuations, may regulate the level of excitability of neural networks. Moreover, sleep deprivation, severe emotional stress, or overloading sensory stimulation may serve as extrinsic triggering mechanisms, decreasing the threshold level for coordinated neuronal firing in vulnerable networks. The ensuing disruptions of the brain's electrical rhythms will be transient or episodic, according to more or less predictable patterns depending on the subject's neural architecture

and the particular pathways involved. These patterns, though often localized, also may propagate to larger neural networks, causing larger-scale disruptions of brain function.

### 1.2.2 BRAIN WAVES

Brain waves are repeating patterns of central nervous system brain activity resulting from the coordinated firing of electric activity of the communicating neurons. Five broad frequency classes exist for the brain waves, which are scored in terms of Hertz (Hz): alpha, beta, delta, gamma, and theta waves. They are 0.5 to 4 Hz slowest known as the delta waves and have been normally associated with non-dreaming, deep sleep. There are the 4 to 8 Hz theta waves, seen during drowsiness and light sleep, also found in the state of meditation, more often associated with creativity and intuition. Alpha waves, usually ranging from 8 to 13 Hz, are found when one is relaxed but awake, and particularly when the eyes are closed, and are associated with rest and quiet contemplation. Beta waves are between 13 and 30 Hz and are seen when there is active thinking, problem-solving, and concentrated mental activities. Finally, gamma waves with frequencies greater than 30 Hz are the fastest and are believed to be involved in higher-order cognitive processes like perception, consciousness, and learning.

Brain waves in epilepsy have a crucial diagnostic and interpretive function. Epilepsy is a neurologic disorder in which a person has recurring and unprovoked seizures, caused by abnormally excessive and synchronized neuronal discharge in the brain. Seizures tend to create characteristic patterns of brain wave activity that can be recorded using electroencephalography (EEG). As the seizure goes on, typical brain wave patterns are lost, often being overtaken by sharp spikes, high-frequency bursts, or rhythmic bursts with an amplitude significantly altered from baseline neural oscillations. For instance, interictal spikes and epileptiform discharges—short, abnormal waveforms observed between seizures—are typically present in patients with epilepsy. Depending on the condition of epilepsy, different brain wave abnormalities can be found; for example, absence seizures are usually comprised of a 3 Hz spike-and-wave pattern, whereas focal seizures may be presented as local rhythmic discharges. Such altered brain wave patterns are not only significant in the diagnosis of epilepsy but also in localizing the seizure location in the brain, assessing the severity of the condition, and quantifying the treatment response. Quantitative EEG and machine learning algorithms further enhance our ability to analyze these patterns of brain waves to better and more personalized management of epilepsy.

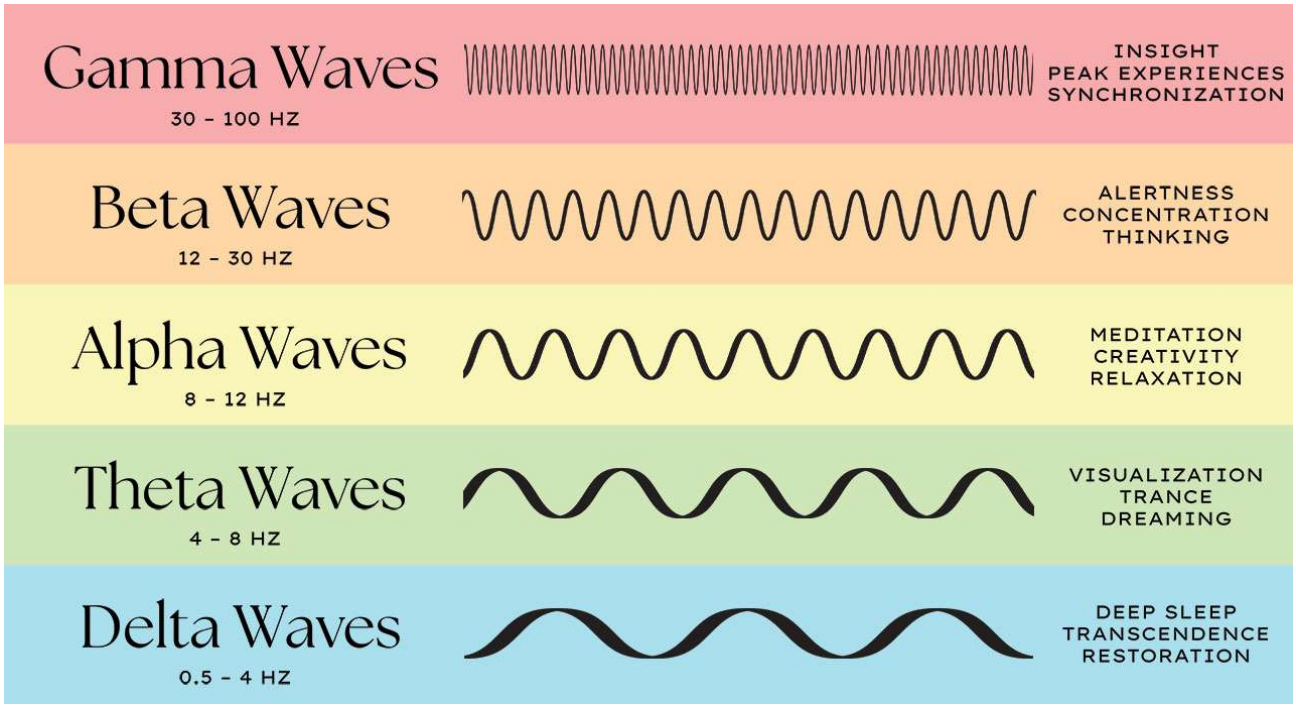



Fig 2: Brain waves

### 1.2.3 MEASURING ELECTRICAL ACTIVITY USING EEG

EEG functions as a method to evaluate brain electrical signals through monitoring of neural-generated electrical discharge. Action potentials connect billions of neurons inside the human brain through which these cells communicate. Large groups of neurons that fire simultaneously produce electrical fields which become detectable on the human scalp surface. A combination of electrodes is attached to targeted scalp regions with conductive substances to maintain skin contact. Application of electrodes follows the 10-20 system standard which brings uniformity in electrode placement between different subjects. The brain cell ionic currents produce voltage fluctuations which electrodes detect and register into electrical signals. Tiny voltage changes occur between microvolts which need both amplification along with noise-reducing filtering processes before analysis. Digital recording follows after the conversion of signals into numbers. EEG measures neurological time patterns with excellent temporal precision which enables investigators to monitor neural activity in live situations including cognitive operations and sleeping states and epileptic episodes alongside brain-machine communication systems. When recorded EEG signals produce waveforms their frequency variations along with amplitude differences correspond to various mental states and brain functions. The evaluation of brain signals depends on studying their wave patterns and frequencies so researchers together with clinicians can discover irregularities while tracking neurological disorders in medical environments and scientific research sites.

Seizure detection depends heavily on EEG because it detects and studies brain electrical waves to identify abnormal seizure-related signals. A seizure produces distinctive waveforms on EEG recordings because brain neurons activate in sudden excessive synchronized patterns. Electrical

brain signals mostly present as sharp waves, spikes and rhythmic patterns during abnormal events that differ from typical neurological patterns. EEG technology detects seizure patterns in real time which enables healthcare providers to determine the presence and classification of seizures as well as their starting region for accurate diagnosis. EEG systems with continuous or long-term monitoring help identify seizures which occur without noticeable physical symptoms in epilepsy patients including non-convulsive cases.

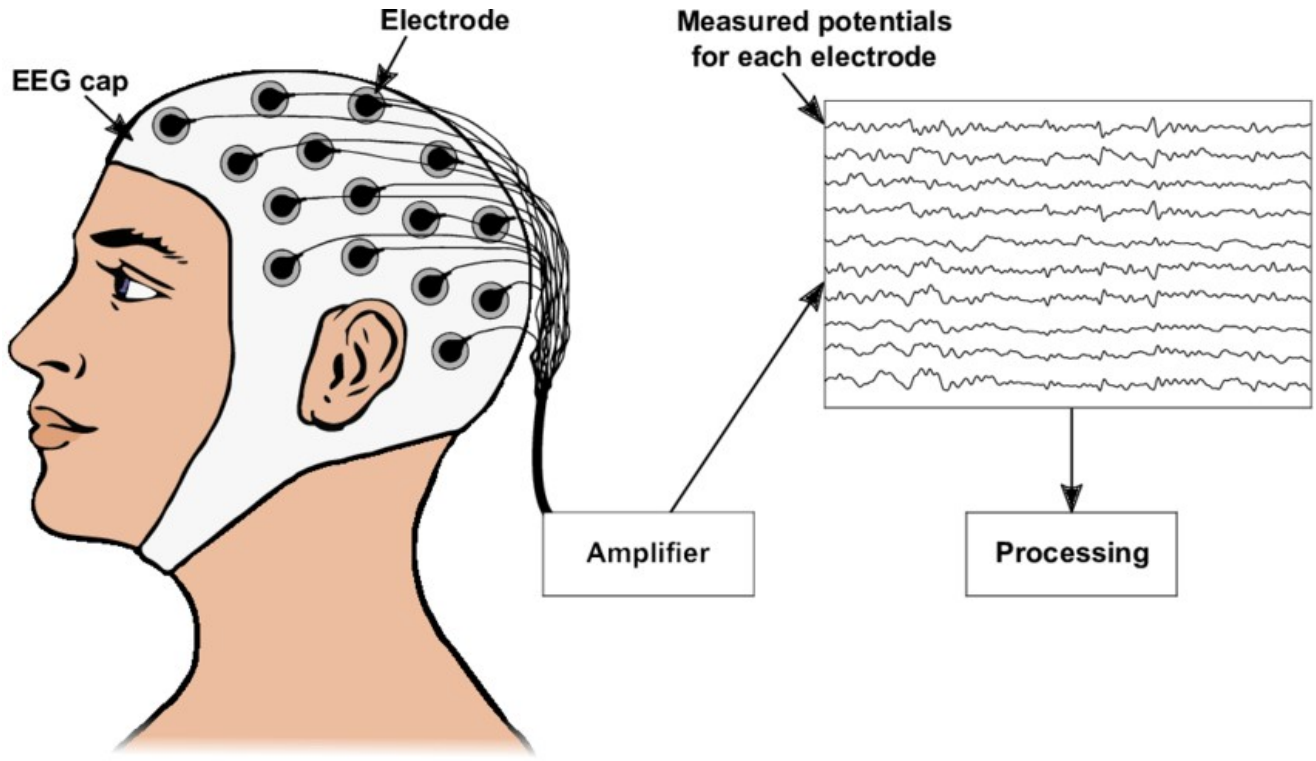



Fig 3: EEG Procedure

The diagram shows how an EEG system works for evaluating brain activities through its operational stages. The EEG cap with its multiple electrodes obtains brain signals by applying to the head surface. The transfer of signals from electrodes occurs through this method to reach an amplifier where signal power receives enhancement because these signals operate at minimum intensity levels. Elements from each processed electrode signal are sent to testing software that examines the brain activity patterns. The research community employs this setup for neuroscience purposes and medical diagnostic testing as well as brain-computer interface operations.

### 1.2.4 SCALP AND INTRACRANIAL EEG

The brain electric activity measurement between scalp EEG and intracranial EEG (iEEG) shows variations across their recording methods and implementation and by their need for surgical intervention. Scalp EEG provides non-destructive measurement of electrical activity through

electrodes on the scalp so it remains available without endangering individuals while allowing extended or multiple sessions of observation. Medical professionals employ this technique for diagnosing epilepsy and for monitoring sleep patterns while they use it to study brain function together with cognitive research. The non-invasive character of scalp EEG stands as a primary benefit because it does away with procedural risks and permits research coverage throughout numerous populations from children to healthy adults. Hospital settings are not required for continuous or ambulatory monitoring through this method. Intracranial EEG requires electrodes that are surgically placed on brain surface or in deeper brain regions because it provides highly precise spatial information with clear cerebral signals. Reliable seizure origin localization and brain functional area mapping processes depend on iEEG as an exceptional diagnostic tool for both drug-resistant epilepsy patients and pre-neurosurgical procedures. Set in opposition iEEG and scalp EEG support different functions where scalp EEG provides safety through easy use and iEEG enables precise monitoring of deep brain areas.

## 1.3 SEIZURE DETECTION

Different approaches exist for detection of seizures where neuroimaging and signal processing remain the principal methods. EEG (Electroencephalography) dominates as the main detection technique because it measures brain electrical activity to detect abnormal spike and sharp wave patterns. The neuronal field detection capabilities of MEG (Magnetoencephalography) produce higher spatial accuracy than EEG (Electroencephalography) at a cost that makes MEG equipment expensive. The diagnostic capabilities of MRI (Magnetic Resonance Imaging) do not involve real-time seizure detection but discover brain structures that increase seizure risk which can help doctors make diagnoses and prepare for possible surgeries. The automatic detection of seizures through EEG and MEG data is performed with machine learning models featuring CNNs while feature extraction utilizing wavelet transform or time-frequency analysis together with classification algorithms serves as their core detection mechanism. The applied methods yield better detection precision and continuous medical surveillance which thus leads to superior patient results.

### 1.3.1 SEIZURE DETECTION USING EEG

The seizure detection system of electroencephalography (EEG) functions as a vital tool in epilepsy management because it consists of both safe surface EEG measurements along with implantable intracranial EEG observations (iEEG) for brain signal assessments. The detection of voltage fluctuations by EEG allows clinical staff and researchers to locate abnormal patterns that signify epileptic seizure events through monitoring neural ionic currents. The popularity of scalp EEG originates from its affordable setup and easy use and its non-invasive nature that benefits medical and mobile evaluation needs. The technology delivers summonable brain signal assessments for generalized seizure diagnosis and multiple focal seizure recognition. Scalp EEG suffers from reduced resolution which together with signal degradation causes by

electrical signals passing through skull and scalp tissues. The use of scalp EEG proves to be inadequate for detecting deep-located epileptic disease sources and accurate brain localization during pre-surgical assessments.

The evaluation of brain pathology during epilepsy surgery relies on intracranial EEG (iEEG) which uses electrodes applied either on brain tissue surfaces or inside brain tissue to achieve superior spatial and temporal resolution that aids precise determination of seizure onset areas particularly when studying deep cortical areas or mesial temporal lobe epilepsy. The method diminishes artifacts while detecting faint changes occurring before an ictal episode which would go undetected in scalp EEG recordings. This advanced invasive procedure requires open brain surgery therefore presenting dangers to patients for example infections as well as bleeding complications in addition to causing discomfort since doctors commonly use it only when patients have epilepsy that cannot be controlled surgically. The spatial design of iEEG restricts data collection from the entire cortex because brain surgery requires limitations due to surgical boundaries which can limit seizure detection outside the implanted area.

The benefits of EEG seizure detection keep several attractive properties. The device can identify both visible seizures together with hidden electrographic seizures for better diagnostic assessments followed by improved treatment strategies. Modern EEG seizure detection systems using machine learning and deep learning algorithms deliver successful real-time detection performance which enables extended home care for epileptic patients while decreasing healthcare worker workload. Intensive care unit continuous EEG monitoring aids in finding non-convulsive seizures which normally escape detection. However, there are also challenges. Automated detection methods face complications because EEG signals display high sensitivity to artifacts created by body movements combined with eye activities and external interferences. System performance in automated EEG detection relies on individual-specific approach methods as well as comprehensive training databases to deliver consistent results.

Scalp EEG together with intracranial EEG operates as key diagnostic methods in seizure detection systems although each instrument features its unique operational problems. Scalp EEG works for most diagnosis needs because of its safety and easy use but iEEG delivers critical accuracy during epilepsy diagnosis of difficult cases. Modern epilepsy care progresses because EEG-based monitoring systems combine with advanced computational models for rapid accurate seizure detection systems. Full EEG seizure detection depends on ongoing development of signal enhancement technologies along with artifact removal methods and algorithms for general use.

### 1.3.2 SEIZURE DETECTION USING MEG AND MRI

Static analysis of brain activity using EEG serves as the main tool for live seizure monitoring while MRI and MEG technologies offer enhanced strengths in epilepsy diagnosis and treatment. The combination of these methods offers essential information about epilepsy's brain structures

and functioning mechanism particularly when EEG tests with them in a comprehensive diagnostic methodology. MRI technology enables healthcare professionals to create detailed images of the brain which reveals vital structural information that shows characteristics such as cortical dysplasia together with hippocampal sclerosis and tumors and vascular malformations capable of triggering seizures. During pre-surgical planning it identifies crucial lesions that might be sources of seizure onset activity. Several advanced MRI methods including functional MRI (fMRI) and diffusion tensor imaging (DTI) together with volumetric analysis enable physicians to detect epilepsy origins better and monitor whole-system task-specific connectivity. Since MRI cannot measure real-time brain activity it remains incapable of detecting actual seizures during operation. The method presents brain structure images yet lacks the capacity to detect live epileptiform activity therefore ensuring only anatomical evaluation and not continuous seizure tracking.

Fast brain signal detection through Magnetoencephalography (MEG) provides similar time-based measurement capabilities as EEG and superior spatial accuracy. The tool detects magnetic fields from neuronal operations that traverse brain tissue with minimal interference compared to scalp and skull distortions of EEG electrical signals. The technique produces clear signals from deeper brain areas and sulcal regions which otherwise cannot be adequately detected through scalp recordings of EEG. The tool MEG functions exceptionally well for detecting interictal epileptiform discharges while extensively aiding surgical planning for epilepsy patients who fail to respond to medication. MEG acts as a diagnostic tool for finding epileptic sources in brain imaging exams when MRI shows no abnormalities and EEG tests yield ambiguous results. The major drawbacks of MEG include its excessive cost combined with the need for magnetically shielded labs which restricts widespread use of this technology. Scientists mainly use MEG systems for recording interictal patterns as they struggle to document spontaneous seizures during the limited laboratory measurement time. Due to its considerable complexity MEG demands both highly experienced professionals and powerful computation systems for proper evaluation.

In comparison to EEG, both MRI and MEG offer distinct advantages but also notable drawbacks. The structural imaging strength of MRI prevents it from tracking fast seizure activity which makes the technology ineffective for identifying seizures in real time. The application of MEG suffers from cost limitations as well as operational restrictions which prevent continuous or ambulatory monitoring of patients. The real-time functionality and accessible monitoring offered by EEG overrides the supplementary role of MRI and MEG which remains optimized for enhancing epileptic disorder comprehension. The combined use of MRI that provides structural analysis with MEG functional mapping and EEG electrical activity evaluation enables a complete approach for epilepsy diagnosis and treatment assessment in cases requiring surgical evaluation.

## 1.4 SEIZURE LOCALIZATION AND LATERALIZATION

Locating both the specific brain area and the side of origin for seizures represents essential diagnostic and treatment procedures for epilepsy management. Brain lateralization helps to find the seizure origin in either the left or right brain hemisphere while localization establishes which brain region like temporal or frontal areas is involved. Accurate identification of which brain hemisphere and specific area hold essential value when planning clinical interventions and surgical treatments for cases of drug-resistant epilepsy. The determination of seizure onset zone (SOZ) merges data from EEG recordings together with neuroimaging along with clinical symptom diagnostics. New developments in AI and neuroinformatics technology have improved the accuracy of electrical seizure localization which helps physicians find the best treatment paths for the epileptogenic zone.

### 1.4.1 SEIZURE LOCALIZATION

The procedure for determining where epileptic seizures start within the brain is known as localization of epileptic seizures. The location of epileptic seizures proves critical for diagnosis purposes as well as surgical preparation of patients with refractory epilepsy. Epileptic brain activity emerges throughout different brain regions yet precise localization enables healthcare professionals to detect between focal epilepsy when seizures begin in one particular brain section while generalized epilepsy labels seizures that show simultaneous brain engagement. Neurologists together with neurosurgeons leverage SOZ localization information to shape better treatment options that should preserve critical brain functions when performing epileptogenic zone interventions. Healthcare professionals achieve localization using clinical observation together with neuroimaging as well as electrophysiological recordings and signal processing technologies supported by machine learning methods.

People commonly use scalp electroencephalography (EEG) as the main technique for localizing seizures by measuring brain electrical signals through surface electrodes. The non-invasive nature of scalp EEG while delivering important information about seizures and interictal discharges proves limited in its capacity to precisely locate deep or subtle seizure origins particularly in mesial temporal lobe regions. Researchers solve this limitation through surgical implementation of two invasive tests: intracranial EEG (iEEG) and stereoelectroencephalography (SEEG). Clinical staff use electrodes implanted directly into brain tissue to perform high-definition three-dimensional detection of epileptic discharges. The identification of seizure-related structural or functional abnormalities is supported by neuroimaging techniques that include MRI and fMRI as well as PET and SPECT. MRI demonstrates its ability to show cortical malformations in addition to tumors and hippocampal sclerosis but PET and SPECT scans reveal separate brain metabolic and perfusion patterns through seizures.

Seizure localization has received significant transformative power from artificial intelligence (AI) and machine learning (ML) systems which employ deep learning models to process EEG signals. Deep learning models based on CNNs and RNNs together with hybrid variations help identify and pinpoint seizure occurrences through raw EEG signals or data representations such as spectral analysis or wavelet analysis. These analytical systems detect unpredictable complex data patterns which expert human analysis cannot detect. The healthcare field depends on explainable AI (XAI) methods to reveal the reasoning systems use for their decisions which strengthens medical practitioners' acceptance of automated localization techniques. The CHB-MIT Scalp EEG Database and Freiburg EEG databases offer publicly accessible EEG data to support training and validation of such models. The examination of functional connectivity analysis and graph theory in seizure-related brain interactions helps researchers to identify additional ways of improving seizure localization. The successful identification of epileptic seizures helps both surgical patients receive better treatment and expands our comprehension of brain processes in abnormal states which benefits the wider fields of neuroscience and neurological disease treatment.

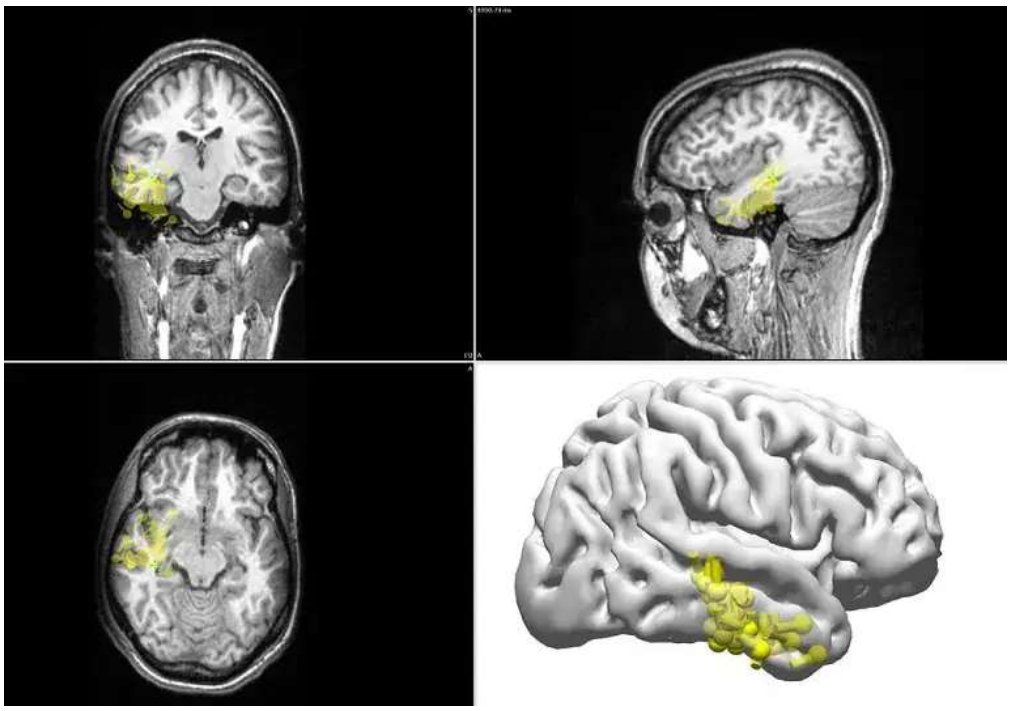


Fig 4: Seizure Localization

An epileptic seizure focus localization becomes evident through the image that links a mesial temporal lobe seizure onset area with structural MRI information as well as functional or electrophysiological data. The highlighted yellow area tracks down the seizure onset zone on all three image views including coronal, sagittal and axial while showing its origin in the brain's specific electrical discharge region. Image analysis through 3D reconstruction in the lower right section provides surgical planning capabilities by showing the studied brain area in its structural

context. This localizes essential information which proves vital for patients dealing with drug-resistant epilepsy because it enables physicians to evaluate seizure tissue removal safety in brain surgery through functional analysis.

### 1.4.2 SEIZURE LATERALIZATION

The process of brain lateralization describes how physical functions operate primarily within a single brain half compared to the other half. Most individuals process language functions together with logical reasoning and analytical tasks through their left brain hemisphere as perceived from scientific research while spatial awareness along with creative functions belong primarily to the right brain hemisphere. The typical left-right brain lateralization pattern becomes disrupted among people who have epilepsy specifically with temporal or frontal lobe origin. Persistent epileptic brain activities result in essential neural network alterations which redirect cognitive functions like memory or language to operate either from one side of the brain to the other or both sides. Neuroplastic changes occur during reorganization as a way for the brain to minimize cognitive effects from ongoing epileptic electrical activity and sustain functional abilities.

The language functions which usually operate in the left brain hemisphere experience right-hemisphere relocation in patients suffering from left temporal lobe epilepsy. Early-onset epilepsy specifically affects brain plasticity because it occurs during brain development. Functional MRI (fMRI) and intracarotid amobarbital testing (Wada test) reveal that the patients show either right-lateralized or complete bilateral language dominance. Language reorganization following this structural change could protect speech abilities but does not necessarily produce peak linguistic performance and patients might face language-related delays. The side of seizure onset determines verbal memory impairment and functional reorganization patterns that influence these memory functions.

The medical procedure for epilepsy surgery requires complete knowledge about which areas of the brain perform language tasks and encode memory because anterior temporal lobectomies involve removing epileptic tissue from the primary region. Surgical removal of epileptogenic tissue from the region controlling language leads to significant chances of language impairment alongside verbal memory decline. Detailed pre-surgical evaluations become essential because they evaluate functional lateralization. Medical professionals use fMRI, MEG, EEG and neuropsychological examinations as standard screening methods to evaluate patients' cognitive decline potential following surgery. The possibility of wider surgical candidacy emerges for patients with atypical lateralization who demonstrate right hemisphere or bilateral language representation because their essential language functions face decreased risk during surgery. Doctors need to develop customized surgical plans because lateralization patterns show diverse patterns in patients.

The exact period when epilepsy begins shapes how lateralization patterns are affected in people with seizures. A significant functional reorganization occurs in children with epilepsy because their epileptogenic area disrupts traditional language areas that include Broca's and Wernicke's regions. When epilepsy appears in adulthood it leads to restricted flexibility in language lateralization and limited reorganization occurs. Additionally, the duration and severity of epilepsy influence lateralization. Seizures of extended duration create increasing pressure on brain cortical tissue that activates structural and functional modifications throughout the brain. Unlimited changes in right-brain lateralization patterns during the lifespan occur because of biological elements and pathological conditions as well as environmental influences.

Neuroimaging techniques combined with machine learning technology introduce modern methods to evaluate and forecast lateralization patterns in epileptic patients. DTI and resting-state fMRI provide neuroscientists with two different methods to understand white matter health and brain functional connections. Reports show that these modalities provide valuable results for determining abnormal patterns of hemispheric dominance as well as surgical outcome forecasting. Lightning-powered lateralization prediction algorithms combining EEG data and neuroimaging information help healthcare providers evaluate brain dominance without surgically invasive methods. Doctors benefit from these methods when treating children as the Wada test proves difficult to use for pediatric patients.

Proper diagnosis of altered brain lateralization patterns leads to effective treatment plans for long-term care facilities and rehabilitation programs. Cognitive therapy methods tailored for patients displaying reorganized or atypical language dominance need to follow their altered brain functional areas. Long-term neuropsychological testing must happen to track lateralization changes particularly in cases of new seizure areas or brain surgery impacts on functional brain composition. Epileptic patients whose cognitive abilities potentially suffer from early-onset epilepsy receive better planning for education and rehabilitative services because of lateralization knowledge.

### 1.4.3 SCALP EEG FOR SEIZURE LATERALIZATION

The procedure of scalp electroencephalography (EEG) proves better at detecting which brain hemisphere starts seizures than it does at finding exact seizure locations within cortical areas. The spatial resolution and sensitivity to artifacts in scalp EEG systems are the main reasons why these systems struggle to achieve reliable results. Scalp EEG detects electrical brain signals arising from big neuronal populations that primarily reside in the outer layers of the cerebral cortex. The skull together with the scalp functions as electrode conductors which distort electrical signals from deep or focal sources when they reach the scalp electrodes. The “blurring” effect reduces scalp EEG precision because it hinders accurate detection of deep or small cortical sources. The limited number of clinical electrodes together with their physical spacing cannot produce accurate resolutions of small spatial features. The medical field can correctly determine which hemisphere contains epileptic activity if a seizure focus produces

noticeable rhythmic discharges at sufficiently high amplitudes or affects significant brain areas. The clinical identification of temporal lobe epilepsy benefits noticeably from such localized discharges because they easily provide lateralized evidence.

Scalp EEG lacks sufficient precision in localization so researchers increase its value by combining it with different neuroimaging and electrophysiological techniques. Linking EEG data obtained from scalp recordings to brain structural abnormalities including cortical dysplasia and tumors and hippocampal sclerosis becomes possible when using MRI technology. PET and SPECT functional imaging deliver metabolic and perfusion data which lead to identifying localized brain areas representing the seizure onset zone. When coupled with high-density EEG systems the ESL algorithms create computational models for finding the probable cortical regions where scalp potentials originate thereby increasing spatial accuracy. When MEG combines with EEG it becomes possible to determine epileptiform activity sources through its excellent spatial precision and unimpeded skull conductivity. SEEG or subdural grid recordings serve as intracranial EEG methods that doctors may utilize after initial lateralization through scalp EEG and imaging approaches. The invasive recording techniques enable scientists to make measurements at specific target locations while promising important information for epilepsy surgical plans. Scalp EEG remains essential for lateralizing seizures yet its localization capability emerges fully when combined use occurs with advanced imaging and iEEG thus creating a multi-method strategy to precisely identify brain regions involved in seizures.

Scalp EEG serves as the initial seizure lateralization method because it is a non-invasive test that exists widely and costs less while providing live functional brain activity information about seizures. The method enables health care providers to rapidly identify the brain's involved hemisphere thus directing their follow-up investigations. Advanced methods such as intracranial EEG or functional imaging cannot replace scalp EEG for lateralization because direct use of these techniques without initial lateralization proves impractical and too expensive and invasive unless testing areas are already identified. Scalp EEG acts as a fast screening and diagnostic tool to provide direction for focusing additional localization techniques which leads to improved procedure safety and precision.

# Chapter 2

# Background

## 2.1 THE RESEARCH PROBLEM

The neurological disorder epilepsy continues to present a substantial worldwide health concern since it affects large numbers of people throughout the world. Epilepsy functions as a neurological condition which manifests through more than one seizure without detectable stimulus while producing major life quality changes among affected patients. Many patients keep having uncontrolled seizures despite the existing treatments while proper diagnosis and therapy remain important to address this condition. Treatment planning together with surgical intervention requires proper identification and exact localization of seizure onset zones. Limited detection and precise localization of these seizures exists because of disparate seizure signs that appear across different patients. Today's seizure detection procedures together with localization methods present major obstacles for early and effective intervention because they are known for being both expensive and time-consuming and invasive.

The combination of MRI and MEG along with iEEG provides valuable information about epilepsy-related brain activity but each of these techniques brings major technical constraints to the process. The highly detailed structural images from MRI fail to provide the necessary heightened checkpoint analysis needed during seizure tracking and pinpointing. The ability of MEG to measure neuronal fields comes with two problems which reduce its practicality: high sensitivity to background interference and exorbitant price tag for equipment maintenance. Doctors regard iEEG as the definitive method for seizure localization but this approach requires invasive surgery to install electrodes directly into brain tissue and creates medical risks and needs extensive operational support. The effectiveness of these diagnostic methods remains limited for daily clinical practice since their accessibility exists only after widely used treatments prove ineffective.

Scalp EEG continues to represent a widespread non-invasive method for superficial discovery of epileptic activity because it tracks neural activity signals recorded from scalp electrodes. The ability of scalp EEG to detect seizure occurrences remains invaluable yet its main drawback includes its lack of spatial detail. Recorded signals display a high level of smoothing on the scalp which reduces the ability to pinpoint the exact brain area where seizures begin. The spatial resolution deficiency prevents doctors from determining exact brain areas involved in seizures thus making treatment planning challenging especially for surgical procedures. The precise seizure localization requires better methods beyond scalp EEG because this tool provides important temporal data yet lacks required spatial resolution in its current form.

## 2.2 LITERATURE SURVEY

The changing face of seizure analysis has witnessed a shift from traditional clinical interpretation to sophisticated, data-driven approaches. Seizure detection, localization, and lateralization are increasingly being addressed from the vantage points of computational neuroscience, signal processing, and artificial intelligence. Electroencephalography (EEG) continues to be the modality of first choice for seizure detection because of its excellent temporal resolution and non-invasiveness. Yet, its intrinsic spatial resolution limitations have prompted the combination of EEG with neuroimaging methods like MRI, PET, and functional MRI (fMRI) to enhance localization precision, particularly in pre-surgical assessment of drug-resistant seizure patients.

The last few years have seen accelerated development in the application of machine learning (ML) and deep learning (DL) methods for seizure analysis automation. From hand-designed algorithms with classical techniques to current neural networks able to extract sophisticated spatiotemporal patterns, these models provide exciting solutions for real-time, high-fidelity seizure detection and classification. Deep learning models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers are increasingly being applied to decode raw EEG signals, identify subtle deviations, and even conduct lateralization of seizure onset zones with no manual annotations.

Additionally, technological improvements in multimodal data fusion have made it possible to fuse electrophysiological and structural imaging data to improve the accuracy of localizing the epileptogenic zone. Computer vision-based video seizure detection, intracranial EEG using implanted electrodes, and adaptive neurostimulation systems are also emerging, providing continuous and real-time monitoring options. These technologies are not only helping with diagnosis but also improving surgical planning and long-term patient management.

This survey of literature brings together the latest developments in seizure detection and localization techniques, emphasizing significant contributions from diverse fields such as signal processing, AI, and multimodal imaging. The aim is to provide an integrated overview of existing technologies, their relative performance, and future trends that are defining the direction of seizure-centric neurodiagnostic systems.

Electroencephalography (EEG) has long been a cornerstone in the detection and localization of epileptic seizures. Traditional EEG analysis involves visual inspection by clinicians, which can be time-consuming and subjective. Recent advancements have introduced automated methods leveraging machine learning and signal processing techniques to enhance accuracy and efficiency.

A comprehensive review by Mahnoosh Tajmirriahi and Hossein Rabbani highlights various EEG-based localization methods, emphasizing the integration of model-based data processing and machine learning algorithms. The study discusses the advantages and limitations of these

methods, noting that while EEG provides excellent temporal resolution, its spatial resolution is limited. To address this, multimodal approaches combining EEG with imaging modalities like MRI and PET have been explored to improve localization accuracy.

Furthermore, the review underscores the potential of multimodal brain data fusion in enhancing the precision of seizure focus localization. By integrating EEG with other neuroimaging techniques, researchers aim to develop more robust and accurate systems for identifying epileptic foci, which is crucial for effective treatment planning.

Resting-state functional MRI (rs-fMRI) has emerged as a valuable tool in the lateralization of seizure onset zones, particularly in temporal lobe epilepsy (TLE). Unlike task-based fMRI, rs-fMRI does not require patient cooperation, making it suitable for a broader patient population.

A study by Zhengyi Yang introduced a machine learning approach utilizing rs-fMRI data to lateralize TLE. The method achieved an 83% accuracy rate by analyzing intra-regional, inter-regional, and whole-brain network connectivities. This approach demonstrates the potential of rs-fMRI combined with machine learning in pre-surgical evaluations.

Building upon this, the authors developed a deep learning model employing a three-dimensional convolutional neural network (3D-CNN) to analyze rs-fMRI data for seizure onset lateralization. The model achieved a 90.1% accuracy rate and utilized gradient-weighted class activation mapping (Grad-CAM) to identify critical regions contributing to the lateralization decision. These advancements indicate a promising direction for non-invasive, accurate seizure localization methods.

Nuclear imaging modalities, such as positron emission tomography (PET) and single-photon emission computed tomography (SPECT), have been instrumental in identifying epileptogenic zones, especially in cases where MRI findings are inconclusive.

A review by another author discusses the integration of PET and SPECT with MRI to enhance localization accuracy. Techniques like PET interictal subtracted ictal SPECT coregistered with MRI (PISCOM) have shown higher sensitivity in identifying epileptogenic zones compared to traditional methods. Additionally, the development of hybrid PET/MR systems allows for simultaneous acquisition of anatomical and molecular data, providing a more comprehensive view of the epileptic focus.

These multimodal approaches have demonstrated improved concordance with surgical outcomes, particularly in patients with MRI-negative epilepsy. The combination of metabolic and structural imaging data facilitates more accurate localization, which is critical for successful surgical interventions.

The application of computer vision (CV) techniques in seizure detection has gained traction due to the increasing availability of video monitoring in clinical settings. CV algorithms can analyze video data to detect and classify seizures, offering a non-invasive and continuous monitoring solution.

A systematic review by Brandon M. Brown evaluated various CV-based seizure detection models. The study found that these models have shown impressive accuracy and efficiency, with the potential to reduce sudden unexpected death in epilepsy (SUDEP) and alleviate resource limitations in epilepsy monitoring units. However, challenges such as the lack of standardized validation measures and concerns about patient privacy remain significant obstacles to widespread adoption.

The integration of CV techniques with other modalities, such as EEG and physiological sensors, is an area of ongoing research aimed at enhancing the robustness and reliability of seizure detection systems.

Deep brain stimulation (DBS) systems, traditionally used for therapeutic purposes, have shown potential in seizure detection and lateralization through intracranial recordings. These systems can provide continuous monitoring of brain activity, offering insights into seizure dynamics.

A case study by Gloria Ortiz-Guerrero demonstrated the feasibility of using thalamic DBS recordings for seizure detection and lateralization. The study observed significant elevations in low-frequency thalamic ictal power during seizures, with peri-ictal power being maximal ipsilateral to the seizure network. This suggests that DBS systems could serve dual roles in both therapy and monitoring, although further research is needed to assess their generalizability across diverse patient populations.

The integration of DBS data with other modalities, such as EEG and imaging, could enhance the accuracy of seizure localization and inform personalized treatment strategies.

Advancements in image processing have improved the detection of epileptogenic zones using MRI. Techniques like regional homogeneity (ReHo) and amplitude of low-frequency fluctuations (ALFF) analyze functional MRI data to identify abnormal brain activity associated with epilepsy.

Another study highlighted the use of ReHo and ALFF in detecting regions with abnormal synchronization and metabolic demands. These methods have shown comparable sensitivity and specificity to traditional PET imaging in localizing epileptogenic zones. Additionally, contralateral asymmetry analyses of ReHo and ALFF maps have improved the detection of lesions, particularly in temporal lobe epilepsy.

These non-invasive techniques offer valuable tools for pre-surgical evaluation and have the potential to enhance the accuracy of epilepsy diagnosis and treatment planning.

# Chapter 3

# Proposed Solution

## 3.1 THE APPROACH TO THE PROBLEM

The seizure lateralization approach integrates deep learning approaches with spectral EEG processing to construct a strong, non-invasive, and clinically interpretable pipeline. The method centers on a scalp EEG-trained convolutional neural network (CNN) for seizure activity detection on a per-channel, per-second timescale. Each EEG channel is processed separately, enabling the network to learn spatial and temporal features end-to-end from the raw time-series signals without the need for handcrafted features. This enables the model to detect early ictal changes and generate high-resolution, channel-specific outputs representing seizure likelihood over time. The earliest and largest activations are then used to predict the hemisphere of seizure onset, with a data-driven lateralization approach.

To complement and corroborate CNN-based conclusions, frequency-domain estimates are presented with focus on the alpha band. Topographic power maps are obtained for spatial pattern visualization of EEG power on the scalp. Asymmetric patterns in these maps, including focal suppression or enhancement of alpha, are utilized to corroborate lateralization inferred by the neural network. The maps have a physiological interpretability that is simple and satisfies clinical expectation.

Through the use of both computational precision and neurophysiological understanding through the integration of deep learning and spectral scalp mapping, this method takes advantage of both. The CNN offers objective, sensitive seizure dynamic detection, and the spectral maps provide visual confirmation based on conventional EEG interpretation. Together, they each offer a complementary system that enhances the robustness, interpretability, and clinical utility of seizure lateralization. This multi-modal approach not only adds to current diagnostic capabilities but also sets the stage for extending in the future to even more precise seizure localization and individualized therapy planning.

## 3.2 DATASET USED

In this study, the Epileptic Seizure Recognition dataset from Kaggle and the Siena Scalp EEG dataset have been used for seizure detection and lateralization.

### 3.2.1 EPILEPTIC SEIZURE RECOGNITION DATASET

The "Epileptic Seizure Recognition" dataset on Kaggle provides us with preprocessed data taken from the well-known Bonn University EEG dataset. The database includes EEG signals which monitor both epilepsy patients and healthy participants alongside extensive

measurements during normal brain activity and seizures of different varieties. This system exists to handle machine learning operations in epileptic seizure identification and categorization tasks.

The dataset displays EEG data through four sets that represent normal conditions both with eyes open and closed followed by interictal periods and focal seizures and generalized seizures. The data originates from 5 healthy subjects along with 5 epilepsy patients thus providing an even distribution of seizure and non-seizure clinical instances. The data segments are 4,096 samples long so they represent approximately 23.6 seconds of EEG recording collected at 173.61 Hz sampling speed with 12-bit resolution.

The raw EEG data acquired thorough preprocessing resulting in its availability on Kaggle after removing noise artifacts and several interferences. Machine learning models benefit from direct application through preprocessed information which emerges during the data preparation process. Data signals from EEG devices most likely received normalization procedures to standardize feature scales for better machine learning algorithm operation. The dataset undergoes additional extraction processes to get significant EEG signal features including power spectral densities and statistical elements (mean, variance) which aid classification methods.

The available Kaggle dataset presents researchers with straightforward machine learning usage by existing segmentation of data for various brain states. The preprocessed data structure available in this dataset enables easy use by researchers and practitioners developing classification models without requiring additional signal processing workload. The dataset provides preprocessed data which speeds up the implementation and experimentations with machine learning algorithms for seizure detection purposes.

The "Epileptic Seizure Recognition" dataset available on Kaggle provides researchers with a ready-to-use epilepsy seizure detection solution with high accessibility features. Researchers benefit from this dataset due to its clean preprocessed EEG signals which creates suitable conditions for building machine learning models that aim to distinguish between brain states of normal and seizure categories. The platform makes EEG analysis simple for researchers allowing them to develop their models and evaluate them while becoming an excellent tool for machine learning seizure detection applications.

### 3.2.2 SIENNA SCALP EEG DATABASE

Scientists use the Siena Scalp EEG dataset hosted at PhysioNet to conduct advanced research on epilepsy analysis and study with its set of meticulously selected electroencephalographic (EEG) measurements. Researchers established this dataset through clinical and research undertakings at the Epilepsy Monitoring Unit of University Hospital of Siena in Italy. The database operates as a platform for designing algorithms along with testing algorithms that detects seizures as well as determines seizure origins and performs analysis of complete EEG

signals. Research personnel obtained their recordings from surgical patient videos related to drug-resistant focal epilepsy diagnosis. Medical staff maintained established clinical acquisition procedures during the process which involved using the international 10–20 system for electrode placement with additional electrodes added for clinical necessity. This dataset holds real neurological signals which medical staff acquired from patients subjected to lengthy neurological assessment procedures.

This data set consists of EEG data from 14 adult subjects, all of which were monitored continuously for multi-day periods intended to capture ictal (seizure) and interictal (non-seizure) states of the brain. Data generated represent a high-resolution description of pathological and physiological neural activity across a range of temporal windows. EEG recordings are saved in European Data Format (EDF), a widely used format for the storage of bioelectric signals that guarantees interoperability with a broad variety of analysis software tools. Recording durations vary among patients depending on the individually tailored nature of clinical treatment and habits of observation. Of particular note, seizure activity captured was annotated by experienced neurologists manually. These seizure onset and offset annotations are the gold standard to researchers developing and validating procedures for automatic seizure detection, classification, and prediction.

Beyond EEG signals and event annotations, the collection also contains a vast quantity of metadata, making it more valuable to clinically oriented studies. Certain of this metadata include patient data such as age and sex and clinically important data for seizure type, lateralization, and localization. These additional data points allow for more focused and directed analyses, e.g., examination of the relationship between particular EEG features and seizure semiology. In addition, the presence of several seizure episodes per subject allows intra-subject comparative analysis and testing of algorithmic robustness and consistency across various seizure manifestations within the same subject. The longer recording duration of EEG also allows for longitudinal studies, such as the construction of seizure prediction models based on subtle preictal EEG changes.

Among the most robust areas of the Siena Scalp EEG dataset is adherence to ethical principles in managing and sharing data. All data have been de-identified very thoroughly to maintain confidentiality of patients, according to institutional and regulatory requirements. The dataset is well organized and easily readable, with each patient possessing an individual directory. Such directories hold the EEG signal files along with the corresponding annotation files, thereby facilitating easy access and integration into research workflows. Extensive documentation accompanies the dataset, e.g., acquisition protocol, file structure, and annotation schema, thereby facilitating researchers to easily integrate the data into their own analysis pipelines.

Finally, the Siena Scalp EEG data set is a dense and authoritative data set for clinical neurophysiologists, biomedical signal processors, and computational neuroscientists. The longitudinal temporal density of the data set, signal heterogeneity, and clinical metadata

longitudinally associated with it make the data set natively well-suited to a variety of inquiry-driven applications, including but not limited to seizure detection, localization, prediction, and characterization. The dataset allows for rigorous, reproducible research and serves as a basis for the construction of sophisticated diagnosis and treatment technology. By making the Siena Scalp EEG dataset openly available, it facilitates open scientific cooperation and makes an essential contribution to our shared goal of understanding and treating epilepsy.

## 3.3 PREPROCESSING

Preprocessing is one of the most important EEG analysis phases that makes raw brain signals clean, standardized, and machine learning algorithm-compatible. The major methods applied are bandpass filtering, dividing the EEG's main frequency components (usually 0.5–40 Hz), and wavelet denoising, eliminating non-stationary noise but not transient features such as spikes. Segmentation has been used to isolate constant signals to constant intervals (for instance, 1-second samples), and resampling is used for synchronized speed of signals for being identical within datasets. Normalization employs standardized signal values in terms of Z-scores to same amplitude, and because it is standardized, convergence at a model level is feasible. SMOTE or Synthetic Minority Oversampling Technique also balances examples by artificially creating new examples in the minority class. These preprocessing procedures collectively improve the comparability and quality of EEG signals, which are the foundation of efficient seizure detection and SOZ localization.

### 3.3.1 BANDPASS FILTERING

EEG signals inherently carry information over a broad frequency range, but seizure activity is typically within specific bands, especially between 0.5 Hz and 40 Hz. To focus the analysis within the beneficial range and reduce irrelevant noise or artifacts (e.g., muscle activity, line noise, or DC drift), a bandpass filter is applied in preprocessing. This is an important step in removing high-frequency noise (typically greater than 40 Hz) and low-frequency trends (less than ~0.5 Hz), thereby leaving the physiological signal components like delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and low gamma (30–40 Hz) bands.

Mathematically, the bandpass filtering of a continuous EEG signal x(t) can be expressed as:

x_f(t) = inverse_Fourier( H(f) * Fourier[x(t)] )

H(f) is the frequency response of the bandpass filter defined to pass frequencies in the 0.53–40 Hz range.

### 3.3.2 SEGMENTATION AND RESAMPLING

EEG signals are typically observed as continuous streams of data, which must be segmented into workable and processable units. Segmentation consists of partitioning the continuous EEG into stationary-duration windows of time—typically 1-second non-overlapping segments—such that the model can learn from local temporal patterns that are predictive of seizures. But different datasets may have different sampling rates (e.g., 256 Hz for clinical and 173.61 Hz for benchmark), which lead to non-proportional segment lengths of samples. In order to ensure dimensional consistency between datasets, there is the use of resampling. It is at this step that modification of the sampling rate—either by interpolation or decimation—is done so that each 1-second interval has a fixed number of data points (e.g., 178 samples/second). Resampling guarantees all input fragments to be converted into a common frequency and length representation, allowing for consistent training and testing across the model pipeline.

### 3.3.3 STANDARDIZATION

EEG signals tend to differ significantly in amplitude not just between patients but also between electrodes and sessions. Such variability may be biased toward machine learning algorithms, particularly deep networks, as they are sensitive to input feature scaling. Standardization remedies this by converting the raw input signal x into a normalized signal x′through Z-score normalization:

$$x' = (x - \mu) / \sigma$$

where $\mu$ is the mean and $\sigma$ is the standard deviation of the signal. The result is that the transformed signal has a mean of 0 and a variance of 1. This ensures each feature contributes equally to the learning process and avoids dominance by signals of higher amplitude, which is crucial for learning unbiased spatial-temporal patterns in multi-channel EEG data such as the Siena dataset.

### 3.3.4 SMOTE

One of the most significant challenges of EEG-based seizure detection is class imbalance—seizure events are much less frequent than non-seizure ones. Such a bias can cause models to be skewed towards the majority class and miss the minority class (seizures) significantly. SMOTE corrects this by creating new examples from the minority class by performing linear interpolation between minority class samples and their nearest neighbors in feature space.

$x\_new = x\_i + delta * (x\_j - x\_i)$, where delta is a random value in [0, 1]

Here, x_i is a minority class sample, x_j is one of its k-nearest neighbors, and x_new is the newly synthesized sample.

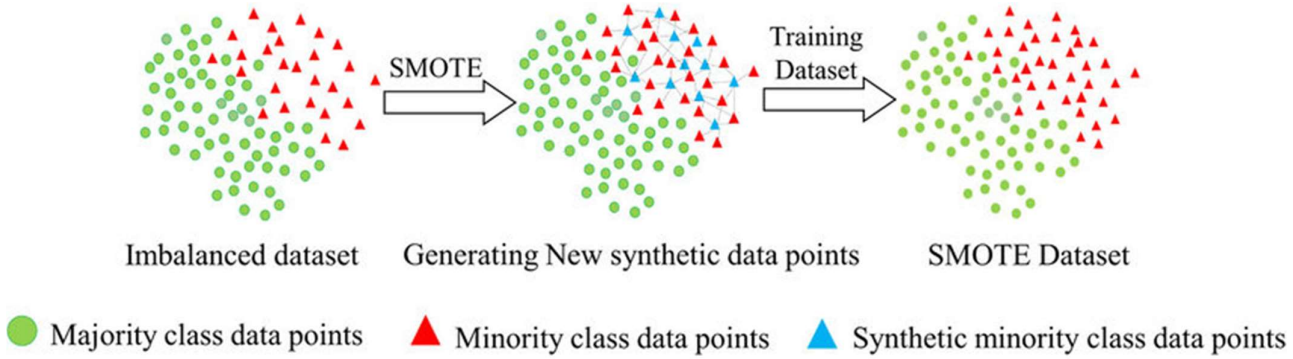



Fig 5: SMOTE

The diagram below demonstrates the Synthetic Minority Over-sampling Technique (SMOTE) applied to solve class imbalance in data sets. The imbalanced data set initially contains numerous majority class data points (green circles) compared to few minority class data points (red triangles). In an attempt to counteract the imbalance, SMOTE creates new data points (blue triangles) by interpolating between available minority class samples. This leads to a more balanced training dataset. The final SMOTE dataset that includes both the original and synthetic minority class samples and the majority class data offers a better representation of classes, improving the performance of machine learning models by mitigating bias towards the majority class.

### 3.3.5 WAVELET DENOISING

A signal processing technique called wavelet denoising effectively removes unwanted noise from EEG signals while preserving important transient features like spikes and sharp waves, which are essential for seizure detection. Unlike traditional linear filters, wavelet denoising is particularly well-suited for EEG because it analyzes the signal at different time-frequency resolutions to manage non-stationary features. The three main steps in the process are reconstruction, thresholding, and decomposition. The EEG signal is first divided into multiple levels using the Discrete Wavelet Transform (DWT), which separates it into detail and approximation coefficients. The detail coefficients, which often contain high-frequency noise, are then subjected to a thresholding process whereby coefficients below a predefined threshold are either reduced (soft thresholding) or set to zero (hard thresholding). The inverse DWT is then used to reconstruct the signal, producing a denoised version of the original signal that still contains important diagnostic data. This entire procedure can be summed up as follows:

$$x(t) = \Sigma A_j(t) + \Sigma D_j(t)$$

where x(t) is the original EEG signal, A_j(t) represents the approximation coefficients at decomposition level j, and D_j(t) represents the detail coefficients. After thresholding D_j(t), the denoised signal is reconstructed by summing the preserved components.

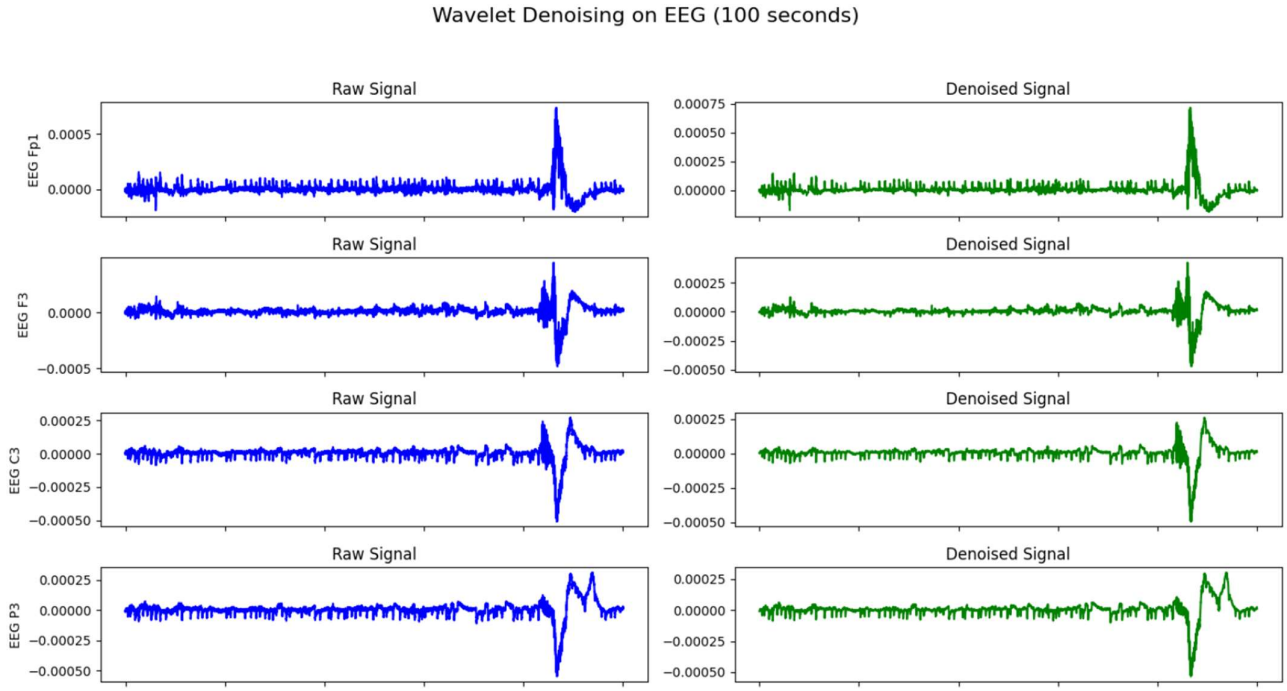



Fig 6: Wavelet denoising

The given image shows the impact of wavelet denoising on EEG signals over a period of 100 seconds. The plot is a comparison of the raw and denoised signals from four EEG channels: FP1, F3, C3, and P3. Each row is from one EEG channel, with the left panel showing the original raw signal in blue and the right panel showing the denoised signal in green. The plot indicates a conspicuous decrease in high-frequency noise following denoising, without compromising the important details and transient aspects of the EEG waveform. This graphical representation substantiates that wavelet denoising improves signal clarity impressively without appreciably altering underlying neural activity patterns. The title on top briefly summarizes analysis conducted.

## 3.4 SYSTEM ARCHITECTURE

For the system in question, we begin by importing the single-channel Epileptic Seizure Recognition dataset utilizing the MNE-Python package, a library widely used to process neurophysiological data. This dataset is presented as time-series EEG data, which plays a key role in seizure analysis and detection activities. Every sample in the dataset is a one-second EEG signal recorded at 178 Hz, thus producing 178 numeric data points per row that are equivalent to the voltage over time from a single EEG channel. In addition to the EEG signal values, there is a categorical label presented in the form of a column named ‘y’ that is the class label for every sample. The ‘y’ values vary from 1 to 5, each corresponding to a distinct brain state: class 1 for seizure activity seen in an epileptic subject, and classes 2 through 5 for non-seizure activity during different physiological conditions, including from healthy subjects both with eyes open and closed, and from seizure-free periods of epileptic patients. For the sake of

binary classification specific to seizure detection, an important preprocessing operation is performed where the multi-class labels are mapped to binary labels. In particular, all rows with a 'y' value of 1 are kept and reclassified as positive seizure samples, and all other rows (i.e., with 'y' values of 2, 3, 4, or 5) are reclassified as 0 to represent non-seizure activity. This conversion reduces the classification task to a binary one, which is exactly what we aim to achieve by distinguishing between seizure and non-seizure EEG patterns. By reducing the problem to this binary form, we not only simplify the model training process but also concentrate the model's ability on learning the most discriminative features related specifically to seizure events. Using the MNE-Python library guarantees strong management of EEG data structures and enables effective preprocessing, visualization, and feature extraction downstream. This first stage is the basis of the proposed system's data pipeline and is critical to preparing the EEG signals for the following deep learning-based classification and interpretability stages.

After the binary conversion of the dataset is done, we move to the phase of data normalization and splitting, which is extremely important in making sure that the model works best and does not get biased as a result of variations in the scale of features. Because EEG data naturally has fluctuations in amplitude that can be highly variable even across the same class, we normalize the dataset through the Standard Scaler in scikit-learn. This normalization method scales the EEG signal values so that they have zero mean and unit standard deviation. Standard scaling brings all features to a common scale without altering the differences in the ranges of values, which is especially useful for models that are based on gradient-based optimization, like deep neural networks. Following normalization, we split the dataset into two major chunks: 80% for training and validation, and 20% held out for final testing. This division is such that the model has enough to learn from but retains some unseen data to test generalization performance. But one of the principal issues with the dataset is the intrinsic class imbalance—samples that are 37abelled '1' (seizure activity) are much fewer than samples 37abelled as '0' (non-seizure activity obtained from original class labels 2 to 5). This biased distribution can cause the model to bias towards predicting the majority class and eventually not learn the subtle but important patterns that signify seizures. To address this problem, we apply the Synthetic Minority Over-sampling Technique (SMOTE) to the 80% training and validation set. SMOTE operates by creating synthetic examples of the minority class by interpolation between available samples, thereby augmenting the occurrence of seizure instances without merely replicating them. This method assists the model in learning a better balanced view of both classes and reduces the danger of overfitting to a small set of seizure examples. The balanced dataset after SMOTE guarantees that the classifier is trained on an equal proportion of seizure and non-seizure samples, enhancing its capacity to generalize to real-world data where seizure instances are rare but important to identify. This preprocessing phase—integrating standard scaling, proper dataset partitioning, and class balancing through SMOTE—provides a solid basis for training a sensitive and trustworthy seizure detection model that performs well under both balanced and imbalanced conditions.

After preprocessing and balancing the dataset, we use a deep learning model based on a one-dimensional Convolutional Neural Network (1D CNN) architecture specifically designed for time-series classification problems like EEG signal analysis. The input data is then reformatted to suit the 1D CNN expectations: each sample of EEG is reshaped into a three-dimensional shape where the first dimension equals the number of samples, the second dimension the time steps (178 features for each sample), and the third dimension a single channel depth. This is accomplished by reshaping the training and validation data using the .reshape() function so that each sample is structured as (samples, 178, 1), which allows the convolutional filters to effectively scan along the temporal axis of the EEG signals. The model architecture consists of a sequence of convolutional layers alternated with dropout layers to avoid overfitting. These convolutional layers make use of numerous filters on the input to gather localized temporal information that describes seizure and non-seizure rhythms. Following three pairs of convolutional and dropout, a max pooling is implemented, which minimizes the temporal resolution dramatically yet retains the salient features eventually leading to a compact yet information-rich representation. This is then followed by a flattening layer that converts the multidimensional tensor into a one-dimensional vector, which is ready for the dense (fully connected) layers. A dense layer of 50 neurons and ReLU activation is added, allowing non-linear combinations of learned features, followed by a final dense output layer with one neuron and sigmoid activation for binary classification.

To seriously test the model's ability to generalize and consistency, we incorporate 10-fold cross-validation into our training pipeline. We split the dataset into 10 equal parts and, in each iteration, use one part as the validation set and the remaining nine parts for training. We repeat this 10 times, so that each data point will be used both for training and validation exactly once. For every fold, the CNN model is trained on reshaped data with a specific number of epochs (set at 200) and batch size of 256, while using early stopping callbacks to avoid overfitting by stopping training after the validation loss no longer improves. This method gives a strong estimate of model performance across data splits, allowing us to calculate the mean accuracy and loss metrics across all folds and determine the best-performing model configuration according to validation performance. By using this ensemble-style cross-validation approach, we improve the robustness of the evaluation, minimize variance in performance estimates, and find a generalized model architecture well adapted to the seizure detection task from single-channel EEG data.

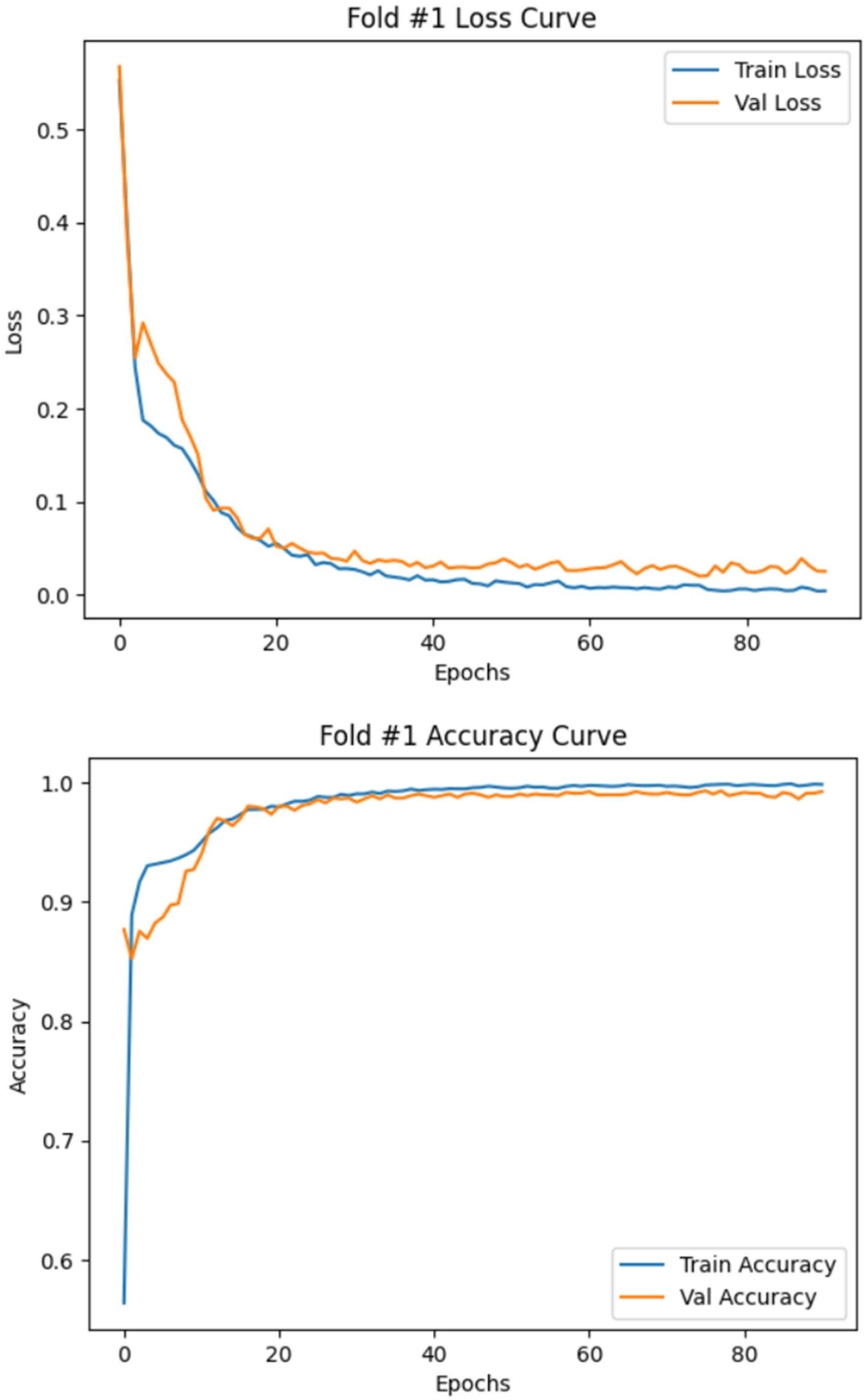



Fig 7: Accuracy and Loss curve for Seizure Detection using 1D CNN

After we finish 10-fold cross-validation and training several models, we test the overall performance of our system by calculating the average scores on all validation and test sets. It gives us an idea of the general behavior of the model independent of any one split and minimizes the variance that would be caused by relying on a single set division. For the validation step, we compute the average accuracy, average sensitivity (or recall), and average specificity by adding up the respective measure taken from each fold and dividing it by the number of folds. Accuracy is the fraction of all correctly predicted instances of seizures and non-seizures out of total cases, as calculated by: Accuracy = (TP + TN) / (TP + TN + FP + FN), with TP representing true positives (identification of seizures by the model correctly), TN for true negatives (identification of non-seizures by the model correctly), FP for false positives (identification of non-seizures by the model incorrectly), and FN for false negatives (identification of seizures by the model incorrectly). Recall or sensitivity calculates the capacity of the model to accurately identify true seizures and is expressed as Sensitivity = TP / (TP + FN). This is a vital parameter in seizure detection since failing to detect a seizure occurrence can have severe implications. Specificity, however, tests the capacity of the model to accurately rule out non-seizure cases and is calculated as Specificity = TN / (TN + FP). High specificity ensures the system keeps the false alarms to a minimum, an important requirement in actual-world diagnostic applications.

Similarly, we calculate the average measures on the fully unseen test data gathered from all of the folds. These averages—test accuracy, test sensitivity, and test specificity—provide a good estimate of how the model will behave in real-world deployment, where the data can slightly vary from the training distribution. Upon comparison of these averages, we also determine the top-performing model of the cross-validation procedure. The top model is chosen by its better performance on the validation set and then tested on the test set to provide its final scores. The results reported are the best accuracy obtained by any model on the test data, showing how accurately it can differentiate between seizure and non-seizure cases. Moreover, the optimal sensitivity is reported to demonstrate the model's ability to identify seizure events, and the optimal specificity is reported to indicate its efficacy in properly rejecting non-seizure EEG signals. Combined, these indicators validate both the system's reliability and robustness as well as confirm the adequacy of the model architecture, training process, and data preprocessing pipeline in the construction of an efficient epileptic seizure detection framework with single-channel EEG data.

After selecting the best-performing model based on its accuracy, sensitivity, and specificity on the test set, we save this model for future inference. Preserving the optimal model allows us to deploy it later on real-world or external datasets without needing to retrain, thus facilitating reproducibility and scalability of the seizure detection pipeline. The stored model is specifically designed for use on more complicated and clinically meaningful EEG data, namely the multichannel recordings of the Siena Scalp EEG database, which comprises real-world patient EEG signals acquired with multiple scalp electrodes. In contrast to the single-channel training

dataset, this new dataset presents a major level of complexity with the presence of multiple spatially distributed channels, increased signal variability, and richer contextual information. In order to prepare this data for prediction, we first load an EEG recording file in European Data Format (EDF), which is a standard clinical EEG recording system format. Utilizing MNE-Python, which is sufficiently capable of processing and analyzing electrophysiological data, we read the multichannel EEG signal from the Siena dataset. Prior to applying the data for prediction, it is subjected to various preprocessing steps to make the input quality consistent with the model's expectations trained on cleaner, filtered data.

First, we pass a bandpass filter with a low cutoff of 0.5 Hz and a high cutoff of 40 Hz. This filtering process plays an important role in EEG processing, as it eliminates both slow drifts and baseline wander that usually occur at frequencies below 0.5 Hz, as well as the high-frequency artifacts above 40 Hz, i.e., muscle artifacts and power line interference. The filtered signal retains the most useful physiological frequency bands, e.g., delta, theta, alpha, beta, and low gamma—frequencies that are known to have significant information within seizure activity. Yet, actual EEG recordings contain non-physiological artifacts like eye blinks, muscle movement, and electrode noise, which cannot be completely eliminated by linear filters. Thus, to further improve the signal quality, we use wavelet-based denoising. Wavelet denoising is done by decomposing the EEG signal into wavelet coefficients at different scales and then thresholding the coefficients selectively to remove noise while preserving the underlying neural activity. This approach is especially appropriate to use with EEG signals, as it provides both time and frequency localization, enabling it to distinguish between transient noise and significant seizure-related patterns. With the use of bandpass filtering along with wavelet denoising, we make the multichannel Siena dataset EEG signals preprocessed up to a level that is consistent with the input specifications of our trained model.

After the signals are standardized and cleaned, they can be segmented and fed through the stored best model to generate seizure predictions for each applicable epoch or window. This allows the use of a model initially trained on controlled single-channel EEG data to more dynamic and complex real-world EEG settings, closing the gap between experimental research and clinical utility in automated seizure detection.

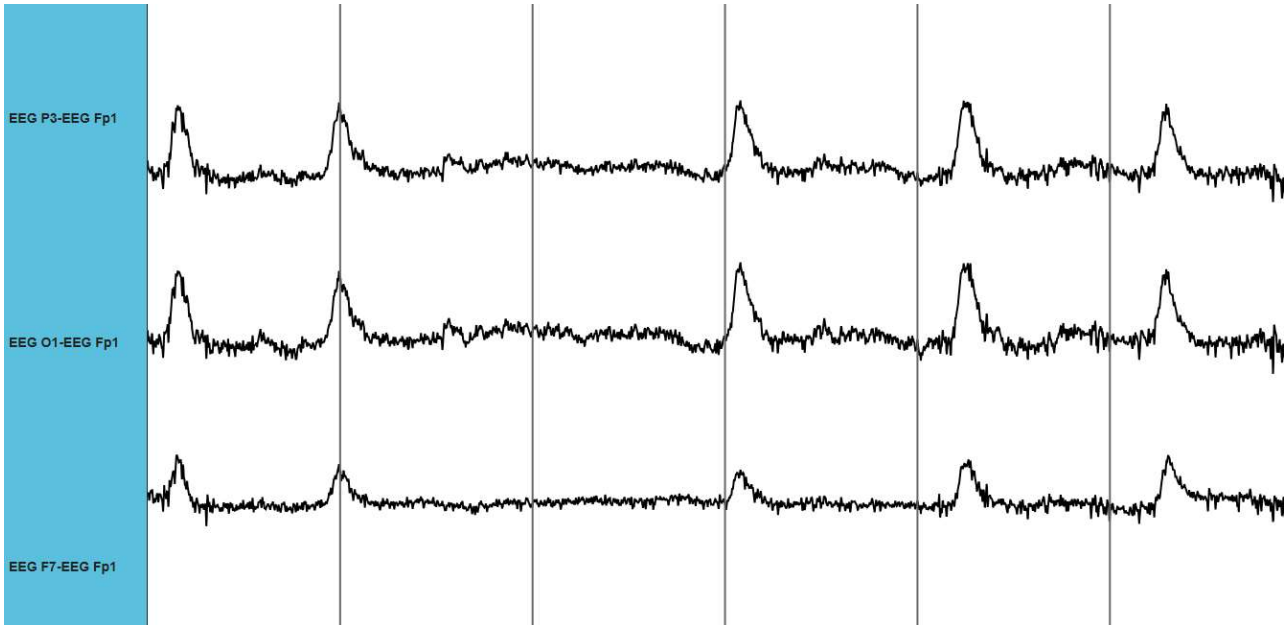
After the preprocessing of the multichannel EEG signal from the Siena Scalp EEG database, the next step in the pipeline involves spatial channel selection and temporal segmentation. To conform the input data to typical clinical EEG analysis procedures, we extract a subset of channels that map to the international 10-20 system, an internationally agreed upon method for positioning EEG electrodes on the human scalp. In particular, we choose the channels "EEG Fp1", "EEG Fp2", "EEG F3", "EEG F4", "EEG C3", "EEG C4", "EEG P3", "EEG P4", "EEG O1", "EEG O2", "EEG F7", "EEG F8", "EEG T3", "EEG T4", "EEG T5", "EEG T6", "EEG Fz", "EEG Cz", and "EEG Pz". They thoroughly cover all the major brain regions—frontal, central, parietal, temporal, and occipital—and are essential in recording spatial seizure dynamics. This choice ensures that the model gets spatially distributed data that are

representative of actual neural activity under seizure and non-seizure conditions, giving a high-resolution snapshot of electrophysiological brain behavior.

Having isolated the channels of interest, we proceed to temporally crop the EEG signal to have only the seizure time. The Siena Scalp EEG database contains fine-grained annotations that define the beginning and ending times of seizure events within each recording. Applying these time stamps, we computationally slice the EDF file to isolate solely the time duration in which there is a seizure. Not only does this limit the amount of irrelevant data but also densify the pattern associated with seizures within the dataset, thereby streamlining the next phase of inference process. It also makes it certain that model predictions are purely derived from the high-risk segments, which can be of utmost value when measuring the system's performance in the actual clinical scenario where fast and accurate seizure identification is paramount.

After extracting the seizure segment on the chosen channels, we then transform the multichannel EEG signal into structured form, generally a Pandas DataFrame. Every row in the DataFrame represents a time point, and every column represents one of the chosen EEG channels. The tabular format presents a simple and intuitive structure for further manipulation, visualization, and feeding into machine learning pipelines. It also supports synchronization between channels and enables easy statistical and temporal analysis. We now spatially and temporally segment the EEG data into a DataFrame that ensures the input is clean, well-structured, and ready for either direct model inference or further feature extraction, depending on the requirements of the downstream application. Such careful preparation now acts as a bridge between the clinical EEG recordings and the computational model trained earlier to implement a practical, scalable, and data-aligned seizure detection framework suitable for use in real medical environments.

Plotting the data using EEG Online Visualization Tool:



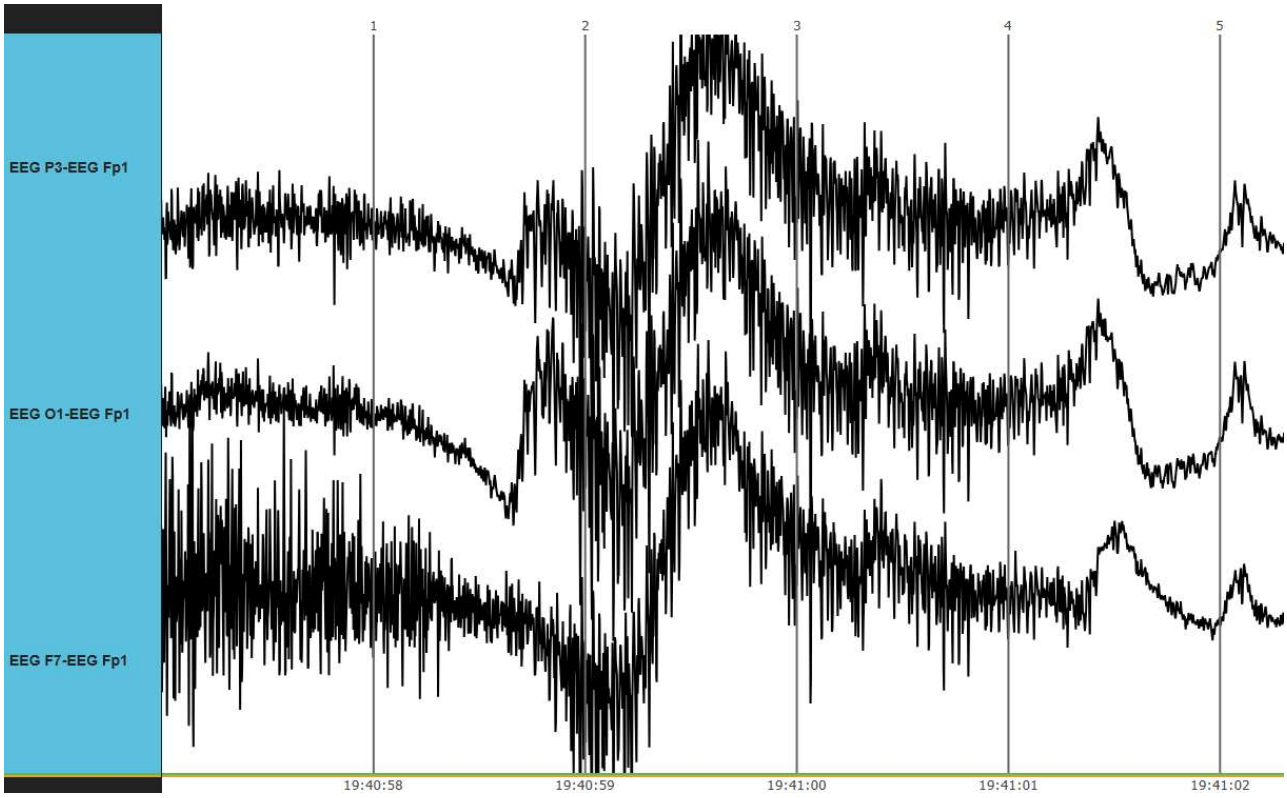



Fig 8: Seizure Visualization

This image describes the difference in EEG signals before the start of the seizure and during the seizure duration.

After the multichannel EEG data for the ictal (seizure) duration has been pulled out and formatted into a structured DataFrame, the second step is to divide the continuous EEG signal into fixed-duration windows. We divide the entire ictal duration into consecutive 1-second epochs to align with the temporal structure employed in the training phase of our seizure detection model. This segmentation is needed not just for temporal granularity but also to guarantee consistency in input dimensions since each second of EEG data is turned into a unique sample for prediction. Each segment of 1 second is dealt with separately, enabling accurate seizure detection at a fine-grained level over time. To ensure consistency with the training data set—initially sampled at 178 Hz—we resample every 1-second segment of the Siena Scalp EEG data to a constant frequency of 178 Hz. This resampling is performed for each one of the 19 chosen EEG channels so that each 1-second window will have precisely 178 datapoints per channel, ensuring compatibility with the model input shape and preventing shape mismatch errors at inference time.

Following resampling, the signal in every 1-second window is still to be standardized in order to get it ready for prediction. Standardization means to convert the data in a way that it will have zero mean and unit variance, thus removing scale differences between windows and

channels. This is especially important in EEG data, where amplitude differences may occur because of electrode position, impedance differences, or patient-specific properties. By standard-scaling each window separately, we normalize the amplitude distribution, and the features become more consistent and less susceptible to outlier-bias. After resampling and standardizing each segment, we store the resulting data in CSV files, one for each EEG channel. The naming of these files is done in a descriptive and consistent manner, utilizing the name of the corresponding EEG channel to facilitate easy identification and traceability. For instance, data from the "EEG Fp1" channel is stored in a CSV file by the same name, and this is done for all 19 channels.

This organization not only simplifies the prediction process by allowing channel-wise data loading but also highly modularizes and interpretable the dataset for further analysis. The CSV file now stands for a clean, standardized, and temporally segmented version of the seizure EEG data for one scalp location. These files can be utilized either separately for channel-specific analysis or in total to fuse multichannel predictions. The method ensures that the whole multichannel ictal dataset is properly prepared for batch processing, cross-channel comparison, and subsequent model inference. Finally, this pipeline converts raw EEG recordings into a format that is analytically robust, model-ready, and easy to visualize or audit—taking us one step closer to real-time, interpretable seizure detection in clinical EEG systems.

With all 19 EEG channels thus segmented, resampled at 178 Hz, standardized, and stored into individual CSV files, we proceed to the final and most critical phase of our pipeline: employing the previously saved and trained 1D Convolutional Neural Network (1D CNN) model to execute seizure detection on the real ictal interval of the Siena Scalp EEG recordings. Each CSV file, corresponding to a single EEG channel, contains a series of 1-second windows—each with 178 data points representing the voltage fluctuations recorded at that scalp location during a seizure. These windows are sequential in time, allowing us to map any detection directly back to the specific second of the ictal event. The already trained 1D CNN model, with which we already achieved high sensitivity and specificity on the single-channel dataset, is now used to make inference on each of these standardized windows. We load every CSV file one by one, and for each row—that corresponds to a single second of EEG data—we pass it through the CNN model in order to get a prediction.

This is carried out row by row, that is, each second is separately given as input to the model to ascertain whether it represents a seizure (classified as 1) or otherwise (classified as 0). The classifications are subsequently gathered and indexed with time, thereby giving approximately a timeline of seizure occurrence as viewed from each EEG channel individually. The outcome is a minute-by-minute, second-by-second annotation of ictal duration, defining whether seizure activity occurred at every time interval for each electrode. The high-resolution temporal detail that this provides enables profound insights into seizure onset, spread, and spatial topology, which are critical in both research and diagnostic applications. For instance, knowing which channels exhibit initial seizure activity can assist neurologists in localizing the seizure onset

zone, a critical step in surgical planning for drug-resistant epilepsy. Further, making predictions at the per-channel and per-second level adds useful redundancy and resilience to the system.

EEG seizures can be prominent in certain channels but subtle in others, depending on the type of seizure and cortical origin. By inspecting each channel separately, the model is afforded the chance to pick up localized patterns of atypical neural activity that could go unnoticed in grouped or meaned signals. Following prediction acquisition, results can be visualized by plotting them via time plots or heatmaps and illustrating seizure occurrence over time and space, hence creating a multi-dimensional representation of the seizure attack. This last prediction step converts static EEG data into dynamic, interpretable diagnostic results—powered by deep learning and grounded on meticulous data preprocessing. It completes an effective seizure detection pipeline not only automated but also modular, relevant to the clinic, and scalable to a wide variety of real-world EEG applications.

Following the production of seizure predictions for each 1-second segment in all 19 EEG channels, the last operation in our pipeline is to synthesize these outputs into a common format for visualization and interpretation. We combine the individual predictions—previously stored separately for each channel—into one complete CSV file. This combined file contains the seizure classification results for each second of the ictal period for all chosen scalp electrodes. Every row in the file is a different second in the seizure episode, and every column is one of the EEG channels. The cell values are binary—1 for seizure, 0 for no seizure—giving a simple and organized picture of how the seizure activity develops both temporally and spatially over the scalp. This combined dataset allows us to monitor the occurrence or lack thereof of ictal patterns on a second-by-second level between and within several regions of the brain at the same time.

With this CSV file, we then create montage-style plots in which each channel is graphed against time. In these diagrams, we utilize a two-color scheme for quick visual interpretation and clarity: black is used for normal, non-seizure intervals (prediction = 0), and red lines or markers to show where seizure activity occurs (prediction = 1). This two-color mapping provides for an intuitive portrayal of the development of the seizure throughout the ictal time. Placed vertically by channel and horizontally by time, these montage plots visually map the progression of the seizure—or its local stay—over time and on the surface of the brain. Such visualizations are essential in interpreting the spatial dynamics of seizures, showing whether activity spreads bilaterally or stays confined to a single hemisphere, and what cortical regions are most involved.

These segments also become strong predictors of seizure lateralization and ascertaining the possible seizure onset zone. If the red segments signaling seizure detection start appearing early within the ictal window on a certain set of channels, and if they persist to dominate the same channels throughout a seizure, then it is a strong clue that those areas are likely to be identified with the seizure onset zone. For instance, if "EEG F7", "EEG T3", and "EEG P3" (all in the left hemisphere) have early and persistent red markings, this indicates a left hemispheric onset.

Spatial-temporal patterning can guide clinicians and researchers to hypothesize lateralization of seizure origin.

In order to validate our inferences, we look back at the metadata and annotations included with the Siena Scalp EEG database, expert-annotated information about the seizure onset zone and lateralization for each patient and seizure recording. In cross-validating our model's predictions and visualized seizure dynamics against these ground-truth labels, we are able to assess the clinical reliability of our system. Where the outputs of the model confirm with the medically confirmed lateralization, this enhances the value of our automated pipeline in supporting diagnostic procedures and validates the applicability of deep learning to assistive seizure localization in actual EEG analysis environments. Finally, this final integration step—aggregating, visualizing, and interpreting predictions—converts raw output to actionable knowledge, reconciling computational analysis with clinical utility.

Finally, spectral maps are utilized for further validation of seizure lateralization, focusing specifically on the alpha frequency range during the ictal period. These maps are generated for 5-second intervals throughout the seizure, providing a clear visual representation of brain activity patterns across different scalp regions. Each spectral map offers a spatial snapshot of how the alpha power is distributed across the 19 EEG channels, revealing asymmetries that may be indicative of the seizure's origin. When viewed across the seizure timeline, these maps can show consistent lateralized patterns, such as reduced alpha activity on one hemisphere, helping to pinpoint which side of the brain is more involved in the seizure process.

If the spectral maps show dominant changes—such as a reduction or abnormal intensification of alpha band power—on specific regions at the onset and throughout the seizure, this supports the hypothesis that those regions may correspond to the seizure onset zone. For example, if in multiple 5-second windows the left temporal and frontal areas consistently display altered alpha power while the right side remains relatively stable, this would reinforce the inference of a left-sided seizure origin. These patterns, when aligned with the earlier CNN model predictions and montage visualizations, serve as a final layer of interpretive clarity. Spectral maps thus act as a critical visualization tool, highlighting the frequency-based dynamics of the seizure and confirming the spatial localization derived from time-domain predictions.

## 3.5 THE BENEFITS OF THIS SOLUTION

In the field of epilepsy research and clinical neurology, lateralization—the process of identifying the hemisphere of seizure origin—is a central component of the pre-surgical assessment of patients with drug-resistant epilepsy. Standard lateralization techniques have relied to a great extent on manual visual analysis of electroencephalogram (EEG) traces, statistical feature extraction, and, in more invasive cases, intracranial EEG (iEEG). These approaches, although valuable, tend to be afflicted with limitations including invasiveness, subjectivity, and non-scalability. A more modern and promising option is the use of

convolutional neural networks (CNNs) applied to scalp EEG data for the automated detection of seizure onset zone, as well as lateralization.

This technique focuses on the training of a 1D convolutional neural network to differentiate between seizure and non-seizure activity based on time-series information from individual EEG channels. What is so effective about this strategy for lateralization is that every channel is independently treated in training and inference so that the network can learn to identify spatial patterns of seizure onset in various regions of the scalp. By examining EEG signals on the basis of per-second and per-channel, this method yields a very detailed temporal and spatial mapping of seizure activity. Plotted against time, these channel-specific outputs can elucidate where the seizure starts and how it propagates, providing an intuitive and data-driven lateralization approach.

Unlike traditional machine learning methods that are highly reliant on features manually crafted—such as spectral power, entropy, or variance of a signal—convolutional neural networks learn complicated features directly from raw EEG signals. Deep feature extraction allows the model to recognize detailed and transient patterns that might be impossible to detect in manual inspection or in simple algorithms. These features often have diagnostic importance that is related to the onset of seizure, especially in the early phases of ictal activity when hemispheric origin discrimination is of paramount concern.

Generalizability and non-invasiveness are some of the strongest features of this CNN-based method. It can perform optimally on standard clinical scalp EEG without requiring surgical placement of electrodes with the exception of when absolutely unavoidable. The model is applicable to patients generally, even if trained on unrelated subjects' data, provided proper preprocessing steps such as bandpass filtering, segmentation, normalization, and resampling are carried out. This generality is a major advantage in terms of its clinical utility, making it usable both for retrospective analysis as well as in real-time.

In the context of lateralization, the model stands out by delivering per-channel seizure probability scores dynamically interpretable. When a seizure starts, the model determines the initial channels above a specific seizure likelihood threshold. Since EEG channels are associated with particular brain hemispheres and regions, the earliest activated channels provide good indications of lateralization. Additionally, the dynamic representation of such activations over time provides a distinct insight into seizure propagation and enables clinicians to differentiate between focal, lateralized onsets and generalized discharges.

The advantages of such an approach are even greater when one considers its possible incorporation into wider clinical pathways. For example, where conventional EEG is uncertain owing to fast seizure spread or low-amplitude discharges, CNN-based analysis adds an objective level of confirmation. It can further assist in the choice of areas for more targeted diagnostic techniques like high-density EEG or functional imaging, essentially simplifying the assessment process.

Notably, this method forms a good foundation for furthering with precise seizure localization. While lateralization directs focus toward one hemisphere, identification of the exact cortical location of seizure onset is typically less possible with invasive or multimodal methods. The CNN output may be a starting point for these methods by indicating the most suitable area to target. For example, its outputs can be utilized to inform source localization algorithms or MRI-based analysis to limit the spatial field before iEEG deployment. Time-resolved output of CNN also allows us to explore seizure dynamics and potential propagation networks, which are often determinant in multifocal or complex epilepsies.

More advanced neural network architectures, like attention-based or temporal recurrent ones (e.g., LSTMs), could be used in extending this framework in order to better detect temporal patterns. Likewise, extending the framework to process high-density EEG or EEG-fMRI multi-modal data would lead to significantly increased spatial resolution and incorporation of more context information to help clinicians. Personalization of the models is also an area of tremendous potential, training the models using patient-specific data to enhance real-time monitoring accuracy.

Overall, application of CNNs to scalp EEG for seizure lateralization offers a strong trade-off between clinical application, computational efficiency, and diagnostic accuracy. With the synergy of deep learning and temporal-spatial EEG data analysis, the approach overcomes the limitations of conventional scalp EEG reading and more invasive localization techniques. It is an important step towards more automated, accurate, and accessible epilepsy diagnosis and a good platform on which more sophisticated localization strategies can be developed.

In addition to the application of convolutional neural network to seizure lateralization, frequency-specific topographic mapping, particularly of the alpha band, was used to supply complementary evidence and improve lateralization performance. Frequency-specific topographic maps display scalp distribution of spectral power and are informative physiological information as a supplement to data-driven model output. If a particular hemisphere is responsible for seizures, changes in power in particular frequency bands—e.g., focal alpha suppression or augmentation—typically have lateralized topography.

By constructing scalp maps to highlight such patterns, clinicians and researchers can identify asymmetry of brain activity with which the expected hemisphere of seizure onset corresponds. It is especially useful for visually confirming lateralization because it portrays model-based classification-carried information in an intuitive and intuitive way. The combination of frequency-domain information and deep-learning prediction creates a synergy paradigm: whereas the CNN extracts high-resolution complex temporal information, the spectral information topographies provide a gross-scale spatial perspective within established neurophysiological theory. Both methods provide a complement to one another to ensure validity of lateralization results and improve their clinical use, paving the way to more rational presurgical decisions.

# Chapter 4

# Results

## 4.1 DETECTION RESULTS

The results obtained from the seizure detection framework demonstrate strong performance and reliability across both validation and test datasets, indicating the robustness of the proposed approach. On the validation set, the system achieved an impressive average accuracy of approximately 95.88%, suggesting that the model is highly effective in correctly identifying seizure and non-seizure instances during training evaluation. Complementing this, the average sensitivity—or true positive rate—reached around 92.93%, reflecting the model's strong ability to correctly detect seizure events among the positive samples. Equally significant is the average specificity of 98.87%, highlighting that the model rarely misclassifies non-seizure events as seizures, which is essential for minimizing false positives in clinical applications. These metrics indicate a well-balanced performance between correctly identifying seizures and avoiding false alarms during model development. Moving on to the test dataset, the model sustained even higher overall performance, with an average accuracy of 97.73%, suggesting strong generalizability to previously unseen data. The average sensitivity on the test set, while slightly lower at approximately 92.06%, still reflects excellent detection capability across real-world scenarios. More notably, the test set's average specificity of 99.09% indicates the model's outstanding consistency in correctly identifying non-seizure events with minimal false positive outcomes. Furthermore, when considering the best-performing model selected from the 10-fold cross-validation process, the results were even more favorable. This optimal model achieved a test accuracy of 98.17%, sensitivity of 94.84%, and specificity of 98.97%, reinforcing the model's capability to not only generalize well but also excel in high-stakes clinical contexts where accurate seizure detection is critical. Overall, these results validate the effectiveness of the proposed deep learning-based system and support its potential use in automated seizure detection tasks with a high degree of reliability and precision.

## 4.2 MONTAGE PLOTS

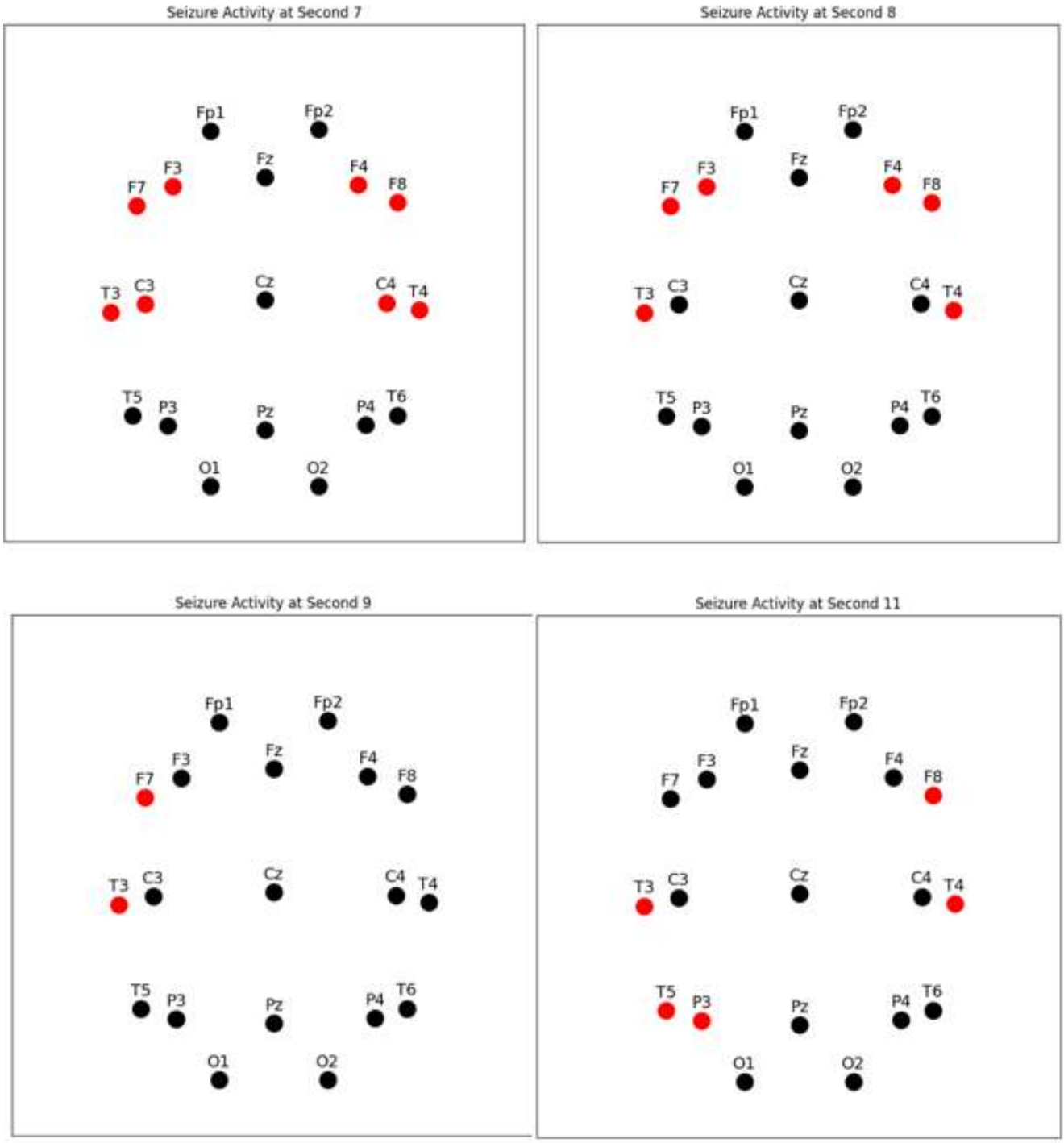



Fig 9: Seizure Visualization on Montage

For this patient PN00 we can see that the seizure is active both in the right as well as left half of the brain during the beginning of the seizure, especially in F8, T4, F7 and T3.

If we visualize the signals for 11th second:

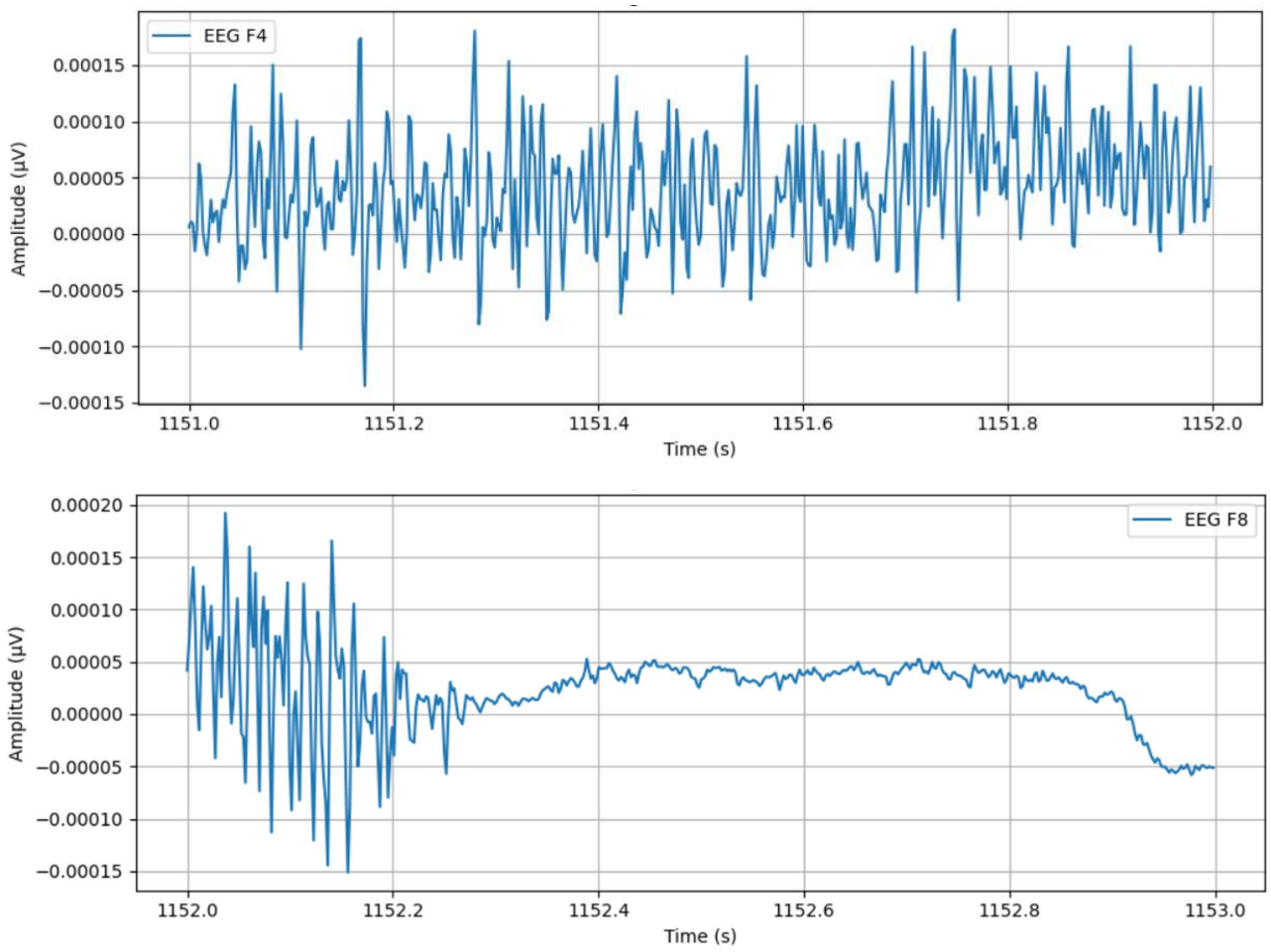
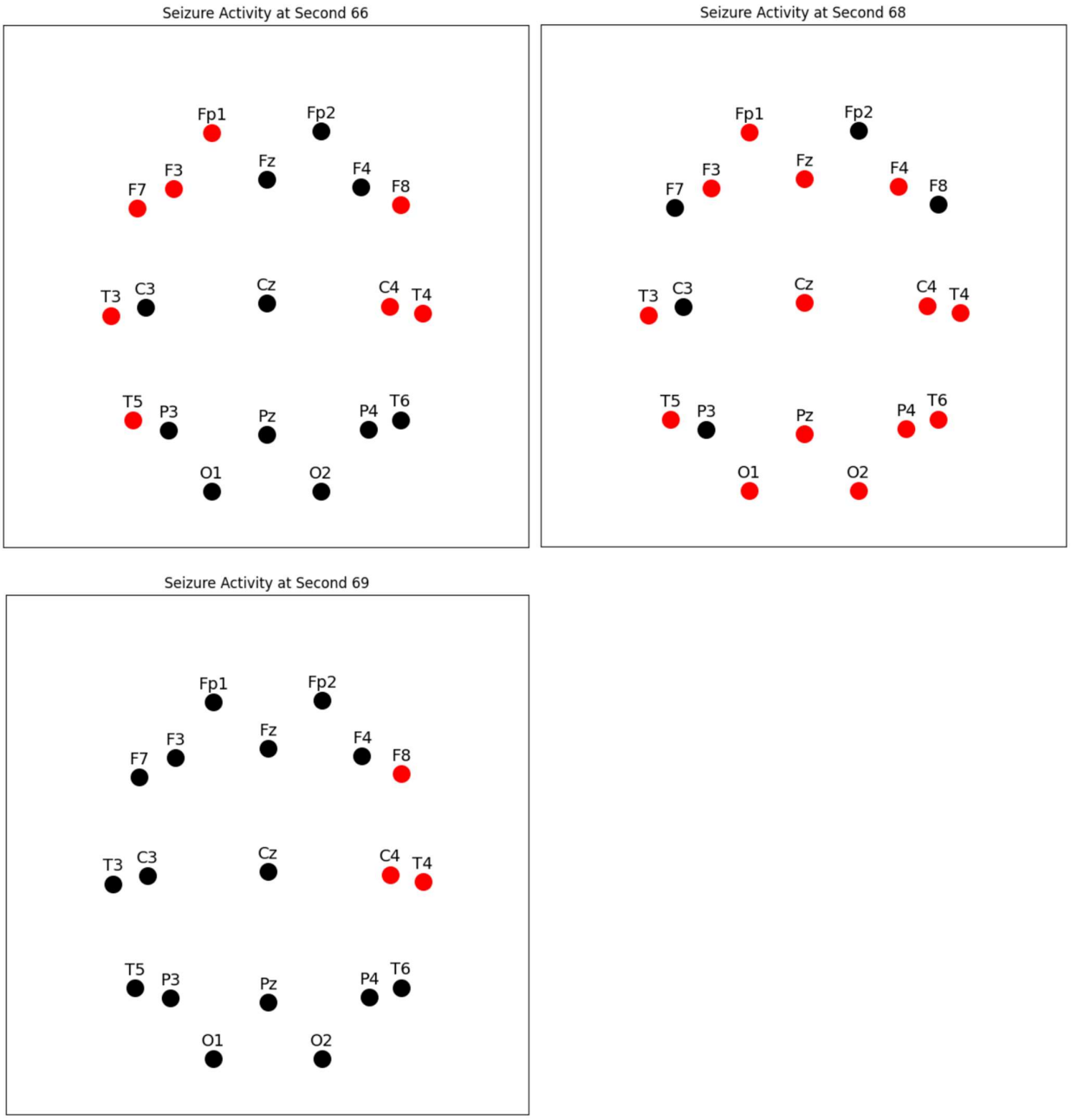



Fig 10: Seizure Signal on single channel for 1 second

From the plot we can see that seizure occurs at F8 and is represented by red and F4 is black at that time. The same can be observed in these signal plots as well.




During the end of the seizure we see that electrical activity has spread throughtout the brain but it ends at electrodes F8, C4 and T4 which is in the right half of the brain. From this we can say that seizure onset zone might be at the right side of the brain.

We further confirm this using Spectral maps for the alpha range which denotes electrical activity during relaxed wakefulness

## 4.3 TOPOGRAPHIC EEG MAPS

EEG topographic maps (also called EEG scalp maps or topoplots) visually represent the distribution of electrical activity across the scalp. They are a powerful way to show spatial patterns in brain activity over time or frequency domains.

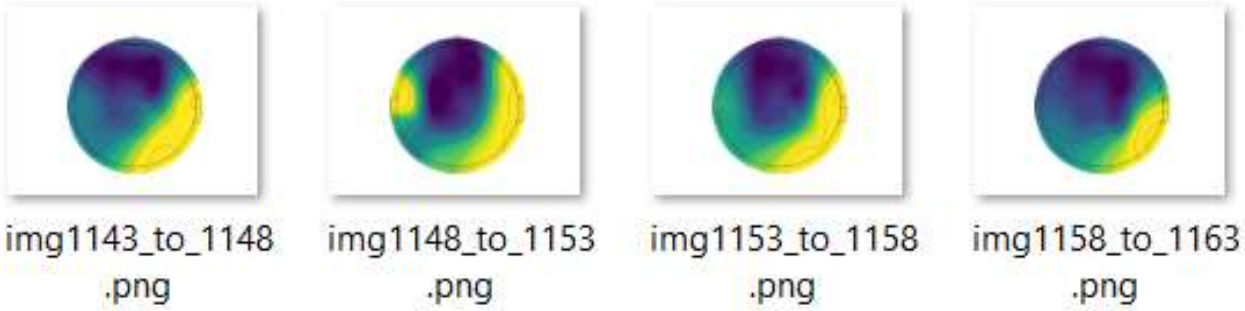
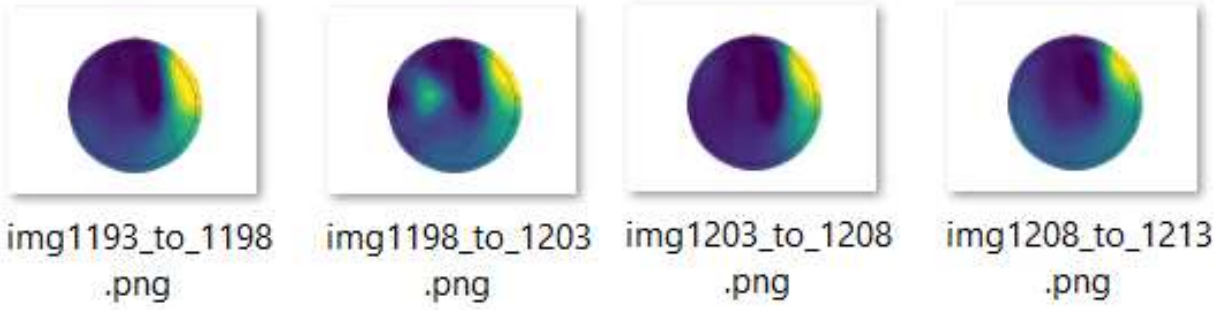



Fig 11: Topographic EEG Maps

These Topographic Maps show electrical activity during the beginning of the ictal period, each for 5 seconds.




The following Topographic Maps show electrical activity during the end of the ictal period, each for 5 seconds. We can observe from these plots that the electrical activity is dominant in the right part of the brain and by the end of the seizure period it stays at the upper right part of the brain.

This is similar to our previous observations on the Montage Plots. Hence we validated that for patient PN00, the seizure lateralization is on the right side.

# Chapter 5

# Conclusion and Future Work

## 5.1 CONCLUSION

In conclusion, this work presents a comprehensive and effective framework for the automated detection and lateralization of epileptic seizures using EEG data, combining deep learning methodologies with classical EEG analysis techniques. By initially leveraging a well-structured single-channel dataset for model development, rigorous preprocessing, and robust evaluation through cross-validation, the system was able to achieve high performance in terms of accuracy, sensitivity, and specificity. These promising results established a reliable foundation for applying the model to multichannel real-world scalp EEG data, specifically targeting seizure events. The pipeline was designed to ensure data consistency, temporal alignment, and channel-wise segmentation, enabling second-wise seizure prediction across 19 standard EEG electrodes based on the 10–20 system. The predictions were aggregated and visualized through montage plots, which effectively illustrated the spatial distribution and temporal evolution of seizure activity across the scalp. These plots served as an intuitive and informative tool for identifying hemispheric asymmetries in seizure involvement, which is critical for determining lateralization. Additionally, alpha-band spectral maps provided further insight into the spatial frequency characteristics during the ictal period, reinforcing observations from the model predictions and visualizations. Together, these multi-layered analyses offer a robust and interpretable system capable of assisting clinicians in evaluating seizure characteristics with greater efficiency and reduced subjectivity. The entire approach not only streamlines the seizure detection process but also offers meaningful support in lateralization analysis, which is especially valuable in pre-surgical planning for drug-resistant epilepsy patients. This study lays the groundwork for future developments that may integrate more advanced EEG features, multimodal data, or real-time clinical deployment, moving closer to intelligent, assistive tools for epilepsy diagnostics and management.

## 5.2 FUTURE WORK

Looking ahead, there are several promising directions for future work that can significantly enhance the capabilities of the current seizure detection and lateralization framework. One of the foremost extensions involves transitioning from lateralization to precise localization of the seizure onset zone (SOZ). While the current system effectively determines which hemisphere is primarily involved during a seizure, pinpointing the exact cortical region or network responsible for seizure initiation would allow for a much finer granularity of clinical insight. This can be achieved by integrating advanced spatial filtering methods such as source localization techniques, including beamforming or electrical source imaging (ESI), which can

help back-project scalp EEG data onto cortical surfaces to estimate the origin of seizure discharges more precisely. Incorporating these techniques into the pipeline would empower clinicians with not only lateral but also regional information regarding seizure dynamics, improving the confidence and specificity of pre-surgical evaluations.

Another major avenue for expansion is the integration of the system into an Internet of Things (IoT)-based infrastructure to enable real-time, continuous monitoring and seizure detection in ambulatory or home-based settings. With the increasing availability of portable, wearable EEG headsets and edge-computing platforms, the proposed deep learning model could be deployed on low-power devices such as Raspberry Pi or NVIDIA Jetson boards. These devices could receive streaming EEG data from wearable sensors, process the signals locally using the pretrained model, and instantly flag seizure events or changes in lateralization patterns. Such a setup would allow continuous patient monitoring outside hospital environments, providing early warnings and allowing caregivers or healthcare professionals to respond promptly. Real-time alerts could be transmitted to mobile applications or cloud dashboards via secure wireless protocols, enabling longitudinal seizure tracking and facilitating telemedicine consultations. Furthermore, the system could be enhanced with a feedback loop to adapt the model based on ongoing data collection, allowing personalized seizure profiling for each patient.

From a clinical integration perspective, future work could also focus on extending the system to support multimodal data fusion. Combining EEG with other physiological signals such as ECG, EOG, and EMG, or imaging modalities like MRI and PET, could enhance the robustness and reliability of both seizure detection and localization. This multimodal approach may help resolve ambiguous cases where EEG alone is insufficient or where artifacts complicate signal interpretation. Deep learning architectures, particularly those based on attention mechanisms or transformer models, could be employed to intelligently weigh and combine information across modalities, further improving classification performance and interpretability.

Additionally, explainability and interpretability of the model predictions are crucial for clinical adoption. Future research should explore incorporating explainable AI (XAI) techniques, such as saliency maps, Grad-CAM, or LIME, to highlight which parts of the EEG signals most influenced the model's decision. This would provide transparency into the decision-making process, making it easier for neurologists to validate and trust the system's outputs. A visual dashboard combining model predictions, EEG plots, and explainability overlays could be developed to assist clinicians during review, potentially accelerating diagnosis and treatment planning.

Finally, the system could benefit from being adapted and validated on a broader and more diverse set of EEG datasets, encompassing pediatric, geriatric, and multifocal epilepsy cases. Custom training and fine-tuning for specific epilepsy subtypes, seizure morphologies, or patient populations would increase the model’s clinical generalizability. Creating a large-scale, federated learning framework involving multiple hospitals and research institutions could

further improve the model while preserving patient data privacy. As technology continues to evolve, the ultimate goal is to build a fully automated, interpretable, real-time seizure detection and localization ecosystem that bridges the gap between computational intelligence and practical neurology, paving the way for more precise, personalized, and accessible epilepsy care.

# Appendices

## Appendix A: Explanation of Evaluation Metrics (Accuracy, Sensitivity, Specificity)

In the context of seizure detection using machine learning models, evaluation metrics play a critical role in quantifying model performance. The key metrics used in this study include **Accuracy**, **Sensitivity** (also called Recall or True Positive Rate), and **Specificity** (True Negative Rate). These metrics are derived from the confusion matrix, which categorizes predictions into four classes: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

**Accuracy** is a general indicator of how often the model is correct, and is calculated using the formula:
**Accuracy = (TP + TN) / (TP + TN + FP + FN)**

This metric is useful for understanding the overall effectiveness of the model but can be misleading in imbalanced datasets. For example, if seizures (positives) are rare compared to non-seizure data (negatives), a model can have high accuracy by simply predicting the majority class.

**Sensitivity**, also known as **Recall**, measures the proportion of actual seizures that were correctly identified by the model. It is defined as:
**Sensitivity = TP / (TP + FN)**

This is particularly important in seizure detection because failing to detect a seizure (false negative) can have significant clinical consequences. A high sensitivity means the model is capable of detecting most seizure events.

**Specificity** measures the proportion of non-seizure data correctly identified as such, and is calculated as:
**Specificity = TN / (TN + FP)**

This metric ensures that the model does not misclassify normal brain activity as seizures, thereby avoiding false alarms. In clinical practice, a high specificity reduces the burden of unnecessary follow-up assessments.

Together, these three metrics provide a comprehensive understanding of model behavior. In this study, the validation set yielded an average accuracy of 95.88%, sensitivity of 92.93%, and specificity of 98.87%. On the test set, accuracy was 97.73%, sensitivity was 92.06%, and specificity was 99.09%. These values indicate a well-performing model capable of accurately identifying seizure events while minimizing misclassification of non-seizure data.

## Appendix B: Montage Plot and Its Role in Seizure Lateralization

The montage plot is a critical visualization tool in EEG analysis, particularly when assessing seizure spread and localization. In the context of this project, montage plots are used to visualize the spatial and temporal distribution of seizure predictions made by the 1D CNN model across various EEG channels during the ictal period. These channels are arranged according to the internationally accepted 10-20 electrode placement system, which provides spatial coverage of both hemispheres of the brain.

Each channel's seizure prediction, classified on a per-second basis, is displayed in the form of a timeline where color coding is used—**red for seizure** and **black for non-seizure**. This simple but powerful representation allows for quick identification of asymmetries in seizure activity. If a particular hemisphere shows earlier and more persistent seizure predictions, this suggests that the seizure likely originated from that side. For example, if left-sided channels (e.g., Fp1, F3, C3, P3) exhibit red segments before right-sided ones, and if this pattern is consistent throughout the ictal period, it supports a left-hemisphere lateralization.

Montage plots are especially valuable because they offer an interpretable format for clinicians, who are accustomed to reviewing EEG traces and channel-based data. Unlike traditional raw EEG signals, these visualizations incorporate automated model outputs and are aligned in a manner that mirrors standard clinical reading formats. Additionally, by tracking how seizure activity evolves across time and across electrodes, montage plots can also help infer seizure propagation pathways and the dominant hemisphere involved.

In this study, montage plots derived from the CNN predictions provided a clear and interpretable visualization of seizure patterns. These were cross-referenced with ground truth annotations from the Sienna Scalp EEG database to validate the lateralization suggested by the model. This dual-layer validation—machine-based and clinical—helps enhance the reliability and utility of the model in real-world neurology settings. Ultimately, the montage plot not only aids in visual assessment but also bridges the gap between data-driven predictions and practical clinical diagnostics.

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