الجمهورية الجزائرية الديمقراطية الشعبية
République Algérienne démocratique et populaire

وزارة التعليم العالي و البحث العلمي
Ministère de l'enseignement supérieur et de la recherche scientifique

جامعة سعد دحلب البليدة
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Ref : Instrum8

Mémoire de Master

Filière Électronique
Spécialité Instrumentation

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Detection of epileptic seizures in EEG signals using Deep Learning

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Année Universitaire 2024-2025

Acknowledgments

Above all, we wish to thank God with whom everything is possible. I also pass my sincerest gratitude to my supervisor, Madam Yahiaoui Amina, for her continuous support, guidance, and invaluable feedback, and for dedicating her time and effort to patiently work with me from the beginning to the end of this project.

I am also grateful to the members of the Jury, Mr. Ykhlef Farid and Mrs. Amirouche Nesrine, who are also taking their time to give their advice and input, which will be highly valued on this project.

Special thanks to all the professors who have contributed to my academic journey and shared their knowledge throughout the years, both under the programs of biomedical engineering and electronic instrumentation. Not forgetting to extend my sincere thanks to the head of department, Dr. Hocine ATT SAADI for his leadership and fostering a supportive academic environment.

On a personal note, I also wish to take this moment to thank my family and friends, in particular Ts'ireletso Anastacia Noka and Busisa Ncube, who supported me in everything.

Dedication

This work is dedicated to my parents, Sekhereisi Daniel Macheli and Masechele Angelina Macheli who always sacrificed for our education in many ways. To my siblings who also manage to always inspire me academically. Lastly, this work is dedicated to everyone who ever contributed in any way towards my education.

ملخص

يهدف هذا المشروع البحثي إلى استكشاف استخدام التعلّم العميق للكشف عن الصرع من إشارات تخطيط كهربية الدماغ، وهي حاجة متزايدة لأن الصرع هو أحد أكثر الاضطرابات العصبية شيوعًا .في هذه الدراسة، نقترح منهجية تتضمن عدة مراحل مثل جمع البيانات، والمعالجة المسبقة للإشارة، واستخراج السمات، وتصميم النموذج، والتدريب، والتقييم باستخدام مقاييس الأداء .وقد تم اختيار الشبكة العصبية التلافيفية (CNN) نظرًا لفعاليتها في تعلم الأنماط المكانية والزمانية في بيانات تخطيط كهربية الدماغ .وقد تم تصميم كل مرحلة من مراحل العملية بعناية لضمان قدرة النظام على تعلم الميزات ذات الصلة من البيانات مع تقليل الإفراط في التخصيص وضمان قابلية التعميم .كانت النتائج واعدة وتم دمجها في واجهة المستخدم كوسيلة مساعدة للتشخيص الطبي.

الكلمات المفتاحية :الكشف عن الصرع، تخطيط كهربية الدماغ، المؤشرات الحيوية، التعلم العميق، الشبكة العصبية التلافيفية، الشبكة العصبية التلافيفية.

Résumé

Ce projet de recherche vise à explorer l'utilisation de l'apprentissage profond pour détecter l'épilepsie à partir des signaux EEG, un besoin croissant puisque l'épilepsie est l'un des troubles neurologiques les plus courants. Pour cette étude, nous proposons une méthodologie qui implique plusieurs étapes telles que la collecte de données, le prétraitement du signal, l'extraction de caractéristiques, la conception de modèles, l'entraînement et l'évaluation à l'aide de mesures de performance. Le réseau neuronal convolutif (CNN) a été choisi en raison de son efficacité dans l'apprentissage des modèles spatiaux et temporels dans les données EEG. Chaque étape du pipeline a été soigneusement conçue pour s'assurer que le système puisse apprendre des caractéristiques pertinentes à partir des données tout en minimisant l'ajustement excessif et en garantissant la généralisation. Les résultats étaient prometteurs et ont été incorporés dans une interface utilisateur comme aide au diagnostic médical.

Mots-clés: Détection de l'épilepsie, électroencéphalographie, biomarqueurs, apprentissage profond, réseau neuronal convolutif.

Abstract

This research project aims to explore the use of deep learning for detecting epilepsy from EEG signals, a rising need since epilepsy is one of the most common neurological disorders. For this study, we propose a methodology that involves several stages such as, data collection, signal preprocessing, feature extraction, model design, training and, also evaluation using performance metrics. Convolutional neural network (CNN) was chosen due to its effectiveness in learning spatial and temporal patterns in EEG data. Each stage of the pipeline was carefully designed to ensure that the system could learn relevant features from the data while minimizing overfitting and ensuring generalizability. The results were promising and incorporated into a user interface as an aid to medical diagnosis.

Key words: Epilepsy detection, Electroencephalography, Biomarkers, Deep learning, Convolutional Neural Network.

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List of Abbreviations

ADHD	Attention-deficit/hyperactivity disorder
AE	Auto-Encoder
AI	Artificial Intelligence
CNN	Convolutional Neural Networks
DCT	Discrete Cosine Transform
DL	Deep Learning
DWT	Discrete Wavelet Transform
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
FN	False Negative
FP	False Positive
FPR	False Positive Rate
IED	Interictal Epileptiform Discharge
ML	Machine Learning
PCA	Principal Component Analysis
PSG	Polysomnography
REM	Rapid Eye Movement
RF	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TPR	True Positive Rate
WHO	World Health Organization

GENERAL INTRODUCTION

GENERAL INTRODUCTION

Epilepsy is one of the most common neurological disorders worldwide, affecting approximately 50 million people according to the World Health Organization. It is characterized by recurrent seizures resulting from abnormal electrical activity in the brain, which are normally observed on the electroencephalogram (EEG). Accurate and timely detection of these anomalies is very important for correct diagnosis, treatment, and improving the quality of life for patients. To this day, the EEG remains one of the most used tools for monitoring brain activity and diagnosing epilepsy, as it is non-invasive, painless and safe for all ages since it does not use any form of radiation and it is cost-effective.

Overall, EEG biomarkers, such as sleep, stress, Ictal phases and interictal epileptiform discharges (IEDs), are characterized as specific patterns or anomalies detected within EEG recording that correlate with epileptic activity. The interrelation between sleep quality, stress and epileptic seizures reveals a complex landscape that warrants a thorough examination. Notably, sleep plays a crucial role where non-rapid eye movement sleep can significantly amplify IEDs, suggesting that these biomarkers are instrumental in epilepsy modulation.

Traditionally, the interpretation of EEG signals relies heavily on expert manual analysis, which can often be subjective and time consuming, all while risking human error and as a result, there is a growing interest in developing automated systems capable of detecting epileptic seizures from EEG signals with high accuracy and efficiency. These recent developments have led to machine learning (ML), especially deep learning (DL), which has shown promising results by harnessing the power of its algorithms to analyze physiological signals such as EEG signals. DL approaches allow for the elimination of manual feature extraction, which has been a bottleneck in traditional ML techniques. Instead, these models can automatically learn relevant features from raw EEG data, efficiently identifying patterns that may indicate seizure activity.

In the detection of epilepsy, leveraging DL techniques has emerged as a promising approach, yet several significant challenges hinder the technology's effectiveness and widespread application. One of the principal challenges is the limited availability of high-quality labelled data, which is crucial for training deep models. Another considerable challenge is the inherent variability in EEG data due to individual patient differences and environmental factors, which can affect the performance of the deep learning models. The integration of EEG biomarkers and deep learning techniques enhances the capability to provide immediate, accurate and personalized detection of epilepsy, ultimately improving patient’s care outcomes.

This study explores the application of EEG biomarkers with deep learning techniques for the detection of epileptic seizures in EEG signals, while additionally shedding more light on epilepsy biomarkers and detecting them as well. The objective is to design and evaluate a model that does all this, using publicly available dataset, with the final aim of the model being integrated into real-time monitoring systems to assist clinicians.

This work is structured into four main chapters. **Chapter I** introduces the medical context of epilepsy, including its neurological basis, types, causes, and the critical role of EEG in diagnosis. **Chapter II** reviews existing literature, highlighting conventional and modern approaches to EEG-based seizure detection, including feature extraction and classification techniques. **Chapter III** presents the theoretical foundations of the study, focusing on machine learning and deep learning principles, with special emphasis on neural networks applied to EEG analysis. **Chapter IV** details the implementation process, including data preparation, model development, and evaluation of a CNN-based framework for classifying EEG biomarkers while also presenting the results obtained and discussing them.

CHAPTER I. MEDICAL CONTEXT

Chapter I . MEDICAL CONTEXT

I .1 . INTRODUCTION

To break down one of our keywords, in this chapter we are first going to dive deep into the question of what is epilepsy? A chronic neurological disorder characterized by recurrent, unprovoked seizures (which are brief episodes of involuntary muscle movement that might involve the whole body or some parts of the body) resulting from abnormal electrical activity in the brain. According to the World Health Organization (WHO), this disorder affects around 50 million people around the world, making it one of the most common neurological diseases around the world [2].

Over the years, the electroencephalography (EEG) has been one of the mostly used diagnostic tools for epilepsy, this is due to its many benefits, like being non-invasive, offering real-time monitoring of the brain activity and being affordable among others.

The interpretation of the EEG however, requires expert knowledge and can be prone to subjective variability and oversight, especially in prolonged recordings and to fix the problem, we have combined the use of technology, specifically artificial intelligence to interpret these results.

In this chapter, we are going to begin by exploring the pathophysiological basis of epilepsy and the role of EEG in its diagnosis.

I .2 . Anatomy of the Brain

Brain, the mass of nerve tissue in the anterior end of an organism. The brain integrates sensory information and directs motor responses; in higher vertebrates it is also the center of learning. The human brain weighs approximately 1.4 kg (3 pounds) and is made up of billions of cells called neurons. Junctions between neurons, known as synapses, enable electrical and chemical messages to be transmitted from one neuron to the next in the brain, a process that underlies basic sensory functions and that is critical to learning, memory and thought formation, and other cognitive activities. The brain and the spinal cord together make up the system of nerve tissue in vertebrates called the central nervous system, which controls both voluntary movements, such as those involved in walking and in speech, and involuntary movements, such as breathing and reflex actions. It also is the center of emotion and cognition. [3]

The brain is composed of the cerebrum, cerebellum and brainstem. The cerebrum, the largest part of the human brain is divided into four distinct lobes, being the frontal, parietal, temporal and occipital lobes. Each lobe is responsible for various functions that are essential for cognitive processing, sensory perception and motor control. Seeing that this is the largest part of the brain, it is no surprise that this is also where most neurological disorders are rooted. [4]

I . 2 .1 Conditions and Disorders

There are many types of brain disorders and conditions that vary in severity. Some of the most common include:

- Alzheimer's disease and dementia
- Amyotrophic latera sclerosis
- Autism spectrum disorder
- Brain bleed
- Brain tumor
- Concussion
- Depression
- Multiple sclerosis
- Parkinson's disease
- Stroke
- Traumatic brain injury
- Epilepsy

I .3 . EPILEPSY

Epilepsy is a group of non-communicable neurological disorders affecting over 50 million people worldwide and it involves recurrent, unprovoked seizures [2]. However, this does not mean that all seizures are epileptic. The diagnosis involves ruling out other conditions that might cause similar symptoms, such as fainting, and other causes like alcohol withdrawal or electrolyte (ions in the blood, urine, serum or other fluids) problems. This may be done by imaging the brain or performing blood tests but ultimately, epilepsy is often confirmed with an electroencephalogram [5].

I . 3 .1 Seizures

Seizures are neurological events characterized by abnormal electrical activity in the brain that can be categorized into either epileptic or non-epileptic and the latter are often psychogenic, stemming from psychological factors rather than physiological activities in the brain. An epileptic seizure on the other hand, is the clinical manifestation of an abnormal, excessive and synchronized electrical discharge in the neurons. The occurrence of two or more unprovoked seizures defines epilepsy while the occurrence of just one seizure may warrant the definition (set out by the International League Against Epilepsy) in a more clinical usage where recurrence may be able to be prejudged [6].

Epileptic seizures can vary from brief and nearly undetectable periods to long periods of vigorous shaking due to abnormal activity in the brain and these episodes can lead to physical injuries, either directly, such as broken bones or through causing accidents. It, sometimes, tends to recur and may have no detectable underlying cause.

I . 3 .2 What is happening in the brain during a seizure?

The underlying mechanism of an epileptic seizure is excessive and abnormal neuronal activity in the cortex of the brain all at the same time, which can be observed in the electroencephalogram (EEG) of an individual. However, it is unknown under which circumstances the brain shifts into the activity of a seizure with its excessive synchronization.

During an epileptic seizure, the resistance of excitatory neurons to fire during this period is decreased and this may occur due to changes to ion channels or inhibitory neurons not functioning properly and this therefore results in a specific area from which seizures may develop, known as a seizure focus [5].

Another mechanism of epilepsy may be the up-regulation of excitatory circuits or down-regulation of inhibitory circuits following an injury to the brain. These secondary epilepsies occur through processes known as *epileptogenesis.* Failure of the blood-brain barrier may also be a casual mechanism as it would allow substances in the blood to enter the brain.

Any part of the brain can be affected by epilepsy. It could be a one, specific (for focalized seizures) or all over the cortex of the brain (for generalized seizures). The reason this occurs in most cases in unknown (cryptogenic) while some of course may occur as a result of the aforementioned causes [7].

Epilepsy mostly affects in children and older people in developed countries while in developing countries, onset is more common at the extreme ages – in younger children and in older children and young adults due to differences in frequency of the underlying causes. It must also be noted that not all cases of epilepsy are lifelong, and many improve to the point that treatment is no longer needed.

I . 3 .3 Classification of seizures

Seizure are classified according to where they start in the brain, whether the patient stays conscious or not and it has been proven that epileptic seizures are usually not random events but are often brought on by some factors (also known as triggers or biomarkers) like stress, flickering lights, lack of sleep or excessive use of alcohol to mention a few [8].

In epileptic seizures, a group of neurons begins firing in an abnormal, excessive and synchronized manner, which results in a wave of depolarization known as '*a paroxysmal depolarizing shift*'. The figure (I-1) below shows three classes of EEG signals, the last one exhibiting excessive and synchronized firing of neurons during an epileptic seizure.

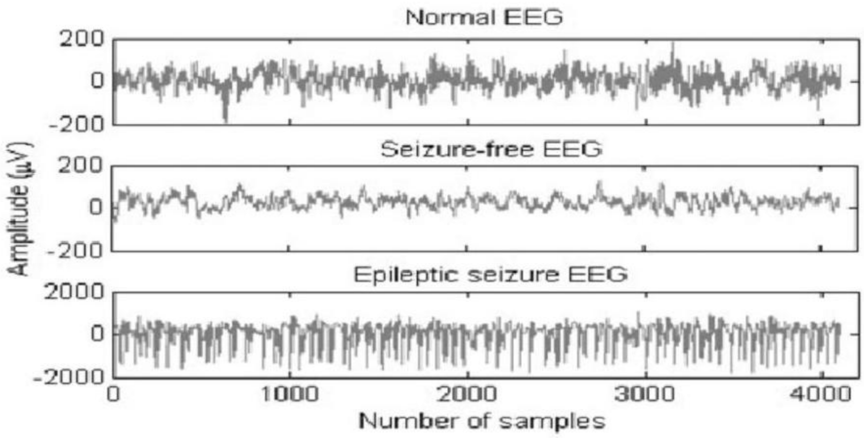

Figure I-1. Three classes of EEG signals [54]

The most common class is the partial (focal) seizures which account for almost 60% of new epilepsy cases and originate in a specific area of the cerebral cortex. Their manifestations depend on the particular region involved and they can further be classified into major subcategories including aware and impaired awareness seizures. The remaining 40% are generalized seizures which differ in that they simultaneously affect both hemispheres of the brain, leading to widespread neurological effects [9] [10].

I . 3 .4 Types of seizures

Tonic-clonic seizures (most common): They occur with a contraction of the limbs followed by their extension and arching of the back, which lasts 10-30 seconds (the tonic phase). Due to contraction of chest muscles, it is usually accompanied by a cry, followed by a shaking of limbs in unison (clonic phase). Tonic seizures produce constant contractions of the muscles. A person often turns blue as breathing is stopped.

Focal aware seizure: It starts in the small area in the brain and the patient remains conscious during the seizure. A person may have twitching on one part of their body.

Generalized absence seizures: Absence seizures can be subtle with only a slight turn of the head or eye blinking with impaired consciousness; typically, the patient does not fall over and returns to normal right after it ends. The patient will be present this second and absent the next, maybe even in the middle of a sentence and they are normally aware that there are lapses of time missing from their memories.

Myoclonic seizures: These seizures involve very brief muscle very brief muscle spasms in either a few areas or all over and sometimes cause the person to fall, which can consequently cause injury.

Atonic seizures: They involve losing muscle activity for greater than one second, typically occurring on both sides of the body.

I . 3 .5 Known causes of seizures

Like most neurological conditions, the underlying causes of seizures are complex and can develop from a range of events, from faulty wiring during brain development to brain inflammation, or from physical injuries or infections. Epilepsy is the most common cause of seizures but other factors like head injuries, brain tumors, infections, metabolic issues, and genetic disorders. Some triggers may include; stress, lack of sleep, flashing lights, and use of alcohol or drugs to mention a few [7]. Treatment might include diet therapy, medication, surgery, and neuro-modulation.

I .4 . DETECTION OF EPILEPSY

The diagnostic procedures for distinguishing between epileptic and non-epileptic seizures are multifaceted and involve various clinical approaches. While electroencephalography (EEG) is the basic tool for diagnosing seizure disorders, its effectiveness in confirming the type of seizure can vary significantly. Due to these challenges, the application of video-EEG monitoring represents a more refined diagnostic approach as it allows for simultaneous recording of EEG data and video of the patient's activity, giving insights into the semiological features of seizures. Other methods include, Computed tomography (CT) scan, magnetic resonance imaging (MRI), positron emission tomography (PET), single photon emission computed tomography (SPECT) and simple blood tests. Studies suggest that EEG and MRI are the two principal techniques used in the diagnosis of epileptic seizures [10].

I .5 . EEG

The EEG was first developed in 1924 by the German physicist Hans Berger, who was always very intrigued by the connection between the brain (the physical organ) and the mind (the consciousness, thoughts and emotions). He wanted to find a way to measure brain activity in real-time and he used a galvanometer and placed electrodes on his scalp to record his first human EEG. Berger discovered rhythmic oscillations in brain activity, which he called the "alpha waves", typically observed when a person is awake but relaxed with closed eyes. Though the machine has been developed further over the past years, his first findings were published in 1929, marking the formal introduction of the EEG to the scientific world [11].

The electroencephalogram is a non-invasive test that measures electrical activity in the brain. It uses electrodes (small metal discs that attach to the scalp, usually using international 10-20 system) to detect bio-signals. These bio-signals are then amplified and appear as a graph on a computer screen to be interpreted by a doctor. Brain cells (neurons) communicate via electrical impulses and this activity appears as waves on an EEG recording. Neurons are always active, even when the patient is sleeping [11].

I . 5 .1 EEG EQUIPMENTS

Electroencephalography (EEG) is an important component in diagnosis and management of epilepsy, using the electroencephalograph which interprets the electrical activity from the scalp through a series of electrodes. Typically, a standard EEG uses a minimum of 21 electrodes arranged in accordance with the international 10-20 system, which allows for the capture of brain wave patterns and the identification of interictal epileptiform discharges (IEDs) that are crucial in diagnosing various epileptic conditions. Furthermore, the selection and calibration of amplifiers are critical factors as they must possess adequate bandwidth and gain settings to accurately capture the subtle changes in electrical activity, often filtered to minimize noise [12].

EEG electrodes: These are small metal discs that are typically attached to the scalp during an EEG test so as to work as sensors in order to detect electrical activity in the brain. They are usually made of stainless steel, gold, carbon or silver covered with silver chloride.

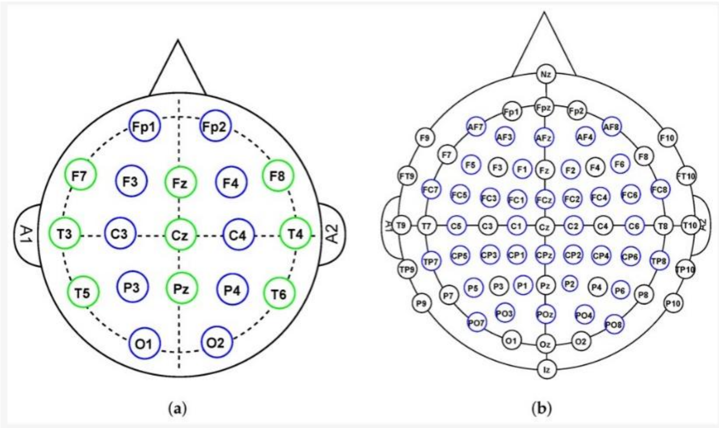

Figure I-2. 10-20 and 10-10 international systems [55]

The international 10-20 system provides 21 electrodes distributed proportionally on the scalp. The distance between two adjacent electrodes is 10 to 20% of the skull extremities' total distance. The 10-10 standard was developed with more electrodes because it uses smaller distances of 10% between all electrodes, resulting in a higher density of electrodes [13]. Figure (I-2) above shows both 10-20 and 10-10 international systems as 'a' and 'b', respectively.

Data acquisition system: This is where the EEG signals are captured, digitalized and stored. It is often considered the core of the EEG system where the actual "recording of data" takes place. In some systems, the writing unit can be a dedicated device that logs and stores the brainwave data onto digital format for further analysis. This system also includes analog to digital converters (ADC), and sometimes a direct data storage mechanism to ensure that the recorded signals are stored for long-term analysis [15].

Amplifier: The electrical signals produced by the brain are very weak (typically in the range of microvolts) and therefore too small to be directly recorded by most instruments. So, the amplifier increases the signal strength to a level where it can be easily detected and analyzed. It does this by taking energy from a power supply and controlling the output to match the input signal shape but with a larger amplitude [15].

Filter: It is used to process and improve the quality of the electrical signals recorded from the brain. Like every other physiological signal, EEG can be contaminated by various types of noise and artifacts, such as muscle activity, eye movements and electrical interference and filters help isolate the specific frequency bands of interest and remove unwanted signals. Band-pass filters are mostly used because they allow specific frequency bands (such as delta, alpha, beta and gamma waves) to pass through, which are crucial for understanding different states of brain activity [15].

Display: It is the visual interface of an EEG system where brainwave activity is shown in real-time and it typically displays continuous waveforms that represent the electrical activity of the brain recorded by electrodes placed on the scalp. This way the practitioners can observe different types of brainwave patterns such as alpha, beta and delta waves over time. Multiple channels are shown simultaneously, with each channel representing data from a different electrode or region of the brain. The display screen helps in identifying normal and abnormal brain activity. It may also highlight artifacts (unwanted signals like eye blinks) to help clinicians interpret the data accurately [15].

I . 5 .2 Acquisition chain of EEG

The EEG is recorded using the technology of a differential amplifier. The amplifier takes two electrical inputs to give out one output and this means that with the help of the electrodes placed on the scalp, an EEG can find changes in brain activity that might help in diagnosing brain conditions. As shown in figure (1-3), the steps are as follows :

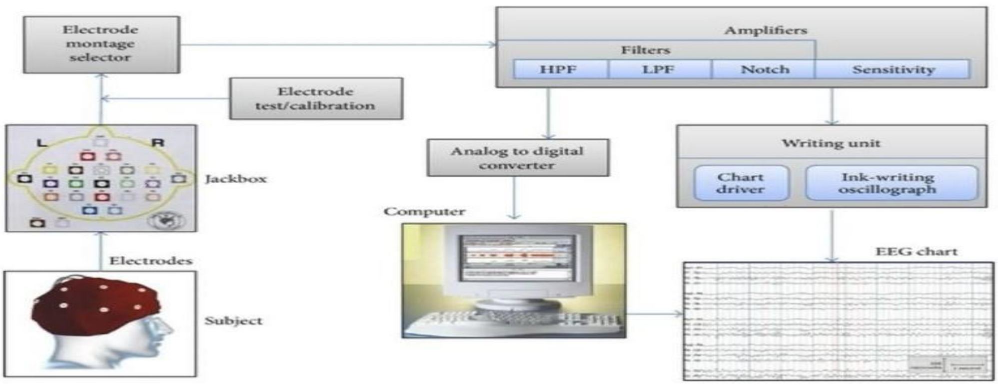

Figure I-3. Acquisition chain of EEG signals. [56]

- The brain generates electrical signals when neurons (nerve cells) communicate with each other. These signals arise from the synchronized firing of neurons, creating electrical fields.
- The electrodes are placed on the scalp to detect the electrical signals generated by the neurons according to standardized systems like the international 10-20 (which is the most

frequently used) or 10-10 (used when more spatial resolution is needed, which it achieves by using more electrodes than the international 10-20) system to mention a few.

- The electrodes pick up the electrical potentials from groups of neurons firing together. However, these signals are very weak (in microvolts) and they therefore need to be amplified to increase their strength so they can be recorded and analyzed.
- The amplified electrical signals are then sent to the recording unit where they are displayed on the screen as continuous waveforms representing the overall activity of the brain over time.
- The last step in an EEG test is interpretation of results. The different patterns produced by the brain are known as waveforms (alpha, beta, theta and delta waves) and they are categorized by frequency and amplitude. It is through these waveforms that the practitioners will understand the state of the brain, like whether the person is awake, deep in sleep or if they are having seizures.

I . 5 .3 EEG waves

The observed frequencies range from 1 to 30 Hz with amplitudes of 20-100ùV and are subdivided into various groups; alpha (8-13Hz), beta (14-30Hz), delta (0.5-3.5Hz), and theta (4-7Hz) as show on the figure (1-4) below.

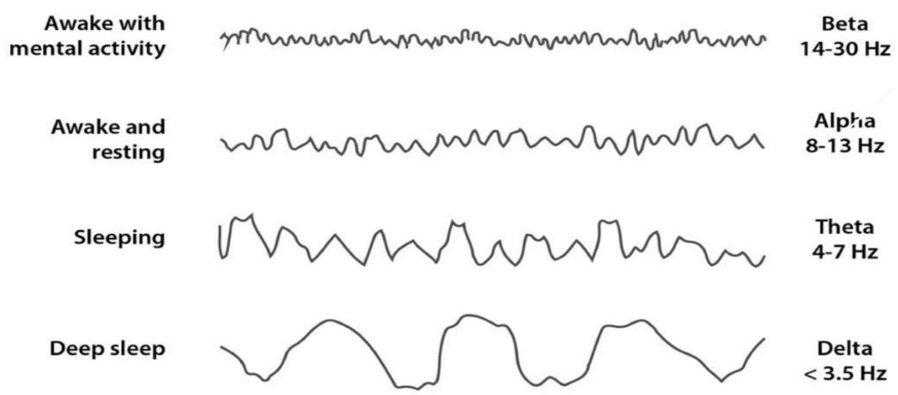

Figure I-4. EEG waves **[53]**

***Alpha* waves:** They were the first observed over the occipital cortex when human subjects were relaxed or closed their eyes. However, alpha and theta are now known to be involved in many different waking tasks in many parts of the brain. In many cases, these near 10 Hz waves may function when the person is in the state of relaxed wakefulness and mostly prominent over the parietal and occipital sites.

***Beta* waves**: More prominent during intense mental activity. They are shown mostly in the frontal region as well as other regions. If a relaxed person opens their eyes, the alpha activity decreases and the beta activity increases.

***Theta* waves:** These rhythms may appear normally during relaxed wakefulness. The patterns of normal EEG that predominantly involve theta frequencies are the slow alpha variant, rhythmic temporal theta activity of drowsiness, midline theta rhythms are generally not seen in wakefulness but if they are, it's a sign of brain dysfunction.

***Delta* waves:** They are the slowest recorded brain waves in human beings. They are often found in young children and infants and are associated with the deepest levels of relaxation and restorative, healing sleep. Delta is prominently seen in brain injuries, learning problems, inability to think and severe ADHD. If this wave is suppressed, it leads to inability to rejuvenate the body and revitalize the brain and poor sleep. Adequate production of delta waves helps us feel completely rejuvenated and promotes the immune system, natural healing and restorative/ deep sleep.

I . 5 .4 Labels and their meaning

After understanding the waves used in EEG, it is also very important that we understand both the labels used in accordance to the electrode placement and the different EEG montages, so as to be able to comprehend the display of the results. Figure (1-5) below represents the placement of EEG electrodes.

F- Frontal

C- Central

P-Parietal

O- Occital

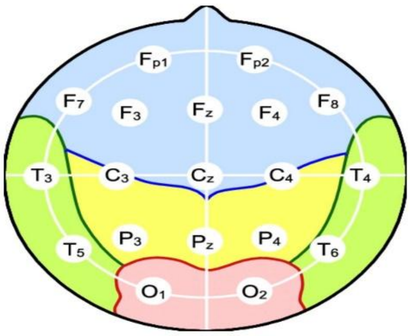

Figure I-5. EEG electrodes placement [56]

Odd numbers are on the left and even numbers on the right. The lower numbers are closer to the center/midline. The midline itself is represented by a ‘z’, which means zero.

- Fp1, Fp2: Frontopolar electrodes, located on the forehead, left and right side.
- F3, F4: Frontal electrodes, on the left and right side of the forehead.
- C3, C4: Central electrodes, placed above the left and right hemispheres of the brain.
- P3, P4: Parietal electrodes, located on the upper back portion of the head, left and right side.
- O1, O2: Occipital electrodes, positioned at the back of the head, near the visual cortex.
- T3, T4, T5, T6: Temporal electrodes, situated on the left and right sides of the head near the ears. They are often involved in monitoring auditory functions.
- F7, F8: Frontal-temporal electrodes, located at the front of temporal lobes.
- Fz, Cz, Pz: Midline electrodes, located at the frontal (Fz), central (Cz) and parietal (Pz) positions on the midline of the head.
- EKG: Electrocardiogram electrode, which records the heart’s electrical activity. It is not directly related to brain activity but can be important in some EEG analyses, an example can be when reducing ECG artifacts in EEG in order to get more accurate results after filtering the former from the latter.

I .6 . Epilepsy Biomarkers

Electroencephalography serves as a critical tool in the assessment of epilepsy, providing insight into the electrical activity of the brain whenever a seizure occurs. Epilepsy biomarkers are characterized as specific patterns or anomalies detected within EEG recordings that correlate with epileptic activity. These biomarkers facilitate the identification of seizures, frequency and potential onset, thereby playing a pivotal role in diagnosing and managing epilepsy [14].

I . 6 .1 Stress Biomarkers

The early diagnosis of stress symptoms is essential for preventing various mental disorder such as depression and epilepsy as high levels of stress could trigger a seizure. Electroencephalography (EEG) signals are frequently employed in stress detection research and are both inexpensive and non-invasive modality. Stress can be triggered by the change in the body's emotional response to various situations such as depression, anxiety, anger, grief, guilt, low self-esteem, etc. It can be classified as positive stress (eustress) or negative stress (distress) [16]. There are different ways to measure stress levels. Traditionally, the stress level of an individual has been calculated only through self-reports. Recently deep learning has been widely used in the domain of stress recognition through EEG as it can directly take input from raw data and identify the most prominent features automatically without any feature engineering and pre-processing.

I . 6 .2 Sleep Patterns

Sleep patterns play a crucial role in understanding both normal brain function and the pathophysiology of neurological disorders such as epilepsy, especially because sleep deprivation could also trigger an epileptic seizure. Healthy sleep consists predominantly of non-rapid eye movement and rapid eye movement (REM) stages, each contributing to restorative processes in the brain.

I . 6 .3 Interictal Epileptiform Discharges

Interictal epileptiform discharges (IEDs) represent a significant biomarker in the context of epilepsy diagnosis as they commonly indicate the potential for epileptic seizures. IEDs manifest as abnormal spikes or sharp waves on the electroencephalogram and their detection is critical for evaluating seizure disorders. Notably, the identification of IEDs is complex due to the inherent variability of these discharges, which can be influenced by numerous factors including patient state (awake, drowsy, sleep, etc.) and individual anatomical and neurological differences. For example, variations in duration, morphology and localization can render the distinction between IEDs and normal EEG activity particularly challenging [17].

I . 6 .4 Ictal Activity

Ictal activity refers to the altered state of consciousness, behavior, and cognitive function associated with an epileptic seizure. During an ictal episode, the brain exhibits distinct electroencephalographic (EEG) patterns that can be analyzed for seizure detection. Ictal patterns can vary significantly across individuals, necessitating a patient-specific approach for accurate detection [18]. The development of a patient-specific epileptic seizure detection algorithm incorporating spectral features and classifiers, yielding improved performance in real-time seizure detection tailored to individual EEG characteristics. Such advancements underline the importance of recognizing the unique attributes of ictal activity for effective seizure identification.

I .7 . Conclusion

In summary, this chapter reviewed that epilepsy is a complex and widespread neurological disorder that is characterized by recurrent seizures that result from abnormal electrical activity in the brain, but despite how common it is, its diagnosis remains a challenge. The most common tool used for epilepsy detection, the electroencephalogram (EEG), plays a critical role in the clinical evaluation as well and it has its many advantages, which include but are not limited to being non-invasive and having no radiation exposure.

EEG signals provide valuable insights into the brain’s electrical patterns and are important in detecting epilepsy-related events, including both ictal and interictal activity and abnormalities in these signals such as spikes, sharp waves and rhythmic discharges serve as important biomarkers for epilepsy.

This chapter has laid the foundation by outlining the clinical significance of epilepsy and the role of EEG in its assessment and the next chapter will outline the advances in signal processing and machine learning that have further enhanced the ability to analyze EEG data, allowing for the development of automated systems.

CHAPTER II. STATE OF THE ART

Chapter II . STATE OF THE ART

II .1 . INTRODUCTION

The accurate detection and classification of epilepsy-related activity using electroencephalogram (EEG) has gained significant attention in both research and clinical fields and with the growing demand for automated tools, a number of studies have explored different signal processing techniques and machine learning algorithms to analyze EEG data for epilepsy detection.

Various features, data processing methods, and classification algorithms have been applied for detecting and classifying seizures using EEG signals. However, in some studies, features used together in the classification process may carry similar information and this overlap can lead to redundancy, meaning that some features do not contribute new or useful insights to the model and may reduce its overall efficiency. The current methods utilized in epileptic seizure detection and classification are based on the use of artificial intelligence (AI), especially, Machine learning (ML) and Deep Learning (DL). Intelligent models have enabled the integration of EEG biomarkers, such as seizures, interictal epileptiform discharges (IEDs), stress, sleep, and postictal states, to improve detection, prediction, and clinical decision for epileptic seizure.

In this chapter, we will establish a review of the methodologies employed in epilepsy research based on EEG, presenting a broad-spectrum angling from conventional techniques to the integration of biomarkers.

II .2 . Related Work

Historically, epilepsy diagnosis via EEG involved visual inspection by neurologists, a process that is time-consuming, subjective, and prone to errors in long-term recordings. To address these limitations, researchers have employed signal processing techniques such as Fourier Transform, Wavelet Transform, and empirical mode decomposition to extract relevant features from EEG signals and artificial intelligence (AI) [19].

II . 2 .1 Traditional methods

- **Subasi, A. (2007):** Here, the author decomposes EEG signals into sub-bands frequencies using discrete wavelet transform (DWT). Then these sub-band frequencies were used as the input to an Expectation-Maximization network with two discrete outputs: normal and epileptic. In order to improve accuracy, the outputs of expert networks were combined according to a set of local weights called the “gating function”. The performance of the proposed model was evaluated in terms of classification accuracies and the results confirmed that the proposed network structure has some potential in detecting epileptic seizures [20].
- **Huang, X. et al. (2009):** This study presents a novel feature extraction method based on an autoencoder (AE) which was proposed to extract the features of EEG signals in the time domain for providing an efficient feature extraction algorithm for real-time epilepsy detection. The obtained features were fed into three classical classifiers for automatic epilepsy detection. Meanwhile, the performance of the proposed method was compared with PCA, and the results demonstrated that the AE-based features achieved a prediction accuracy of 97%, which was much higher than that of the features extracted from PCA. A limitation of this study might have been that the analysis was mainly conducted on the EEG analysis on only time domain which is less sufficient [21].
- **Tzallas, A. et al. (2009):** This research demonstrates the suitability of the time-frequency analysis to classify EEG segments for epileptic seizures. The authors also used several methods for time-frequency analysis of EEGs, such as, Short-time Fourier transform and several time-frequency distributions, to calculate the power spectrum density (PSD) of each segment. The methods are evaluated using three classification problems obtained from a benchmark EEG dataset, and its shows good results [22].
- **Ling Guo et al. (2010):** This paper presents the first method for automatic epileptic seizure detection that combines entropy features derived from multiwavelet transform with an artificial neural network to classify the EEG signals regarding the existence or absence of seizure. The original EEG signal is firstly decomposed into several sub-signals through 4-level multiwavelet transformation with repeated-row preprocessing. For each sub-signal, the approximate entropy feature, which measures the regularity or predictability of the signal, is calculated. Then, a three-layer with Bayesian regularization back-propagation training. The high accuracy obtained for two different classification problems verified the success of the method [23].

II . 2 .2 Features extraction methods

❖ **Boonyakitanont, P. et al. (2020):** This paper summarizes feature descriptions and their interpretations in characterizing epileptic seizures using EEG signals to review classification performance metrics [24].

❖ **Cherifi et al. (2022):** In this study, authors developed three different approaches to extract features from the filtered EEG signals. The first approach was to extract eight statistical features directly from the time-domain signal while the second approach they used only the frequency domain information by applying the Discrete Cosine Transform (DCT) to the EEG signals, extracting two statistical features from the lower coefficients. In the last approach, they used a tool that combines both time and frequency domain information, which is the Discrete Wavelet Transform (DWT). For Epilepsy detection (healthy vs epileptic), the first approach performed badly. Using the DCT improved the results, but the best accuracies were obtained with the DWT-based approach. For seizure detection, the three methods performed quite well [25].

❖ **Yongqiang Y (2022):** In this paper, the four dimensions of time domain analysis, frequency domain analysis, time frequency analysis and nonlinear kinetic analysis are reviewed for feature extraction, with the purpose of summarizing and prospecting the research content and possibilities of epilepsy EEG feature extraction, and providing new ideas for clinical epilepsy diagnosis and treatment [26].

❖ **Zhang, D. et al. (2022):** The authors developed a method of EEG feature extraction based on wavelet packet transform and improved fuzzy entropy. The Wavelet packet Transform is used to decompose the EEG signal with multi-resolution and make it into the signal with different characteristics. The original Fuzzy entropy algorithm was enhanced to improve its ability of reflecting the degree of irregularity and complexity of time series. Finally, by combining these techniques, the method effectively extracted meaningful features from epileptic EEG signals. The results show that this approach can accurately identify characteristic patterns associated with epilepsy [27].

II . 2 .3 Machine Learning methods

Machine learning approaches are intensely being applied to this problem due to their ability to classify seizure conditions from a large amount of data, and provide pre-screened results for neurologists.

❖ **Ihsan Ullah et al. (2018):** They propose a system that is an ensemble of pyramidal one-dimensional convolutional neural network models. It works on the concept of refinement approach and it involves 61% fewer parameters compared to standard CNN models and as such it has better generalization. To overcome the limitations of the small amount of data, they propose two augmentation schemes. The results gives an accuracy of 99.1% [28].

❖ **Y. Yuan et al. (2019):** Presents a unified multi-view deep learning framework to capture brain abnormalities associated with seizures based on multi-channel scalp EEG signals. The proposed approach is an end-to-end model that is able to jointly learn multi-view features both unsupervised multi-channel EEG reconstruction and supervised seizure detection via spectrogram representation. Authors construct a new autoencoder-based multi-view learning model by incorporating both inter and intra correlations of EEG channels to unleash the power of multi-channel information. By adding a channel-wise competition mechanism in the training phase, they propose a channel-aware seizure detection module to guide our multi-view structure to focus on important and relevant EEG channels. To validate the effectiveness of the proposed framework, extensive experiments against nine baselines, including both traditional handcrafted feature extraction and conventional deep learning methods, are carried out on a benchmark scalp EEG dataset. Experimental results show that the proposed model is able to achieve higher average accuracy and f1-score at 94.37% and 85.34%, respectively, using 5-fold subject-independent cross validation, demonstrating a powerful and effective method in the task of EEG seizure detection [29].

❖ **Dissanayake, T. et al. (2021):** Propose a Patient-independent seizure prediction models to offer accurate performance across multiple subjects within a dataset, and have been identified as a real-world solution to the seizure prediction problem. Two patient-independent deep learning architectures with different learning strategies are designed, that can learn a global function utilizing data from multiple subjects. Proposed models achieve state-of-the-art performance for seizure prediction, demonstrating 88.81% and 91.54% accuracy respectively. The Siamese model trained on the proposed learning strategy is able to learn patterns related to patient variations in data while predicting seizures [30].

❖ **Alsuwaiket (2022):** In this paper, the aim of study is to automate the extraction of electroencephalogram signals without referring to doctors using two feature extraction methods, namely Wavelet Packet decomposition and Genetic Algorithm-Based Frequency-Domain Feature Search. Three machine learning algorithms were applied, namely Conventional Neural Networks (CNNs), Support Vector Machine (SVM), and Random Forest (RF) to diagnose epileptic seizures. The results achieved from the classifiers show a higher accuracy rate using CNNs as a classifier and Genetic Algorithm-Based Frequency-Domain Feature Search as feature extraction reaching 97.93% accuracy while the accuracy rate of the SVM and RF was 94.49% and 88.03% respectively [31].

❖ **Jie Xu et al. (2024):** This review is dedicated to exploring seizure detection approaches based on deep learning, focusing on three distinct avenues. Primarily, they delve into the application of canonical deep learning methods in epilepsy detection. Subsequently, a more in-depth study was conducted on the hybrid models of deep learning. Next, the third is the integration of deep learning and traditional machine learning strategies. Finally, the challenges and future prospects related to this topic are given [32].

Many methods have been proposed for the classification of EEG signals in binary (Normal vs Epileptic and seizure vs non-seizure) classification problems. A comparison with state-of-the-art methods is given in Table (II-1).

Table II-1. Comparative Analysis of Traditional, Feature-Based, and Deep Learning Approaches for EEG-Based Epilepsy Detection and Classification.

Approach	Feature Type	Model	Performance	Category
Multiwavelet + Entropy	Nonlinear	ANN	Entropy boosts pattern detection	Traditional
Time-Frequency Decomposition	TF Distribution	SVM	High specificity in seizure segments	Traditional
DCT	Time + Frequency	SVM, MLP	Hybrid method yielded highest accuracy	Feature Extraction
WPT + Fuzzy Entropy	Nonlinear Dynamic	SVM	Enhances subtle difference capture	Feature Extraction
1D Convolutional Neural Network (P-CNN)	Raw EEG	CNN	99.5% accuracy, real-time capable	Deep Learning
Deep Autoencoder	Learned Latent Space	SVM	Robust feature encoding, high accuracy	Deep Learning
Compact CNN	Raw EEG	CNN	Compact model with good generalization	Deep Learning
Comparative Review	Multi-domain	Multi-model	Feature quality affects overall model success	Feature Extraction + Deep Learning

Sources: [20]–[32].

II .3 . Conclusion

Based on our review, traditional clinical approaches, while effective, are time-consuming and rely heavily on expert interpretation but deep learning has revolutionized epilepsy monitoring by enabling the integration of diverse EEG biomarkers into unified, highly accurate, and interpretable models. These advances support real-time, automated, and clinically relevant epilepsy management, paving the way for more personalized and effective care. As a result, we chose this approach in developing the strategy we propose in this work, which will be examined and explained in detail in the following chapters.

CHAPTER III. THEORITICAL FOUNDATIONS

Chapter III . THEORETICAL FOUNDATIONS

III .1 . INTRODUCTION

In recent years, the application of machine learning and, more specifically, neural networks to biomedical signal processing has shown great promise and this is due to the fact that neural networks are capable of automatically extracting complex patterns and features from high-dimensional data, which in turn makes them well-suited for EEG analysis.

Furthermore, in this chapter we will go in depth about how machine learning can help us in our field, specifically in analyzing EEG data and detecting some pathologies or abnormalities related to epilepsy in our case. To narrow it down even more, we will be mostly focused on artificial neural networks and delve thoroughly into understanding their application in this regard.

III .2 . Machine learning (ML)

It is a field of study in artificial intelligence (AI) concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions [33]. In basic terms, it is the practice of using algorithms to analyze data, and then make a determination or prediction about new data. Applicated in several domains, such as Natural language processing, Computer vision, Speech recognition, Email filtering, Agriculture and Medicine.

The goal of a learning machine is to generalize from its experience, that is, for it to be able to perform accurately on new, unseen examples or tasks after having experienced a learning data set. The training examples come from some generally unknown probability distribution and the learner has to build a general model about this space that enables it to produce sufficiently accurate predictions in new cases. However, the mentioned training sets are finite and the future is uncertain so, learning theory usually does not yield guarantees of the performance of algorithms. Instead, there are problems often associated with machine learning [33].

III . 2 .1 Supervised learning

Supervised machine learning is defined by its use of labeled datasets to train algorithms to classify data or predict outcomes accurately. During training, the model adjusts its weights through optimization methods like gradient descent to fit the data. Cross-validation is then used to evaluate the model's performance and ensure it generalizes well, avoiding overfitting or under-fitting. This approach solves a variety of problems, such as classifying pathologies and some methods used in supervised learning include neural networks, linear regression, random forest, support vector machine (SVM) and Naïve Bayes [34].

III . 2 .2 Unsupervised learning

This method uses machine learning algorithms to analyze and cluster unlabeled datasets. These algorithms discover hidden patterns or data groupings without the need for human intervention. Its ability to discover similarities and differences in information make it ideal for exploratory data analysis, customer segmentation, and image and pattern recognition. It is used to reduce the number of features in a model through the process of dimensionality reduction [34].

III . 2 .3 Semi-supervised learning

As the name suggests, this method offers a medium between supervised and unsupervised learning. During training, it uses a smaller labeled dataset to guide classification and feature extraction from a larger, unlabeled dataset. Semi-supervised learning can solve the problem of not having enough labeled data for a supervised learning algorithm and it is also useful in cases where labeling data is expensive [34].

III . 2 .4 Reinforcement learning (RL)

It is a type of machine learning where an agent learns to make decisions by interacting with an environment. The goal is to maximize some notion of cumulative reward through trial and error. In reinforcement learning, the agent receives feedback (rewards or penalties) from the environment after taking key actions [40]. Over time, it learns which actions lead to best outcomes (i.e. the highest rewards). RL involves concepts like states (the situation the agent is in), actions (choices the agent can make) and rewards (feedback on the action's effectiveness) [39].

III .3 . Principles of Deep learning (DL)

Deep Learning (DL) is a subset of Machine Learning (ML), that teaches computers to do what humans naturally do. The elementary bricks of deep learning are the neural networks, that are combined to form the deep neural networks [35] to learn from data.

Deep learning models have become pivotal in the detection and diagnosis of medical pathologies, such as epilepsy, through various types of data, including images, signals and videos, showcasing remarkable advancements that transform traditional methods. Various types of deep learning architectures have been utilized to address this complex task, each offering unique advantages in processing and analyzing vast datasets.

III . 3 .1 Artificial Neural networks (ANN)

Neural networks, also known as artificial neural networks (ANNs) are a subset of machine learning (ML) that provide the foundation of deep learning techniques. Their name and form are inspired by the human brain, and they replicate the way real neurons communicate with one another [36]. An artificial neural network creates an adaptive system that computers use to learn from their mistakes and improve continuous.

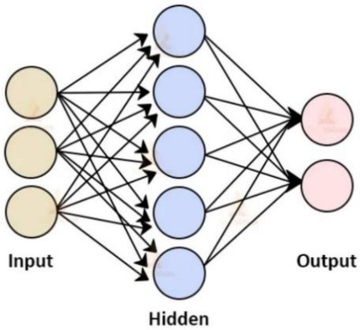

Figure III-1. Structure of an artificial network [57]

In the figure (III-1) above, each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another. Neurons are organized in layers: the first layer consists of three units, which together make the input layer. Each of the three nodes in the input layer represents an individual feature from each sample within our dataset that will pass through the model. Each of the inputs are connected to every single unit in the next layer called the hidden layer.

At its core, an artificial neuron is a function of the input x = (x1, …, xd) weighted by a vector of connection weights wj = (wj,1,…,wj,d), completed by a neuron bias bj, and associated to an activation function φ, namely

$$y_j = f_j(x) = \varphi(\langle w_j, x\rangle + b_j). \tag{1}$$

III .3 .1 .a Activation functions

The most critical part in an artificial neural network, which is a mathematical function applied to the output of a neuron. It introduces non-linearity into the model, allowing the network to learn and represent complex patterns in the data. Activation function decides whether a neuron should be activated by calculating the weighted sum of inputs and adding a bias term. This helps the model make complex decisions and predictions by introducing non-linearities to the output of each neuron [37].

The choice of an activation function is influenced by the specific task, the architecture of the network and the nature of data. While non-linear functions like ReLU are commonly used in hidden layers to mitigate vanishing gradient issues, output layers often use functions like Softmax or Sigmoid depending on whether the task is multiclass or binary classification. Figure (III-2) below shows different activation functions and their graphs.

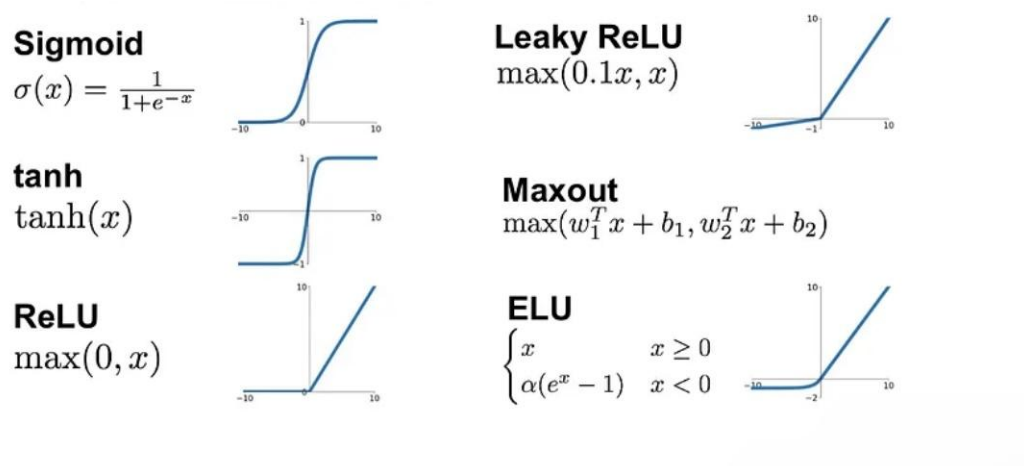

Figure III-2. Activation functions [38]

Historically, the sigmoid was the mostly used activation function since it is differentiable and allows to keep values in the interval [0, 1], but due to its gradient being very close to 0 when |x| is not close to 0, it causes troubles for the backpropagation algorithm to estimate the weights and biases, it was quickly surpassed by the rectified linear unit (ReLU) function [35].

- **Rectified Linear Unit (ReLU)**

Rectified Linear Unit (ReLU) function is defined by A(x)=max(0,x), this means that if the input x is positive, ReLU returns x, if the input is negative, it returns 0.

Although it gives an impression of a linear function, ReLU has a derivative function and also allows for back-propagation while simultaneously making it computationally efficient. The main issue here is that ReLU function does not activate all the neurons at the same time. The neurons will be deactivated if the output of the linear transformation is less than 0 [38]. Since only a certain number of neurons are activated, the ReLU function is far more computationally efficient when compared the sigmoid and tahn functions. It is limited by the "dying ReLU problem" but several variations of the ReLU function are considered to make sure that all units have a non-vanishing gradient and that for x < 0 the derivative is not equal to 0.

III . 3 .2 Recurrent Neural Network (RNN)

Recurrent neural networks (RNN) are type of neural networks designed for processing sequential data, like speech, text, and time series, where order of elements is important [42]. Instead of treating each input as separate, they maintain a hidden state that passes information from one step to the next, where at each time step, the RNN takes the current data and the previous hidden state (I.e., memory from earlier steps), then combines the two to produce a new output (an updated hidden state) which will be used on the next stop, as shown in figure (III-3).

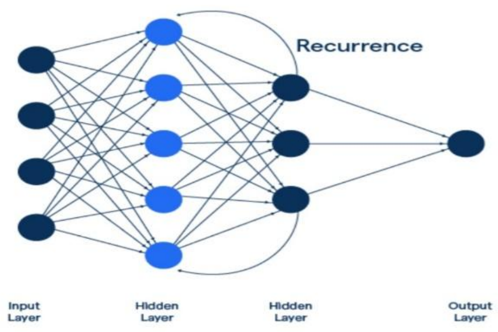

Figure III-3 . Architecture of Recurrent Neural Network. [58]

Another key feature of RNNs is that they use the same set of weights at every time step. Unlike feedforward networks, where each layer has its own unique weights, RNNs share the same parameters as they process each element in a sequence. Though the weights are shared, they are still updated during training using back-propagation through time and gradient descent allowing the network to learn over time.

III . 3 .3 Convolutional neural network (CNN)

A convolutional neural network (CNN) is a specialized type of deep learning algorithm specifically designed for tasks that need object recognition, such as image classification, detection and segmentation [40]. Though CNNs resemble the human brain in many ways, such as the non-linearity of the neuron activation keys and the hierarchical structure, with simple features extracted in early layers while more complex features are built up in deeper layers, they also have obvious differences. One being that CNNs usually rely on supervised learning unlike the human brain, which most of its learning (especially early in development) is unsupervised/ self-supervised.

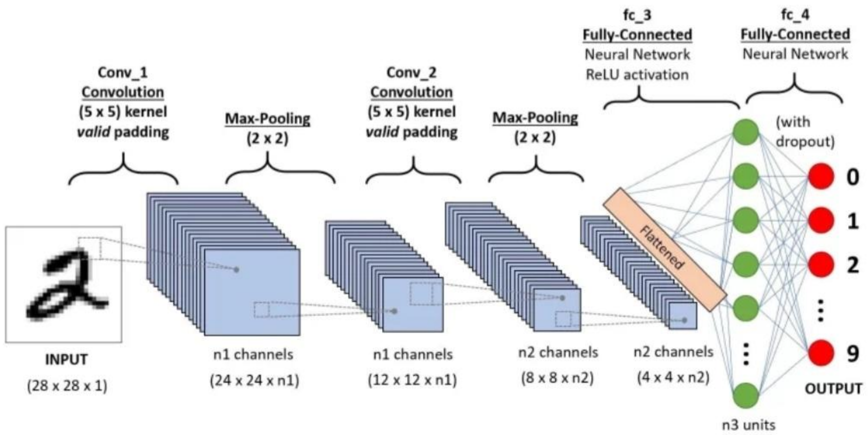

Figure III-4 . Architecture of Convolutional Neural Network. [40]

As illustrated in figure (III-4), the architecture of CNN is decomposed in:

III .3 .3 .a Convolutional layer

This is the fundamental building block of the CNN. As the name implies, its main mathematical task is convolution, a process where a sliding window, known as a filter/kernel moves across a matrix of pixel values representing an image. As the filter moves, it generates a new grid (feature map) which highlights the areas where the pattern was found [40].

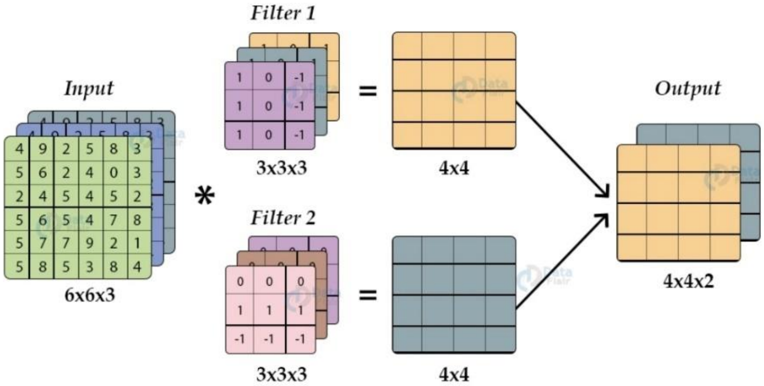

Figure III-5. The convolutional layer [41]

III .3 .3 .b Activation function

Usually using the ReLU function, it is introduced after each convolution to allow the network to learn non-linear mappings and helps in speeding up training and introducing complexity.

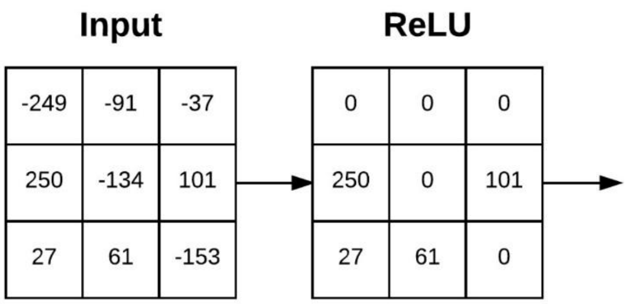

Figure III-6. Input volume going through ReLU [41]

III .3 .3 .c Pooling layer

Its main purpose is to reduce the spatial size (height and width) of the feature maps. This step is necessary as it decreases computation and also, helps avoid overfitting by reducing feature map size. After this step, in practice the first three steps are repeated since deeper layers learn complex structures and this gives CNNs a hierarchical understanding of the image [41]. Pooling has three types; max (selects maximum element), average (computes the average of the elements) and global pooling (reduces each channel in the feature map to one value).

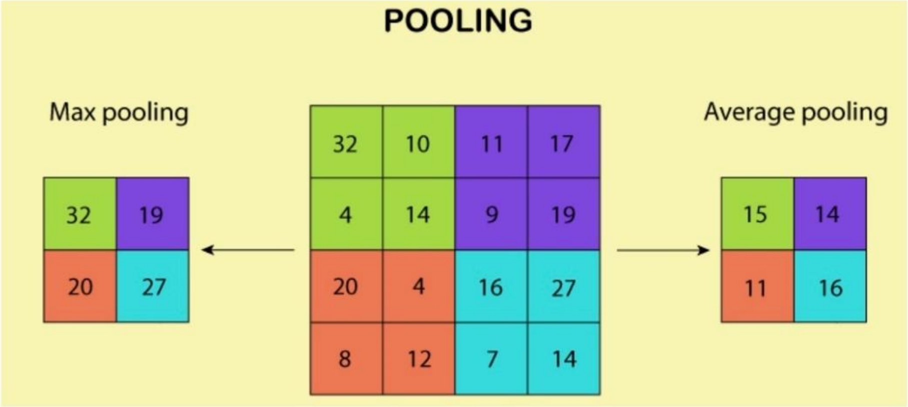

Figure III-7. Max and Average Pooling [41]

III .3 .3 .d Flattening

This stage prepares the data for the fully connected layers by reshaping 3D (height, width, channels) arrays that are feature maps into a single 1D vector, as demonstrated in figure (III-8).

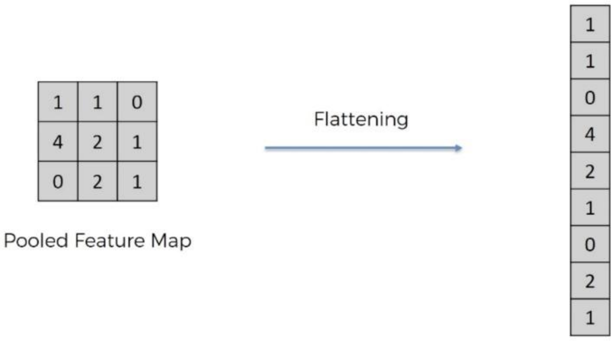

Figure III-8. Flattening on a pooled feature map [41]

III .3 .3 .e Fully connected layer (Dense layers)

Its role is to perform high-level reasoning based on the features extracted and interpret them to make predictions. The way it works is that typically there are one or more fully connected layers where each neuron is connected to all outputs of the previous layer and the weights are learned to associate feature patterns with specific classes or patterns.

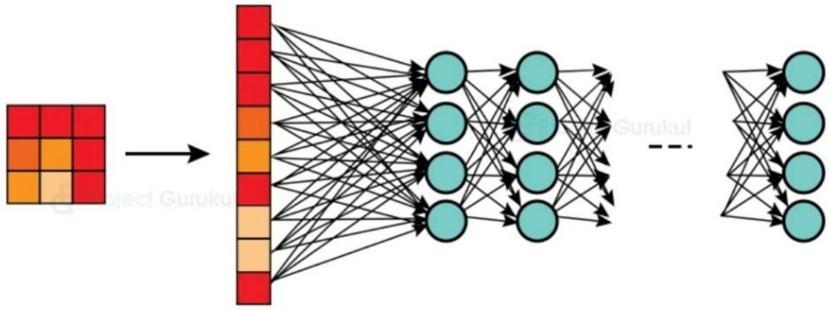

Figure III-9. Fully connected layers [41]

III .3 .3 .f Output layer

As the name suggests, this is where we get our final prediction, which, depending on the task could be classification label, probability scores or regression output.

- **Classification:** Assigning the input to one or more categories, binary or Multi-class classification
- **Regression:** The CNN predicts continuous numerical values instead of classes, like estimating age from a photo, for example. The output in this case can either be a single value or multiple values.
- **Segmentation:** Instead of predicting one label for the whole image, the CNN predicts a label for each pixel and this can be used to highlight tumor regions in medical imaging.

III .4 . EEG Signal Processing

In the first chapter, we explained that the electroencephalography (EEG) records electrical activity from the brain through electrodes placed on the scalp but raw EEG signals are typically noisy and need pre-processing before being used for seizure detection.

The process of detecting epileptic seizures in EEG signals using deep learning involves several steps; including signal processing, feature extraction, and the application of deep learning model for seizure recognition.

III . 4 .1 Pre-processing

EEG signals are inherently **noisy** due to various artifacts like eye blinks, muscle movements, and electrical interference, so we apply band-pass filters to retain only the frequencies that are most relevant to the task, typically between 0.5 Hz and 50 Hz since EEG signals typically range between 1Hz to 30 Hz. This range covers most of the relevant brain activity.

The sliding window technique is a method used in machine learning and signal processing to break down a continuous stream of data into smaller, manageable segments for processing or analysis. The continuous EEG signals are divided into small segments (windows). Each segment might span several seconds (e.g., 1-5 seconds), then these segments can be analyzed individually, and the sliding window technique is commonly used. Each segment is treated as an independent sample for the deep learning model.

Data augmentation: This refers to a technique used to increase the diversity and size of a dataset by creating modified versions of existing data without actually collecting new data. This is to improve the performance of machine learning models, prevent overfitting and to make the model robust to variations (like noise, distortions or shifts). It is commonly by applying transformations such as, rotation, scaling, cropping, noise addition or synthetic data generation.

Normalization: To avoid biases introduced by varying signal scales, normalizing the data standardizes the values of the signal. This brings all EEG data into a similar range, which makes the model more robust.

III . 4 .2 Feature Extraction

Feature extraction is a pivotal step in the automated detection of epilepsy from EEG signals, ensuring that the most relevant characteristics of the signal are emphasized while reducing noise and irrelevant data. A feature can be defined as a unique characteristic that allows to understand the neural activity and assess the state of the brain.

Once common traditional method for feature extraction involves the use of Time-domain features, such as mean, standard deviation, entropy, kurtosis, etc. Below are some traditional features:

Mean (μ) - The average of the signal over a segment, which can provide insight because if the signal is stable, the mean will stay close to zero but if there is abnormal brain activity, the signal will go up and down and the mean will consequently change.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_{\mathrm{i}} \qquad (2)$$

where x_{i} is the EEG signal and N is the number of samples.

Standard deviation (σ) - Measures how much the signal fluctuates from its mean, and this is helpful, knowing that seizure events often show increased variability in EEG. Higher SD means greater signal fluctuation.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{\mathrm{i}} - \mu)^2} \tag{3}$$

Variance - It is the square of variance and it represents power signal in time domain. It detects high-energy events like epileptic spikes or discharges.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_{\mathrm{i}} - \mu)^2 \tag{4}$$

Skewness - It measures the asymmetry of the signal distribution and indicates if the signal events are biased in one direction, which helps because during a seizure, there might be sharp spikes.

$$skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_{\mathrm{i}} - \mu}{\sigma}\right)^3 \tag{5}$$

Kurtosis - It represents the “peaked-ness” of the signal (sharpness of peaks). High kurtosis means the presence of outliers or sharp spikes.

$$kurtosis = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_{\mathrm{i}} - \mu}{\sigma}\right)^{4} \tag{6}$$

Entropy - Measures unpredictability or complexity of the signal and from it we can deduce how random or chaotic the signal is. High entropy suggests that the signal is erratic and unpredictable (e.g., seizure or noisy signals).

$$H = -\sum_{i=1}^{n} p_{\mathrm{i}}\, log_2(p_{\mathrm{i}}) \tag{7}$$

Sometimes temporal analysis may fail to capture key features in EEG signals, especially when recordings have low temporal or spatial resolution and only oscillatory activity is present. In such cases, spectral methods like fast Fourier transform (FFT), wavelet transforms, particularly noted for their ability to handle transient and non-stationary signals like those found in EEG data. FFT can be formulated as;

$$X[k] = \sum_{n=0}^{N} x[n].\, e^{-j2\pi kn/N}\ , k = 0,1..N-1 \tag{8}$$

Where X(k) = frequency domain points, x(n) = time domain samples, n = index of time samples, k = index of frequency points, N = number of input samples in the record

Power Spectral Density (PSD) represents how the power of the signal is distributed over different frequency bands and this is achieved by applying a Fourier Transform to convert EEG from the time domain to the frequency domain. Specific frequency bands (e.g., delta, alpha, beta, theta) are often linked to particular brain states. Seizure activity might show an increase in power at certain frequencies [52]. Mathematically, it can be represented as:

$$PSD\ (f) = \frac{1}{N}\,|F(x)|^{2} \tag{9}$$

Where N is the number of samples in the EEG signal x(t) and F(x) is the Fourier Transform.

III . 4 .3 Model Training and Validation

Model training and validation in the context of detecting epileptic seizure using EEG biomarkers and deep learning algorithms play a crucial role in ensuring the robustness and reliability of the proposed systems. A common challenge in the development of these models is the inherent variability in EEG data, which can be influenced by a multitude of factors including patient demographics, seizure types and environmental conditions. Therefore, a rigorous training and validation approach is imperative to achieve high classification accuracy and generalizability.

III . 4 .4 Performance evaluation metrics for deep learning models

Evaluation metrics are the tools we use to measure how well the model performs. They play a key role in figuring out how accurate the model is, the kind of errors it makes and finally, to evaluate if it is good enough to be used in practice. With the help of evaluation metrics, we can also see if our model is reliable when data changes.

Confusion matrix - It is an important table that summarizes the performance of a classification model by comparing the model's predicted labels against the true labels, table (IV-1).

Table III-1. Confusion matrix

	Predicted: Seizure	Predicted: Non-seizure
Actual: Seizure	True Positive (TP)	False Negative (FN)
Actual: Non-seizure	False Positive (FP)	True Negative (TN)

- True Positive (TP) - In this case, the model correctly identifies a seizure segment as such.
- False Positive (FP) - The model incorrectly labels a non-seizure segment as seizure. In other words, this can be taken as a false alarm.
- False Negative (FN) - This means that a seizure may be missed and be labelled as a non-seizure event.
- True Negative (TN) - The non-seizure segment is correctly labelled as such.

Accuracy: It is a fundamental metric for evaluating the performance in classification problems and it measures the proportion of correct predictions in the total prediction made. It is defined as equation (10):

$$\text{Accuracy} = \frac{\textit{Number of correct predictions}}{\textit{Total number of predictions}} \qquad (10)$$

Mathematically it can also be written as: Accuracy = (TP+TN)/ (TP+TN+FP+FN).

Precision: It is a measure of a model's performance that explains how many of the positive predictions made by the model are actually true. It is given by equation (11):

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (11)$$

Recall/ Sensitivity: It is the ratio of correctly predicted positive instances to the total actual positive instances. It measures how well the model captures all relevant positive cases and it is represented by equation (12):

$$Sensitivity = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \qquad (12)$$

F1 Score: F1-Score is a harmonic mean between recall and precision with the range of [0,1]. This metric usually tells us how precise (correctly classifies how many instances) and robust (does not miss any significant number of instances) our classifier is. It can be expressed mathematically in this way equation (13):

$$F1 = 2 \times \frac{1}{Precision + recall} \qquad (13)$$

Area under curve (AUC) and Receiver operating characteristic curve: The ROC curve is a graphical representation of classification model performance at different thresholds. It is created by plotting the true positive ratio (TPR) against the false positive ratio (FPR). Whereas AUC represents the area under the ROC curve. It therefore provides a single scalar value that summarizes the overall performance of a classifier across all possible threshold values. The formula for TPR and FPR represented in equation (14) and (15) respectively:

$$\text{TPR} = \text{Recall} = \frac{TP}{TP+FN} \qquad (14)$$

$$\text{FPR} = \frac{FP}{FP+TN} \qquad (15)$$

Specificity: It is the ability of a model to correctly identify true negatives (e.g., correctly ruling out seizures when they are absent), meaning that high specificity indicates few false positives (false alarms). Its equation (16) is shown below.

$$Specificity = \frac{True\ Negatives\ (TN}{True\ Negatives\ (TN) + False\ Positives\ (FP)} \qquad (16)$$

III .5 . Challenges in Seizure Detection

While deep learning methods have revolutionized many aspects of healthcare, their implementation in seizure detection is not without obstacles. The need for large, annotated datasets to train deep learning models poses a barrier, seizures can be infrequent, and dataset imbalances might result in overfitting or under-fitting of models. For instance, factors such as noise in EEG recordings from different devices, variations in electrode placement, and patient specific characteristics can affect the reliability of deep learning algorithms. Addressing these challenges will be crucial for the transition from research to clinical practice, where the integration of EEG signals with deep learning model can lead to timely and effective interventions for individuals affected by epilepsy, which is the aim of our project.

III .6 . Conclusion

This chapter has provided an overview of the key concepts behind machine learning and deep learning, focusing on their relevance to EEG signal analysis and epileptic seizure detection. We examined the structure and functioning of neural networks, particularly convolutional neural networks (CNNs), which are well-suited for capturing spatial and temporal patterns in EEG data. By exploiting their ability to learn meaningful features directly from raw input, deep learning models eliminate the need for manual feature extraction and often outperform traditional approaches in complex classification tasks. The principles discussed here lay the groundwork for the practical implementation of a deep learning-based system aimed at detecting epileptic seizures, which will be presented in the following chapter.

CHAPTER IV. IMPLIMENTATION AND RESULTS

Chapter IV . IMPLEMENTATION AND RESULTS

IV .1 . Introduction

So far, we have only discussed the theoretical foundations of our project but in this chapter, we will outline the steps and methods, while also implementing them to finally develop a deep learning-based system for detecting epileptic using EEG signals. Furthermore, this chapter will go into more details about how raw EEG data was processed, modelled and evaluated in relation to seizure detection.

IV .2 . Tools and environments

The development and implementation our project required a robust computational environment capable of supporting data-intensive signal processing, machine learning and visualization tasks. Therefore, a set of tools and programming environments was used to ensure compatibility and efficiency throughout the entire workflow, from data pre-processing to model training and evaluation. These tools were run on an 12th Gen Intel (R) Core (TM) i7-1255U with 8Go RAM.

IV . 2 .1 Google Colab

Google Colaboratory (Colab) is a hosted Jupyter Notebook service that requires no setup to use and provides free access to computing resources, including GPUs and TPUs. Colab is especially well suited to machine learning, data science, and education [43].

Figure IV-1. Google Colab **[43]**

IV . 2 .2 Anaconda Distribution

The implementation of this project was conducted within “Anaconda distribution”, an open-source platform widely adopted for scientific computing and machine learning applications in “Python”. Anaconda provides an integrated environment for managing packages, dependencies, and virtual environments [51], which helped maintain consistency and prevent version conflicts during development.

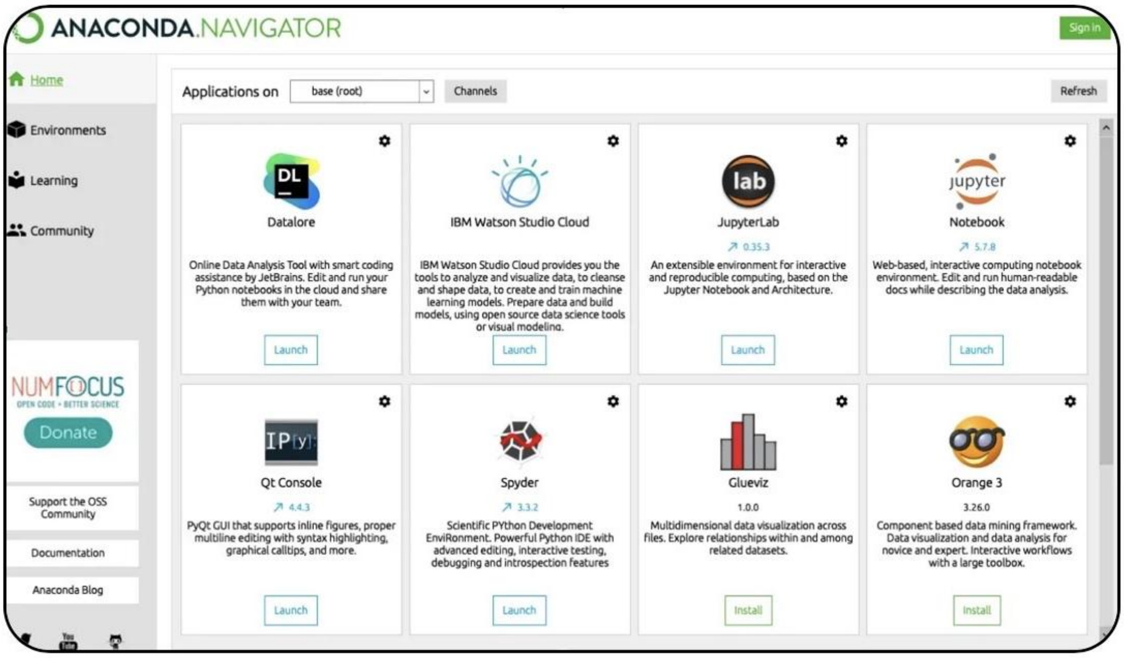

Figure IV-2. Principal Anaconda Navigator (GUI) [51]

The project was developed using Python 3.10, selected for its compatibility with key libraries used in EEG processing and deep learning. Additionally, Jupyter Notebook, which comes bundled with Anaconda, was used as the primary interface for interactive coding, data visualization and debugging. This environment facilitated the implementation of various stages of the methodology.

IV . 2 .3 Visual Studio Code

Commonly known as VS code, is an integrated development environment by Microsoft for Windows, Linux, macOS and web browsers with features that include but not limited to support for debugging, code refactoring, and intelligent code completion. With its multiple features, it is designed for writing and editing code is very easy to navigate [50].

Figure IV-3. Visual Studio Code logo [50]

IV . 2 .4 Key libraries

Several Python libraries were used throughout the stages of this project to support different EEG signal processing and classification. These libraries offered useful tools for tasks like filtering, visualization, and model development. But above all, they were chosen for their compatibility with EEG data formats. Figure (IV-4) shows a list of libraries used in this project.

```python
# Importation of modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.fft import fft
from scipy.stats import kurtosis, entropy
from sklearn.model_selection import train_test_split
from sklearn.metrics import (classification_report, roc_auc_score, roc_curve, auc, confusion_matrix,
                             ConfusionMatrixDisplay)
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import (Input, Dense, Conv1D, MaxPooling1D, Flatten,
                                     Concatenate, Dropout, BatchNormalization,
                                     MultiHeadAttention, LayerNormalization,
                                     GlobalAveragePooling1D)
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.regularizers import l2
import optuna


from scipy.fft import fft
from scipy.stats import kurtosis
```

Figure IV-4. Libraries used

Numpy, short for Numerical Python, is a fundamental library for numerical and scientific computing in Python. It provides support for large for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on those arrays. It is essential for tasks involving data analysis, machine learning, and scientific computing [43].

TensorFlow is an open-source platform for machine learning using data flow graphs. Nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) that flow between them. This flexible architecture allows machine learning algorithms to be described as a graph of connected operations and it was developed for the purposes of conducting machine learning and deep neural networks (DNNs) research [43].

Pandas is a software written for the Python Programming language for data analysis and manipulation. In particular, it offers data structures and operations for manipulating numerical tables and time series [43].

Matplotlib, portmanteau of MATLAB, plot, and library, is a comprehensive library for creating static, animated, and interactive visualizations in Python [43].

Scipy is a free open-source library that is designed for quickly performing scientific and numerical computing in Python. It provides broadly applicable algorithms for optimization, integration, interpolation, statistics, and others [43].

IV . 2 .5 MNE

Short for Magnetoencephalography (MEG) and Electroencephalography (EEG) in Python, MNE-Python is an open-source Python package for exploring, visualizing, and analysing human neurophysiological data such as MEG, EEG, sEEG, ECoG, and more. It includes modules for data input/output, preprocessing, visualization, time-frequency analysis, machine learning, and much more [49].

Figure IV-5. MNE-Python logo [49]

IV . 2 .6 Streamlit

Streamlit is also an open-source Python library that makes it easy to create and share custom web apps for machine learning and data science. It makes it easier to quickly add and deploy powerful data applications [43]. This is what we chose work with when building our interactive interface because of its many advantages like, simplicity, only Python is needed to build so we don't need to convert, and the fact that it works in real-time.

IV .3 . Proposed method

The aim of our study is to develop a fully automatic method for epilepsy detection using the integration of biomarkers on EEG signals, with deep learning classification models.

The methodology involves several stages such as, data collection, signal preprocessing, feature extraction, model design and training and also evaluation using performance metrics. As discussed in the previous chapter, a convolutional neural network (CNN) was chosen due to its effectiveness in learning spatial and temporal patterns in EEG data. Each stage of the pipeline was carefully designed to ensure that the system could learn relevant features from the data while minimizing overfitting and ensuring generalizability. The flow chart of our method is shown in figure (IV-6).

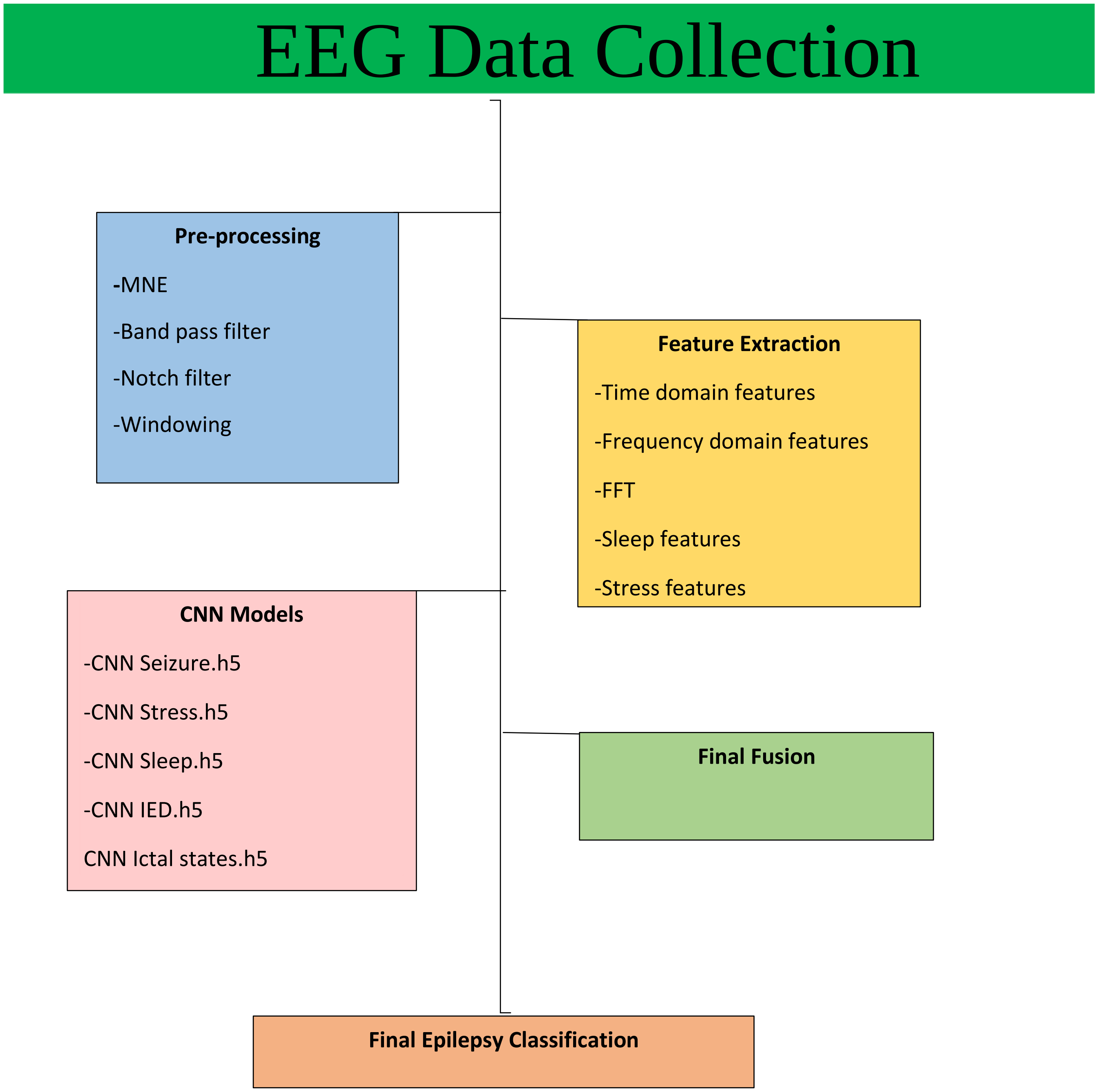

Figure IV-6. System architecture flowchart

IV .4 . EEG Data Collection

IV . 4 .1 Epileptic Seizure Recognition

This dataset was used for seizure classification, obtained from Kaggle [44] and contains electroencephalogram (EEG) recordings intended for the classification of seizure and non-seizure states. It originally consists of 5 different folders, each with 100 files, with each file representing a single subject/patient. Each file is a recording of brain activity for 23.6 seconds and the corresponding time-series is sampled into 4097 data points. Each data point is the value of the EEG recording at a different point in time.

IV . 4 .2 EEG features dataset for stress classification

Since the previous dataset was specifically curated for epilepsy detection, we collected more data from Kaggle [45] to efficiently train our model and, this dataset consists of EEG (Electroencephalogram) signals collected from participants under different stress conditions. It contains 6,000 samples (instances) representing EEG recordings, with each sample corresponding to a short time window (e.g., 1–5 sec) of EEG data. It is also composed of 1,602 columns, where 1,601 features are EEG-derived metrics and 1 target column (Stress level).

IV . 4 .3 Sleep-EDF Database Expanded

When it comes to sleep quality, we first have to explain a few terms related to the diagnosis of sleep disorders.

- **Polysomnography** (PSG) - Sleep study that includes simultaneous recordings of multiple bio-signals to access sleep quality and diagnose sleep disorders, figure (IV-7).

- **Hypnogram**- A visual representation of a person’s sleep stages over the course of a sleep period, which is typically divided into two main types: Rapid eye movement (REM) and Non-REM sleep, which is further divided into three stages (N1, N2, N3) ranging from light, intermediate, and deep sleep, respectively. Basically, a hypnogram is made from sleep annotations mentioned above, figure (IV-8).

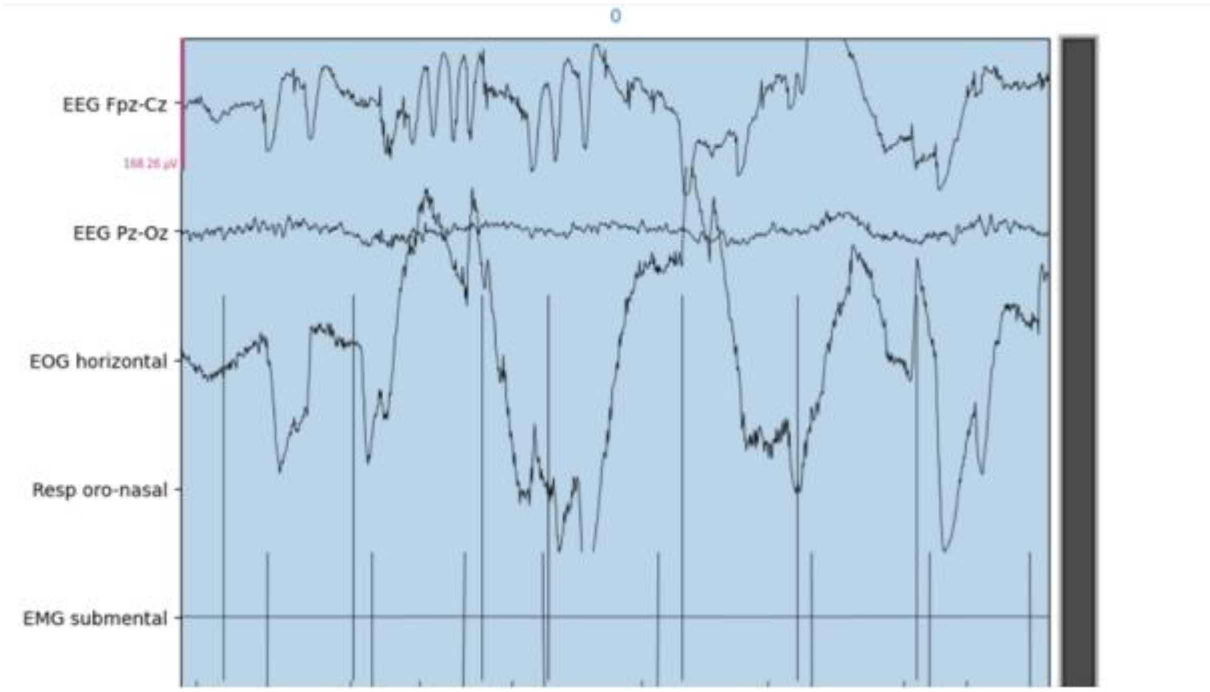

Figure IV-7. The polysomnography of EEG

Our data was collected from [Sleep-EDF Database Expanded v1.0.0] as PSG, figure (IV-7) data (EEG signals) and sleep stage annotations (hypnogram, figure (IV-8)) which we loaded, merged and continued to label (as in, map each sleep stage annotation to a numerical number) in order to prepare for further analysis.

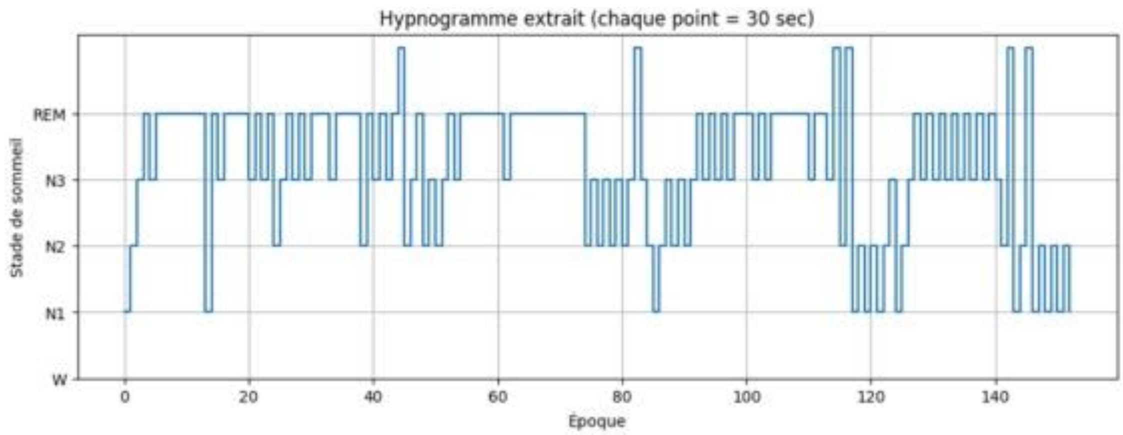

Figure IV-8. The hypnogram coresponding

IV . 4 .4 CHB-MIT

Interictal Epileptiform Discharges (IEDs) are described as abnormal spikes or waveforms on EEG recordings between seizures and are considered as biomarkers of epilepsy and reflect brief, abnormal bursts of electrical activity in the brain. If we are going to diagnose epilepsy, it is therefore essential that we have a model to detect these biomarkers too.

The CHB-MIT Scalp EEG [46] database provides annotated EEG recordings from pediatric epilepsy patients, making it a valuable resource for interictal epileptiform discharge (IED) detection and ictal phase classification [47]. For IED classification, non-epileptic intervals are exploited to extract brief, spike-like waveforms characteristic of interictal discharges. These segments are then labelled and used to form a binary classifier distinguishing IED from non-IED activity, figure (IV-9).

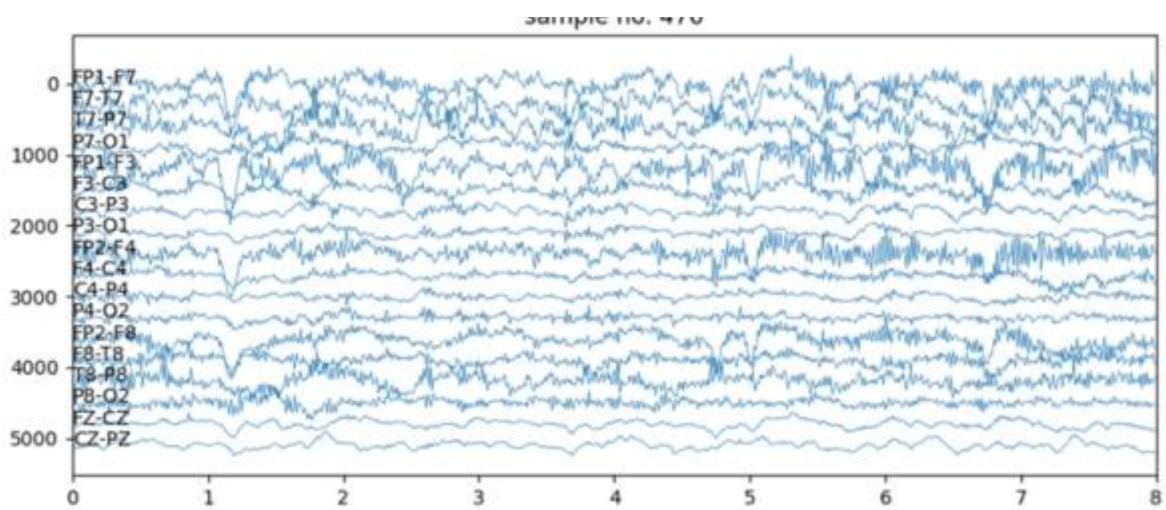

Figure IV-9. Labelled segments

For the classification of the ictal phase, precise annotations of the onset and termination of the seizure enable the EEG to be segmented into pre-ictal, ictal and post-ictal periods. This enables a model to be trained to differentiate ictal activity from baseline brain states. In this way, CHB-MIT facilitates a dual objective: identifying transient epileptiform events (TEEs) and learning the dynamic temporal profile of seizures (ictal phases), both of which are essential for comprehensive epilepsy monitoring and early seizure detection [48].

IV .5 . EEG preprocessing

The first act of pre-processing we come across here is by converting our files to MNE format to be able to read and handle EEG data. Then we continued to filter our signal with both band-pass and notch filters. Band-pass filter, demonstrated in figure (IV-10) was set between 0.5- 40 Hz because with EEG signals, frequencies below 0.5Hz may be drift or movement and above 40Hz are often muscle noise or external interference.

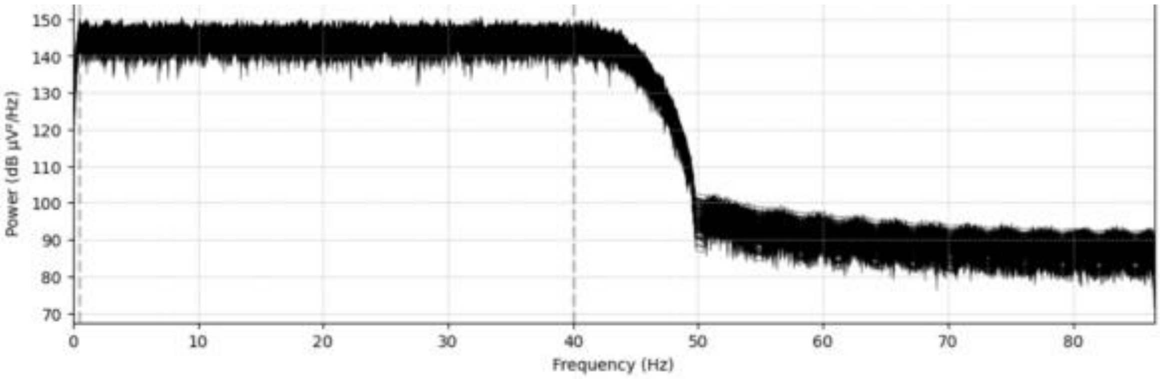

Figure IV-10. Band pass filter of 0.5-40 Hz

By eliminating irrelevant frequencies outside of the target range, band-pass filters reduce noise and artifacts, therefore increasing the quality of the EEG signal. Notch filters are also used to eliminate power line interference (50Hz and its harmonics) that can contaminate the signal, but they are generally used alongside band-pass filters, fig (IV-11).

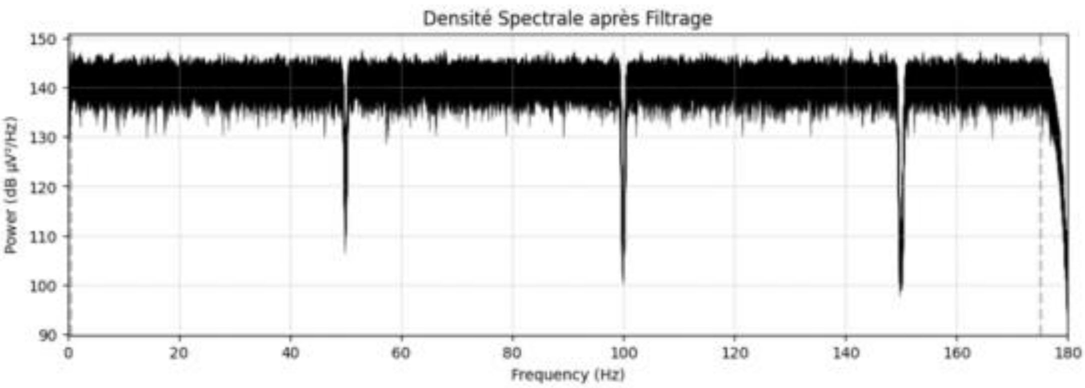

Figure IV-11. Notch filter (50 Hz)

IV .6 . Feature Extraction

For each of the five parameter - seizures, interictal epileptiform discharges (IEDs), stress, sleep stages and ictal phases - feature extraction plays a crucial role in improving the discriminative power of classifiers. EEG signals are first segmented into epochs of fixed length (30 seconds). For each segment, time-domain and frequency-domain features are extracted.

In the time domain, five key features were computed for each EEG segment: (1) the mean amplitude, identifying baseline shifts characteristic of ictal states; (2) standard deviation, quantifying signal variability that increases during seizures; (3) kurtosis, detecting peaked distributions associated with epileptic spikes; (4) Shannon entropy, measuring signal complexity that typically decreases during ictal events; and (5) zero-crossing rate, indicating frequency changes in seizure activity.

For frequency analysis, a Hamming-windowed FFT was applied to compute band power features across five clinically-relevant frequency bands: delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz), and gamma (30-50Hz) as illustrated in figure (IV-12). These bands were selected as they capture the spectral signatures of epileptiform discharges - particularly the gamma band, which contains high-frequency oscillations that are biomarkers for epileptogenic tissue. Together, these features help the CNN identify the signs of seizure, from sudden spikes to ongoing abnormal rhythms.

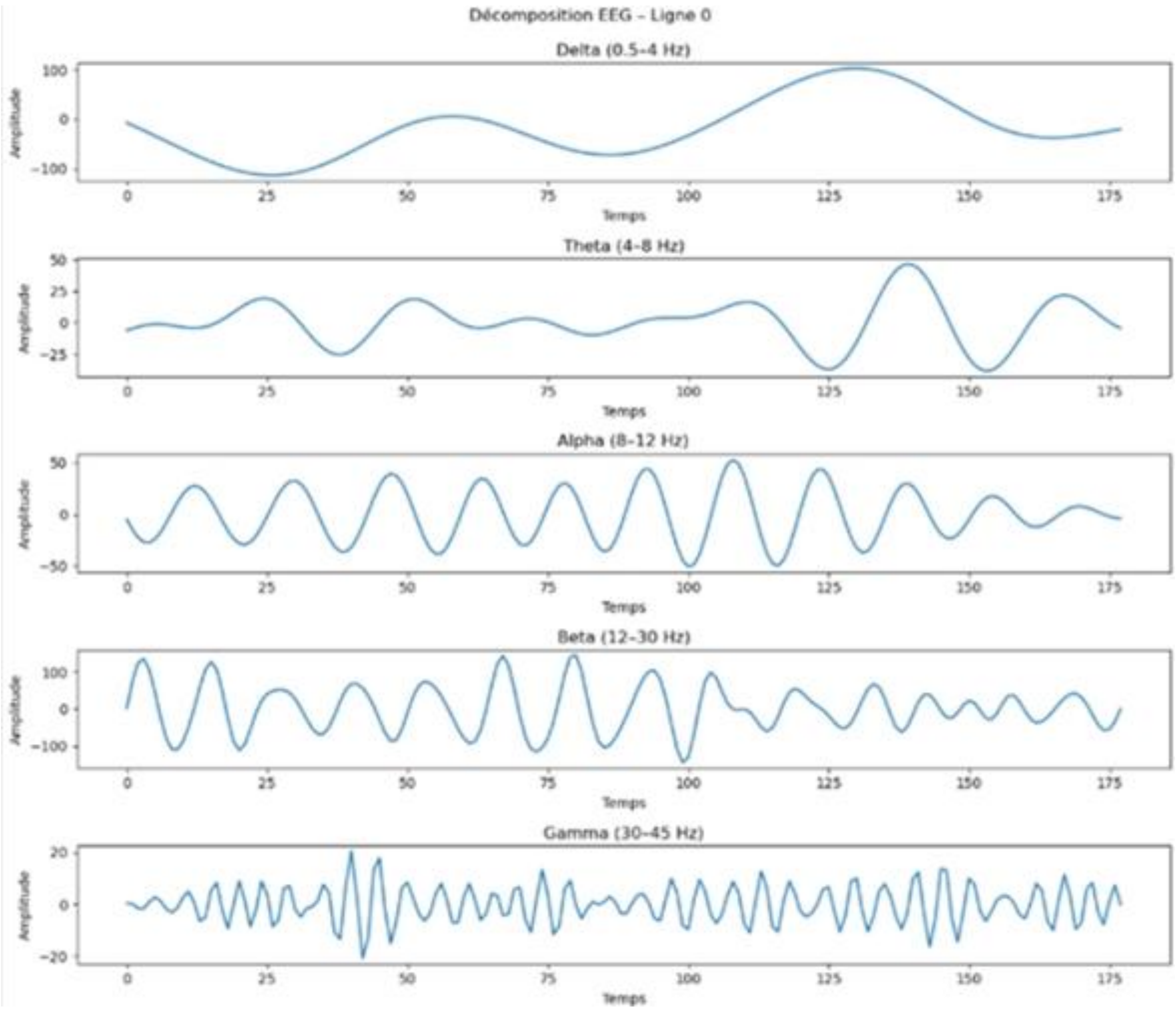

Figure IV-12. Decomposition of an EEG signal in 5 important waves. [53]

For the stress classifier, relative band power ratios are essential to distinguish between different stress stages, figure (IV-13).

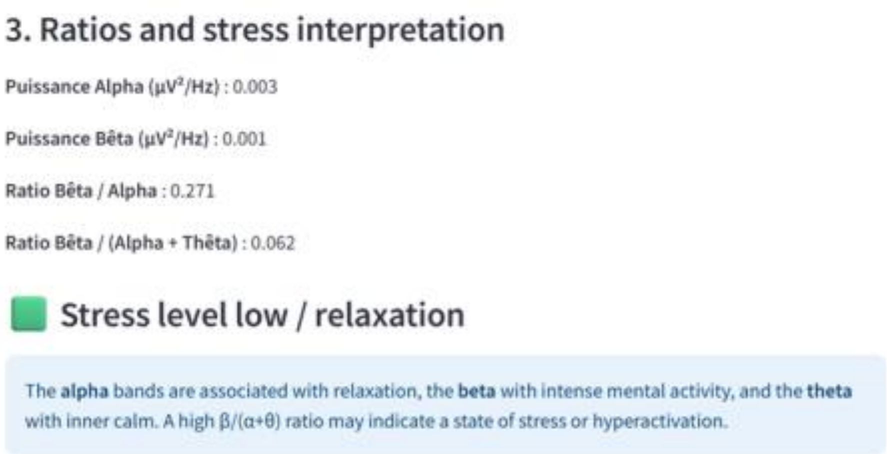

Figure IV-13. Example of Ratios calculated for stress evaluation

In the sleep evaluation model, additional features such as Total sleep time (TST) quantifies the total time spent sleeping during the monitoring period. Sleep efficiency (SE) is the ratio of total sleep time to total time spent in bed, indicating the individual's sleep efficiency. Sleep onset latency (SOL) measures the time taken to go from wakefulness to sleep, reflecting the quality of sleep initiation. Time awake after sleep onset (WASO) quantifies the total duration of awakenings after sleep onset, giving an idea of sleep continuity. The classifier also includes the proportion of time spent in different sleep stages: N1, N2 and N3 (representing progressively deeper stages of non-REM sleep) and REM (Rapid Eye Movement sleep), each associated with different restorative and cognitive functions, figure (IV-14).

Figure IV-14. Sleep evaluation

We designed a complete EEG signal processing pipeline for the detection of five biomarkers: stress, sleep stages, seizures, ictal phase and IEDs. Each biomarker was processed individually via a dedicated CNN model, trained and validated independently from specific databases, before being integrated into a weighted fusion model designed to improve epilepsy detection. However, to avoid complications, the architecture of the CNN model was the same for all biomarkers, the only difference was in the features extracted and pre-processing, fig (IV-15).

IV .7 . CNN Model

CNN models are trained to classify each segment as positive (presence of biomarker) or negative. Once trained and tested, the models are saved in .h5 format, so that they can be called up in the platform. Each CNN model returns a probability in the interval [0, 1] for each segment. The outputs of these models are then transmitted to the fusion layer. The figure (IV-15), shows an example of CNN architecture.

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv1d_10 (Conv1D)	(None, 2558, 32)	2,240
max_pooling1d_10 (MaxPooling1D)	(None, 1279, 32)	0
conv1d_11 (Conv1D)	(None, 1277, 64)	6,208
max_pooling1d_11 (MaxPooling1D)	(None, 638, 64)	0
flatten_5 (Flatten)	(None, 40832)	0
dense_10 (Dense)	(None, 64)	2,613,312
dropout_4 (Dropout)	(None, 64)	0
dense_11 (Dense)	(None, 1)	65

Total params: 2,621,825 (10.00 MB)
Trainable params: 2,621,825 (10.00 MB)
Non-trainable params: 0 (0.00 B)

Figure IV-15. CNN Model Architecture

Conv1D layers: Two consecutive 1D convolutional layers are used to extract local temporal features from EEG signal segments. The first layer produces 32 feature maps and the second 64.

MaxPooling1D layers: Each convolutional layer is followed by a maximum pooling layer to reduce temporal dimensionality and focus on the most important features.

Flattening layer: The resulting feature maps are flattened into a one-dimensional vector.

Dense layers: A fully connected dense layer with 64 neurons is followed by a final output layer with a single neuron and a sigmoid activation function to produce a binary (yes/no) classification.

Dropout layer: The dropout layer is applied after the dense layer to avoid overfitting.

IV .8 . Pipeline Development

The development the pipeline for each biomarker is detailed below.

IV . 8 .1 Stress Detection

The dataset for this CNN model was collected from [EEG features dataset for stress classification], which we preprocessed by; normalization, filtering and augmentation. Afterwards, we extracted spectral and temporal features such as alpha, beta and gamma band power, as well as statistics (mean, variance, RMS), figure (IV-16).

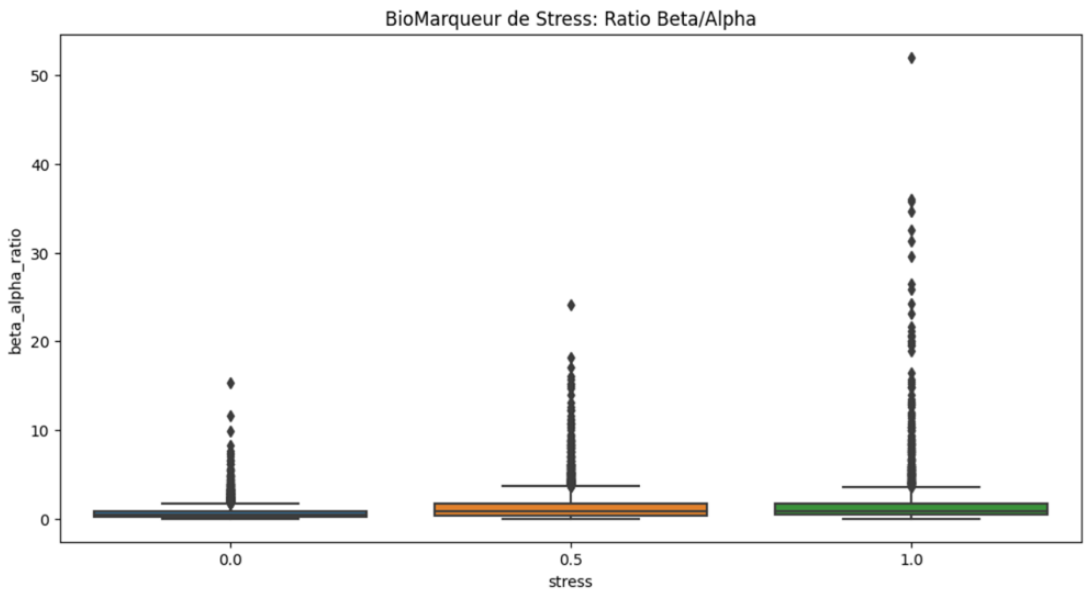

Figure IV-16. Stress biomarker, beta-alpha ratio

These descriptors were fed into a binary CNN model to classify each EEG segment as “stressed” or “not stressed” and the model was then trained with regularization, learning rate adjustment and an early stopping mechanism to give the following results.

```
38/38 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step
              precision    recall  f1-score   support

           0       0.80      0.77      0.79       600
           1       0.78      0.81      0.79       600

    accuracy                           0.79      1200
   macro avg       0.79      0.79      0.79      1200
weighted avg       0.79      0.79      0.79      1200
```

Figure IV-17. Stress classification report

Figure IV-18. Loss and accuracy graphs for stress detection

The classification report in figure (IV-17) shows balanced performance, with precision, recall, and F1-scores of approximately 0.79 for both classes. The model achieved an overall accuracy of 79% on a test set of 1,200 samples, suggesting a reliable ability to differentiate between stressed and non-stressed conditions. The training and validation curves, figure (IV-18) show steady improvement in both accuracy and loss, with no major signs of overfitting, indicating that the model generalizes reasonably well to unseen data. However, despite these encouraging outcomes, the model has some limitations. Its moderate accuracy may not be sufficient for critical real-time applications such as mental health monitoring or workplace stress detection. With more time, we plan to try more architectures and adjust some parameters, like number of layers or/ and batch size.

IV . 8 .2 Sleep classification

Dataset used in this model was collected from [Sleep-EDF Database Expanded v1.0.0].

Sleep quality detection is based on polysomnographic signals manually annotated by experts according to N1, N2, N3, REM and Wake stages. EEG signals extracted from *-PSG.edf files were segmented and aligned with their *-hypnogram.edf hypnograms. Identical pre-processing was applied, followed by extraction of power spectral density features in the different EEG bands. Segments were labeled as “good sleep quality” or “bad sleep quality” (binary classification). The CNN sleep model was trained to discriminate between these two classes. The probabilities derived from this model were stored in sleep_prob.

	precision	recall	f1-score	support
0	0.96	0.94	0.95	2400
1	0.94	0.97	0.95	2400
accuracy			0.95	4800
macro avg	0.95	0.95	0.95	4800
weighted avg	0.95	0.95	0.95	4800

Figure IV-19 Sleep classification evaluation report

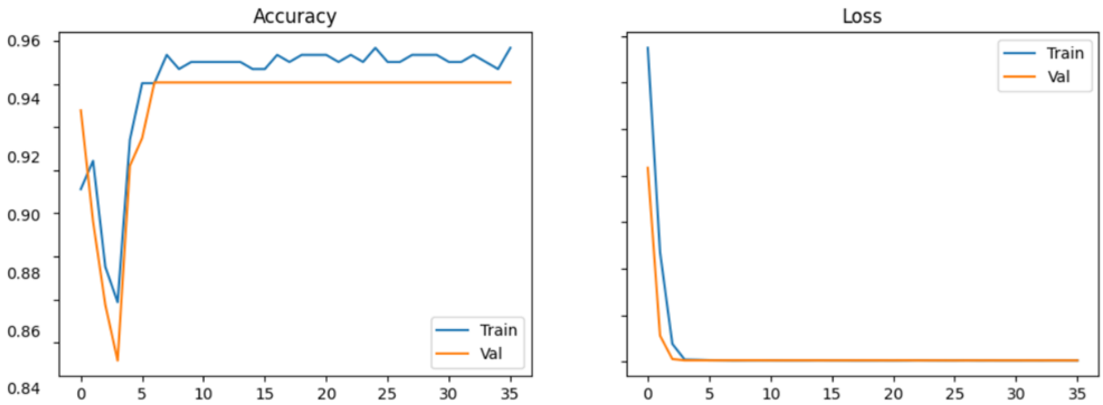

Figure IV-20. Accuracy and Loss graphs for sleep classification

The classification report in figure (IV-19) shows that the model performs very well on both classes (0 and 1), with precision, recall, and F1-scores all hovering around 0.95, also suggesting that the model is not only accurate but also well-balanced. Since the dataset is perfectly balanced with 2,400 samples per class, the high overall accuracy of 95% is a solid indicator of its reliability. The training curves back this up: training accuracy climbs to about 96%, and validation accuracy levels off around 94%, with no signs of overfitting. This model performs very well overall.

IV . 8 .3 SEIZURE

For epileptic seizure detection, we used the tabular dataset [46] seizure_recognition.csv available on Kaggle, which contains features extracted from EEG signals. Each row of the file represents an EEG segment of a few seconds, already pre-processed and transformed into statistical features such as mean, standard deviation, min/max, power in certain frequency bands, or transformed coefficients (FFT). The dataset includes a Seizure target column, which indicates whether the EEG segment originates from epileptic activity (1) or not (0).

The model achieves high accuracy (98%) and AUC (0.9945), showing strong overall performance. However, it struggles with seizure cases, where recall (91%) is lower than for non-seizure cases (99%). This gap is due to class imbalance—there are far more non-seizure samples (1,840) than seizure samples (460), as presented in figure (IV-21).

```
Epoch 49/50
144/144 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.9713 - auc: 0.9902 - loss: 0.0853 - val_acc
uracy: 0.9665 - val_auc: 0.9906 - val_loss: 0.0921
Epoch 50/50
144/144 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.9704 - auc: 0.9861 - loss: 0.0933 - val_acc
uracy: 0.9761 - val_auc: 0.9943 - val_loss: 0.0699
72/72 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1840
           1       0.97      0.91      0.94       460

    accuracy                           0.98      2300
   macro avg       0.97      0.95      0.96      2300
weighted avg       0.98      0.98      0.98      2300

AUC: 0.9945
```

Figure IV-21.Seizure detection evaluation report

The confusion matrix confirms this issue, with 15 false negatives (missed seizures). While precision for seizures is high (97%), meaning most seizures predictions are correct, the model still misses some true seizures, figure (IV-22). To improve this, techniques like class weighting or oversampling should be used to reduce false negatives without sacrificing precision. The model is effective but needs refinement for better crisis detection.

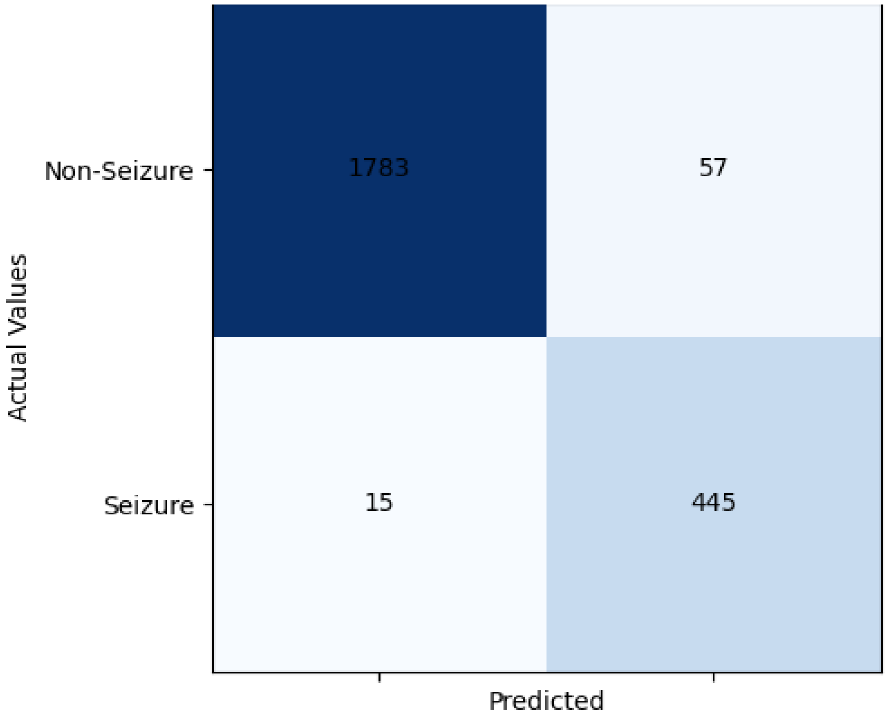

Figure IV-22 Seizure detection confusion matrix

IV . 8 .4 Detection of Interictal Epileptiform Discharges (IEDs)

For automatic IED detection, we exploited EEG signals from the public CHB-MIT database [Temple University EEG Corpus], renowned for its recordings of epilepsy patients under real-life clinical conditions. Files in EDF format were loaded using the MNE-Python library, which provides a standardized interface for processing multi-channel EEG signals. Band-pass filtering between 1 Hz and 40 Hz was applied by means of a linear-phase FIR filter designed by the firwin method, using a Hamming window. The aim was to remove very low-frequency components (drift artifacts) as well as high-frequency noise, while preserving the physiological band of interest.

After pre-processing the EEG signal to remove noise, we implemented adaptive peak detection to identify potential IEDs (Interictal Epileptiform Discharges)—abnormal spikes indicative of epilepsy. Using Python’s *scipy.signal find_peaks*, we first set a detection threshold at **3 times the standard deviation (σ)** of the signal within 10-second windows as shown in figure (IV-23), a common statistical approach to flag significant deviations. However, this strict threshold missed many spikes, prompting adjustments to a lower threshold (**1.5×σ**) or a fixed microvolt value. These refinements improved detection of true IEDs, characterized by their short duration, high amplitude, and distinct polarity, fig (IV-24).

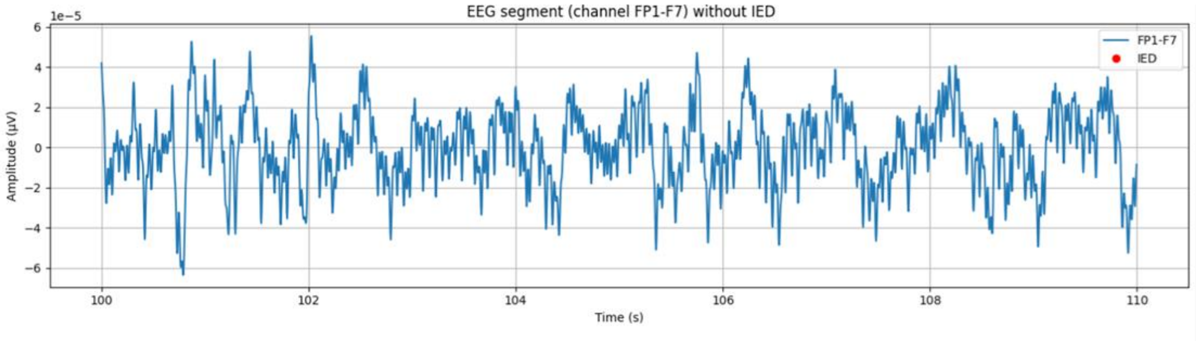

Figure IV-23. IED detection with 3×σ

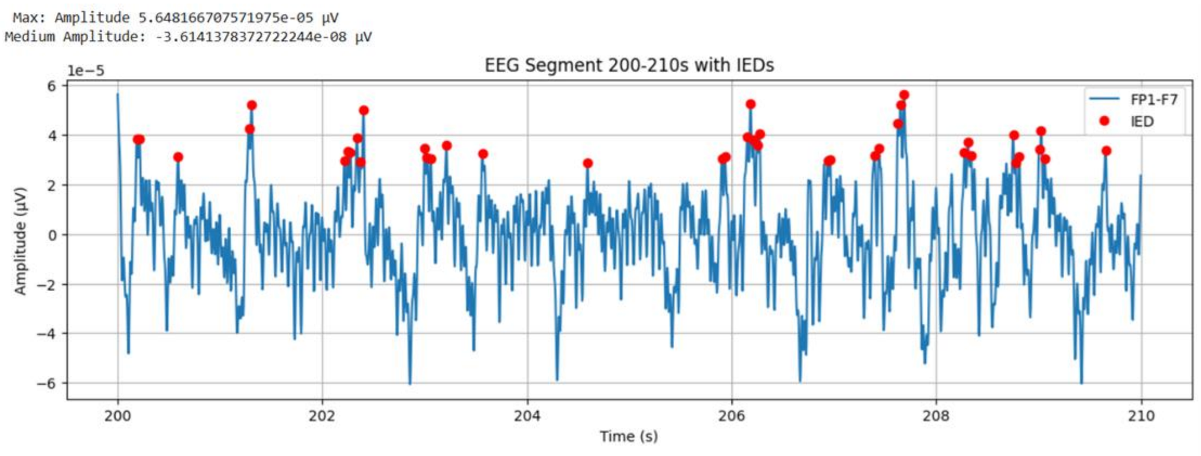

Figure IV-24. IED detection with 1.5×σ

Figure (IV-25) below shows the accuracy plot of the model's performance over 8 training epochs, with both training and validation accuracy increasing steadily from around 86% to 96%. The close alignment between training and validation curves indicates good generalization without significant overfitting.

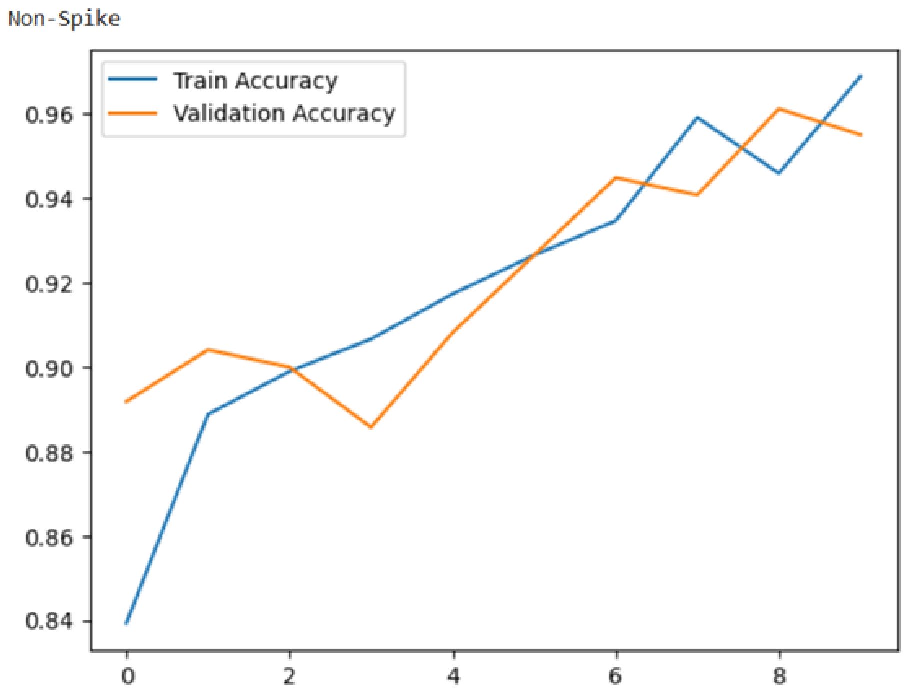

Figure IV-25. IED Accuracy plot

IV . 8 .5 Ictal States Detection

The detection of ictal phases was carried out using EEG data from the CHB-MIT database, the same one used for IEDs since they mostly possess the same features. EEG recordings are provided in EDF format, and some files include manual annotations of seizure onset and termination times, in seconds. The first step was to load the signals via the MNE-Python library, enabling efficient manipulation of multi-channel data.

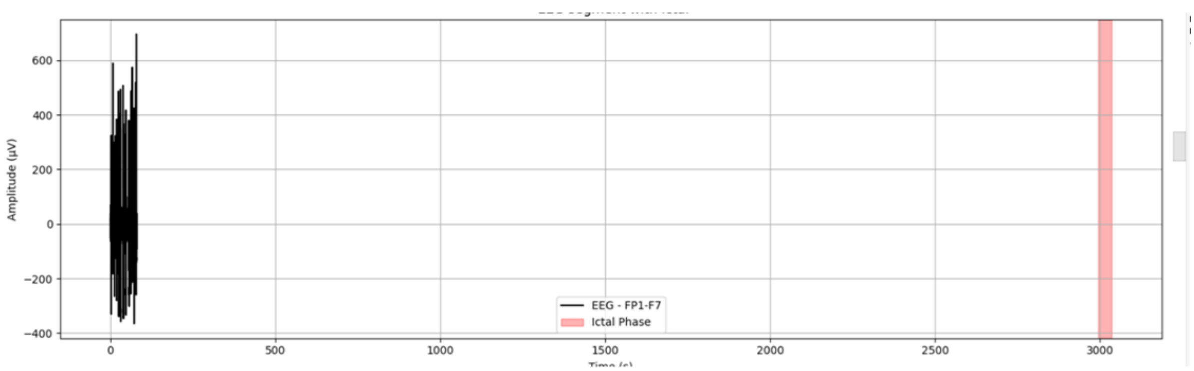

Figure IV-26. Pre-ictal segment

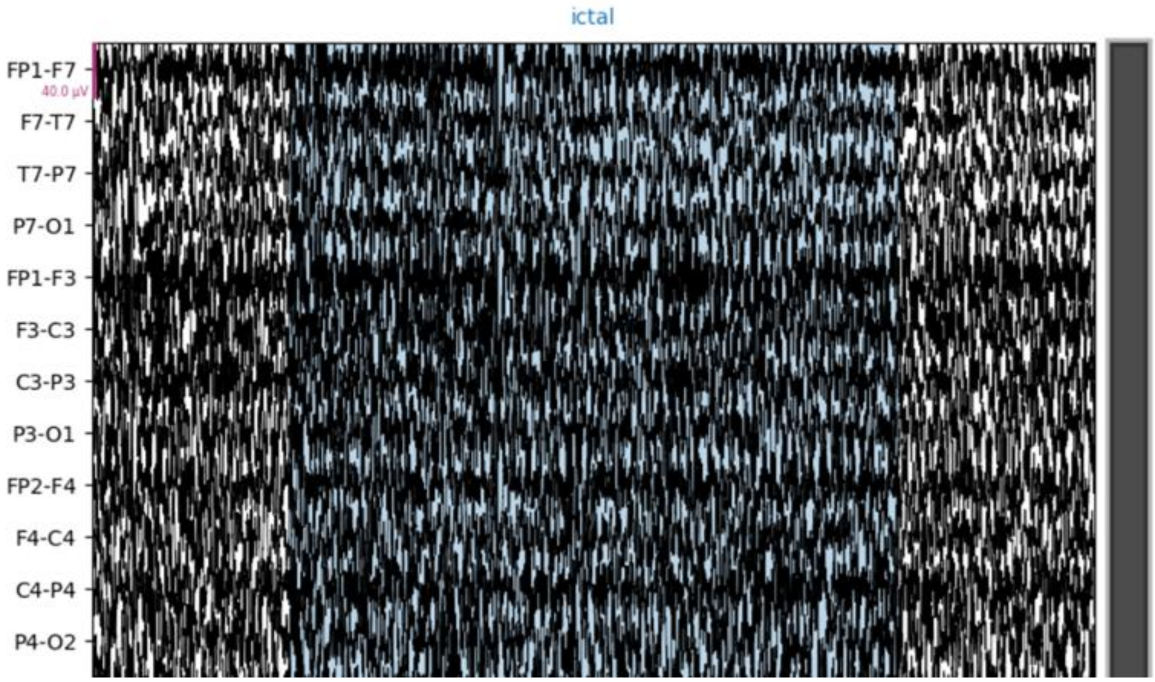

Figure IV-27. EEG segment during ictal state

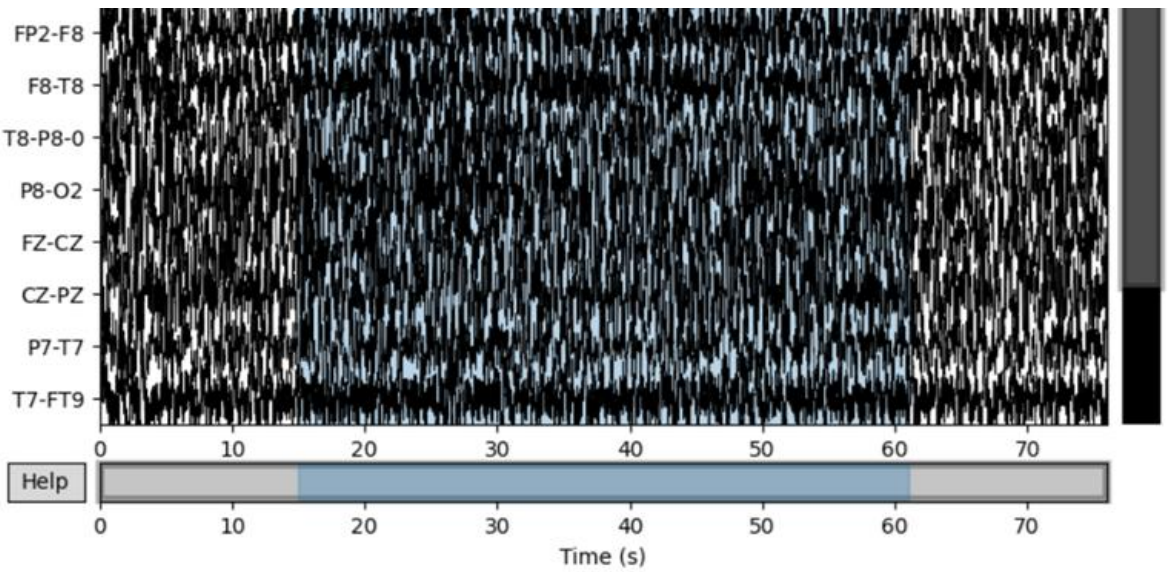

Figure IV-28. EEG segment during ictal phase

Spectral pre-processing was applied by bandpass filtering from 1 to 40 Hz with a non-causal, linear-phase FIR filter, using a Hamming window to ensure sufficient attenuation in the transition bands. This filtering aims to remove low-frequency (<1 Hz) and high-frequency (>40 Hz) noise, while retaining EEG components relevant to seizure detection. In addition to the pre-processing steps, and for the detection of Ictal phases using, we proceeded to the Automatic Segmentation step, slicing the entire EEG signal into fixed 10-second segments (with no overlap), and labelling each segment according to its position:

Label 1 if the segment is in an ictal phase (e.g. between 1467 s and 1490 s).

Label 0 otherwise.

For classification, a CNN (Convolutional Neural Network) model was trained on the EEG segments. The model inputs are the multichannel segments in the form of normalized tensors (standardization per segment), and the output is a probability of seizure presence. An early stopping function and adaptive learning were used to avoid overlearning and optimize convergence. Figure (IV-26) shows the segment of pre-ictal phase while figures (IV-27 and IV-28) shows the signals during the seizure/ ictal phase.

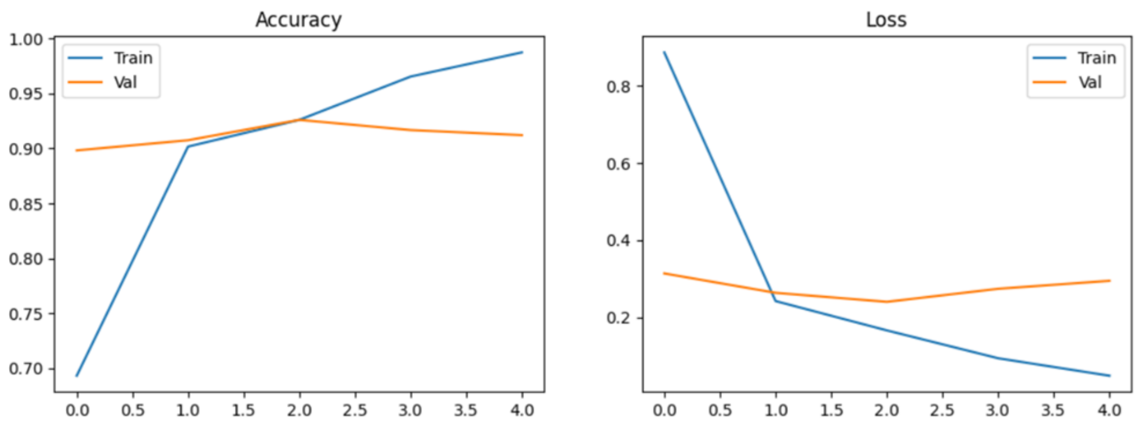

Figure IV-29. Accuracy and Loss graphs for Ictal phases

Figure (IV-29) shows that our model learns well and improves steadily. The accuracy goes up from 75% to 95% in just 4 training epochs, while mistakes (loss) drop quickly from 0.6 to 0.2. The fact that both training and test results improve together means the model works properly without overfitting and gets better bit by bit. It reaches very good performance (95% accuracy) fast, then stops improving much after 4 epochs. This means it learns efficiently.

IV . 8 .6 Final Fusion

For the automatic detection of epilepsy from EEG signals, a multi-biomarker approach has been adopted, exploiting five independent classifiers, each dedicated to a specific biomarker: stress, sleep, IEDs (Interictal Epileptiform Discharges), ictal, and seizure. Each classifier is based on a convolutional neural network (CNN) model trained separately on adapted databases, and provides an output probability indicating the presence or absence of the biomarker under consideration on a given EEG segment.

In order to integrate these different sources of information and produce a robust final decision on the occurrence of epilepsy, two decision fusion strategies can be considered:

IV .8 .6 .a CNN Fusion Model

CNN-based fusion involves using a second convolutional neural network (CNN) model as a meta-classifier to combine the outputs of several classifiers specialized in the detection of different EEG biomarkers (e.g. stress, sleep, IEDs, ictal, seizure). This strategy, known as deep learning decision fusion, enables the system to learn the complex interactions between biomarkers, rather than simply aggregating their predictions. To integrate the predictions of all biomarker classifiers, we construct a feature vector for each EEG segment, figure (IV-30).

```
# training
st.write(f"CNN training for {biomarker}...")
model, history, y_true, y_pred_proba = train_cnn_model(X, y, biomarker)
models[biomarker] = model
predictions[biomarker] = y_pred_proba
```

Figure IV-30. CNN results for fusion

According to figure (IV-31) and (IV-32) below, our fusion model shows strong performance in detecting epilepsy, achieving an accuracy of 86.11%, with precision, recall, and F1-scores all around 86% for both epileptic and non-epileptic cases. The confusion matrix shows 5 false positives and 5 false negatives, indicating that the model maintains a good balance without favoring one class over the other. Additionally, the high AUC-ROC score of 0.9305 shows its strong ability to distinguish between the two conditions.

```
Epoch 29/100
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 0.9619 - loss: 0.0954 - val_accuracy: 0.8793 - val_los
Epoch 30/100
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - accuracy: 0.9880 - loss: 0.0785 - val_accuracy: 0.8793 - val_loss: 0.5072 - learning_rate: 5.0000e-04
Epoch 31/100
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - accuracy: 0.9792 - loss: 0.0877 - val_accuracy: 0.8793 - val_loss: 0.4970 - learning_rate: 5.0000e-04
Epoch 32/100
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 0.9937 - loss: 0.0623 - val_accuracy: 0.8621 - val_loss: 0.4779 - learning_rate: 5.0000e-04
Epoch 33/100
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - accuracy: 0.9674 - loss: 0.0814 - val_accuracy: 0.8621 - val_loss: 0.5143 - learning_rate: 5.0000e-04
Epoch 34/100
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 0.9745 - loss: 0.0897 - val_accuracy: 0.8621 - val_loss: 0.4925 - learning_rate: 5.0000e-04
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step

Classification Report:
              precision    recall  f1-score   support

         0.0     0.8649    0.8649    0.8649        37
         1.0     0.8571    0.8571    0.8571        35

    accuracy                         0.8611        72
   macro avg     0.8610    0.8610    0.8610        72
weighted avg     0.8611    0.8611    0.8611        72

AUC-ROC: 0.9305019305019304
```

Figure IV-31. Fusion Model training log and metrics

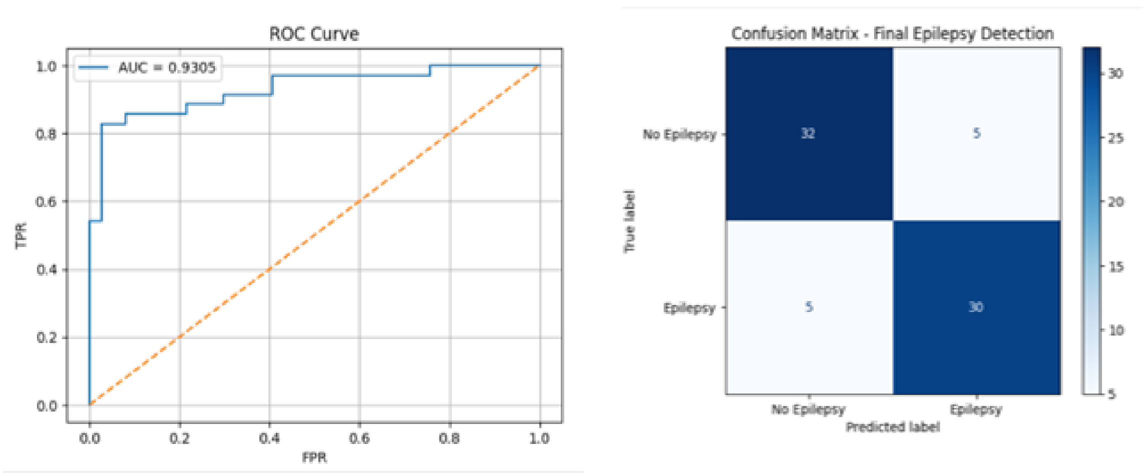

Figure IV-32. ROC Curve and Confusion matrix

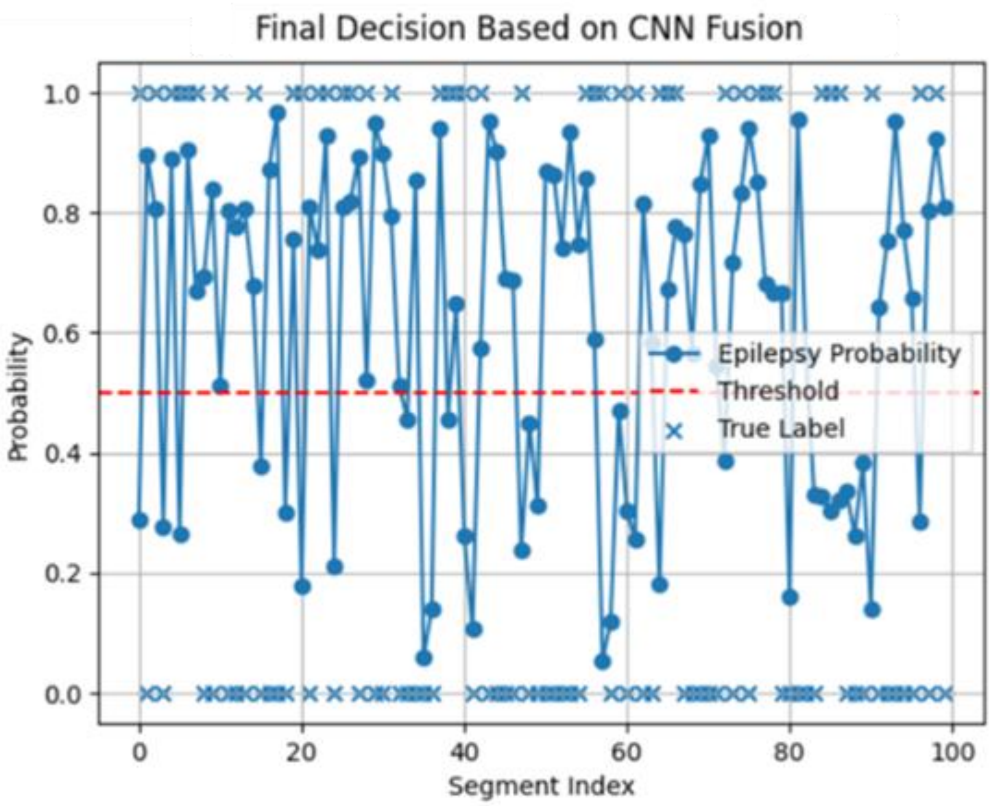

Figure IV-33 Final results based on CNN Fusion Model

While the model shows promising accuracy, there are some limitations, for example, occasional mismatches occur where the model misses seizures (red bars without blue spikes) or raises false alarms (blue spikes without red bars). However, these are outweighed by the many correct detections where probability spikes align perfectly with confirmed seizures. The model's ability to consistently identify clear seizure events while providing interpretable confidence scores makes it valuable as automated tool. With further refinement and additional training on rare seizure types, this could become an even more reliable diagnostic tool.

IV .8 .6 .b Weighted fusion

In this case, each classifier output is multiplied by a weight reflecting its relevance (reliability, accuracy, or medical importance) in the context of epilepsy detection. These weights can be fixed prior. For example, if the biomarker “seizure” or “ictal” correlates highly with critical events, their contribution will be accentuated in the final calculation (>=30%), compared with indirect markers such as stress or sleep (<20%). An example of weights is given in figure(IV-33).

```python
# Default weights based on clinical importance
default_weights = {
    'seizure_prob': 0.35,
    'ied_prob': 0.3,
    'ictal_prob': 0.2,
    'sleep_prob': 0.1,
    'stress_prob': 0.05
}
```

Figure IV-34 Models with their allocated weights

The final score is computed as a weighted sum of the normalized probabilities from each biomarker classifier, where the weights reflect the clinical importance or reliability of each biomarker in the context of epilepsy detection. The equation is defined as:

Final score $= \sum (w\_i \times P\_i)$ (17)

• wi: The pre-defined weight assigned to biomarker ii, such that the sum of all weights equals 1 ($\sum wi=1$). These weights prioritize biomarkers like "seizure" or "ictal" (weights ≥ 0.3) over indirect markers like "stress" or "sleep" (weights <0.2).

• Pi: The normalized probability (0 to 1) output by the classifier for biomarker i.

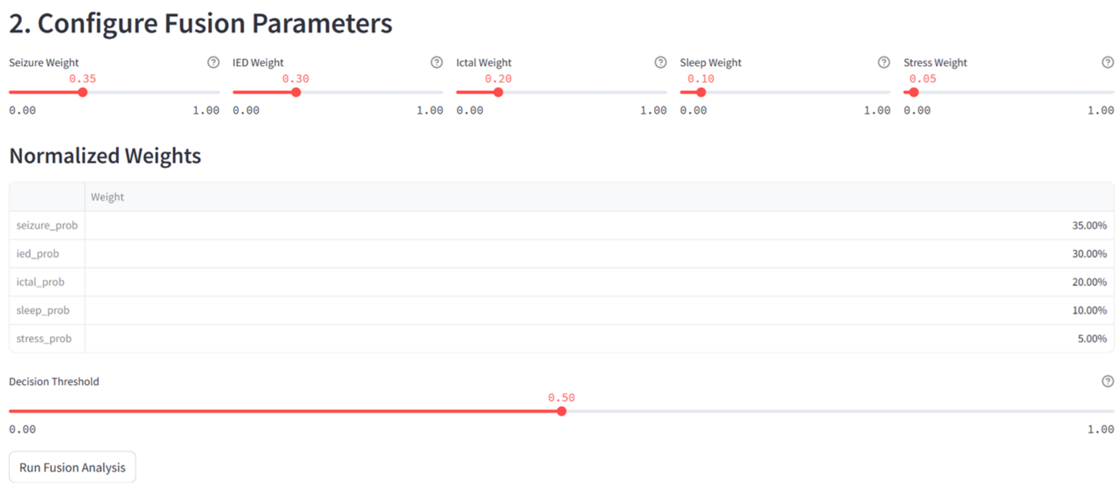

Figure IV-35. The platform allows for the customization of biomarker weighting parameters

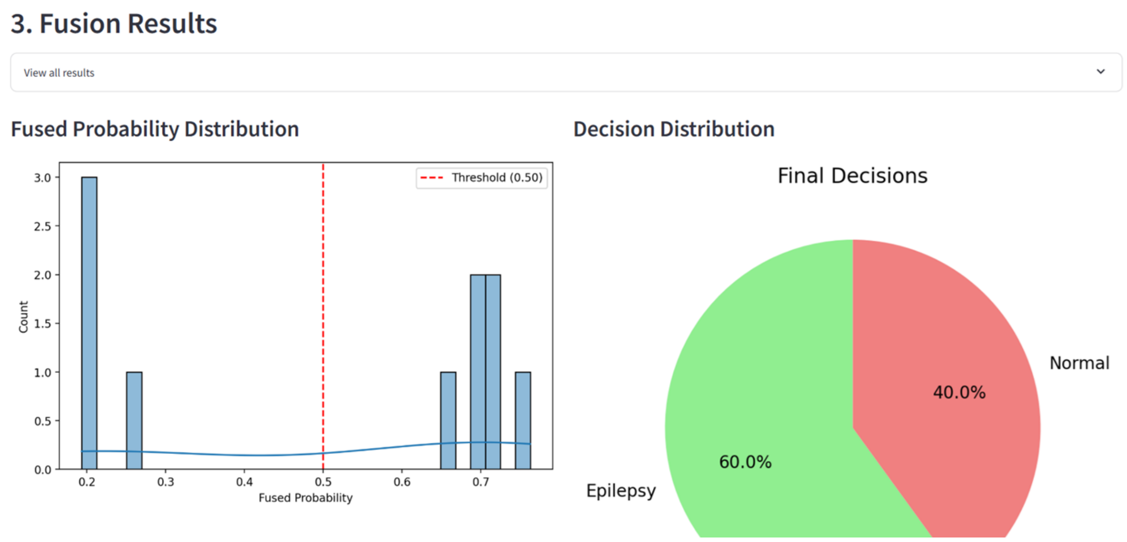

Figure IV-36. Fusion Results

As shown in figure (IV-36), this CNN model demonstrates strong potential for epilepsy detection, with several key strengths visible in the results. The probability-based output (blue line) correctly identifies multiple seizure events, showing the model can recognize true epileptic patterns. The adjustable threshold line allows customization for different clinical needs, depending on each patient's personal circumstances and this plays a huge role in better and precise diagnosis. The clear visual output helps doctors quickly verify detections and spot errors.

IV .9 . Streamlit Interface

At the completion of our project, we needed to connect it to the real world, so we built an interactive user interface that combines all five of epilepsy biomarkers to give conclusive results on whether the patient is epileptic or not, and what their state of mind is. We did this using streamlit, which is easier to use and requires no conversion since we were already in Python.

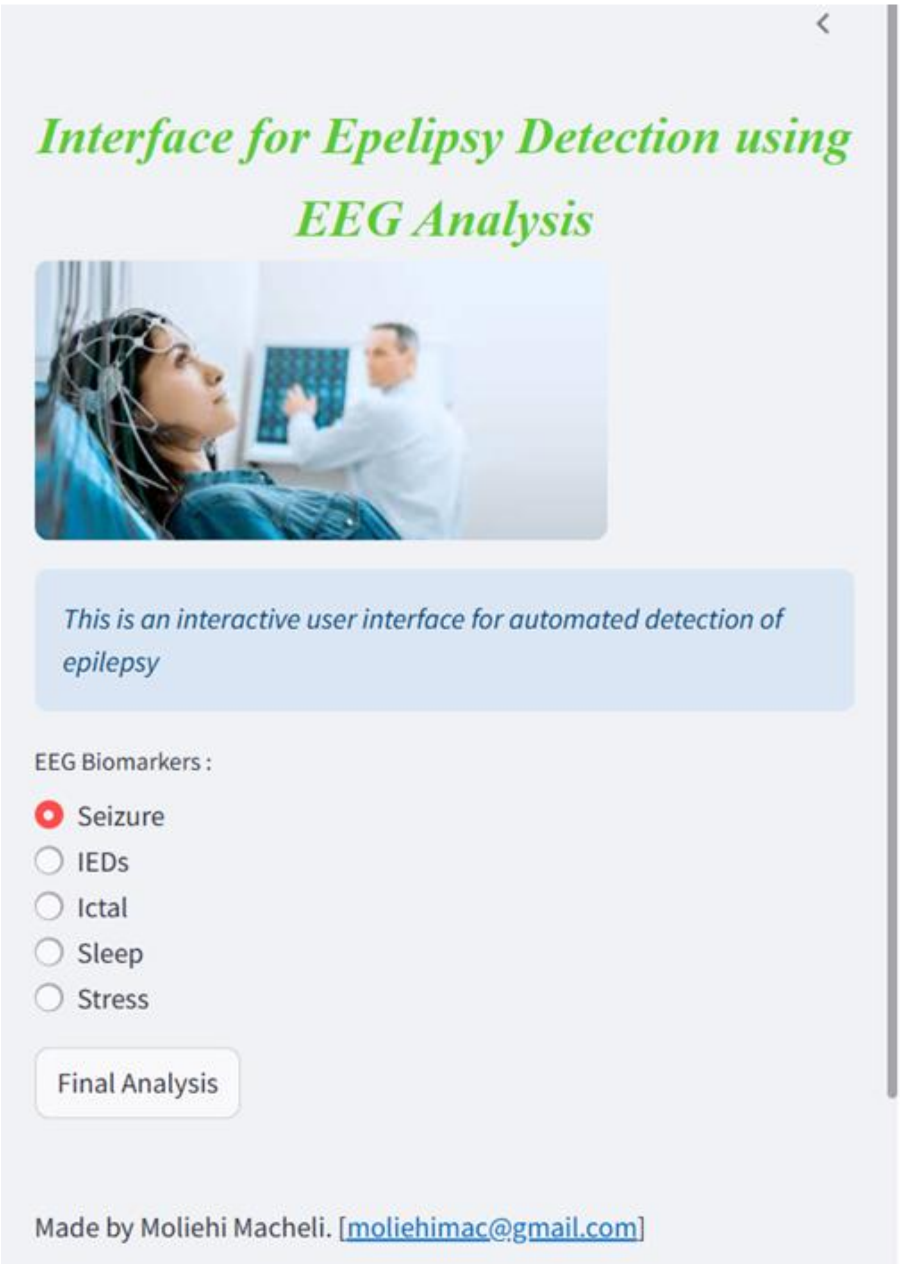

Figure IV-37. Streamlit user interface

Figure (IV-37) shows the sidebar of our user interface, displaying all the five EEG biomarkers that can be detected with our epileptic seizure system. Upon clicking on one biomarker, it allows the user to upload their EEG file, in EDF or CSV format. The "final analysis" button allows the user to get the final results of whether the patient is epileptic or not.

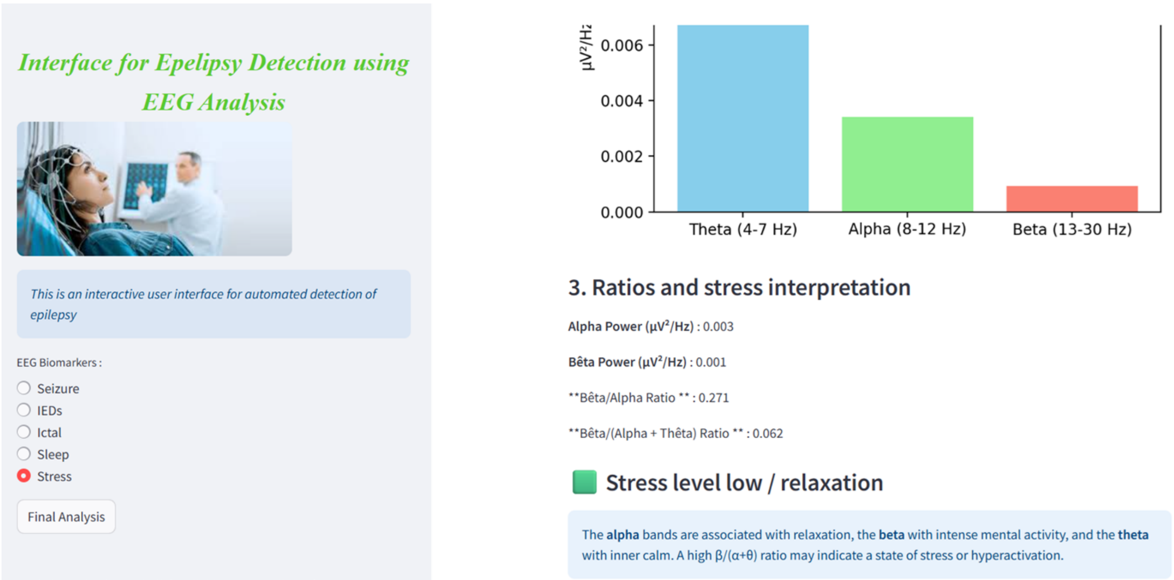

Figure IV-38. Streamlit UI in use

The figures (IV-38) and (IV-39) show our interface in interface, the first one shows stress analysis results of the patient after being run. The analysis (in green) shows that the patient was not stressed but rather in a relaxed state of mind. The comments below the results (in blue) explaining how stress was diagnosed. The second figure below, shows files of all five of the biomarkers selected, ready to be run and processed by our system.

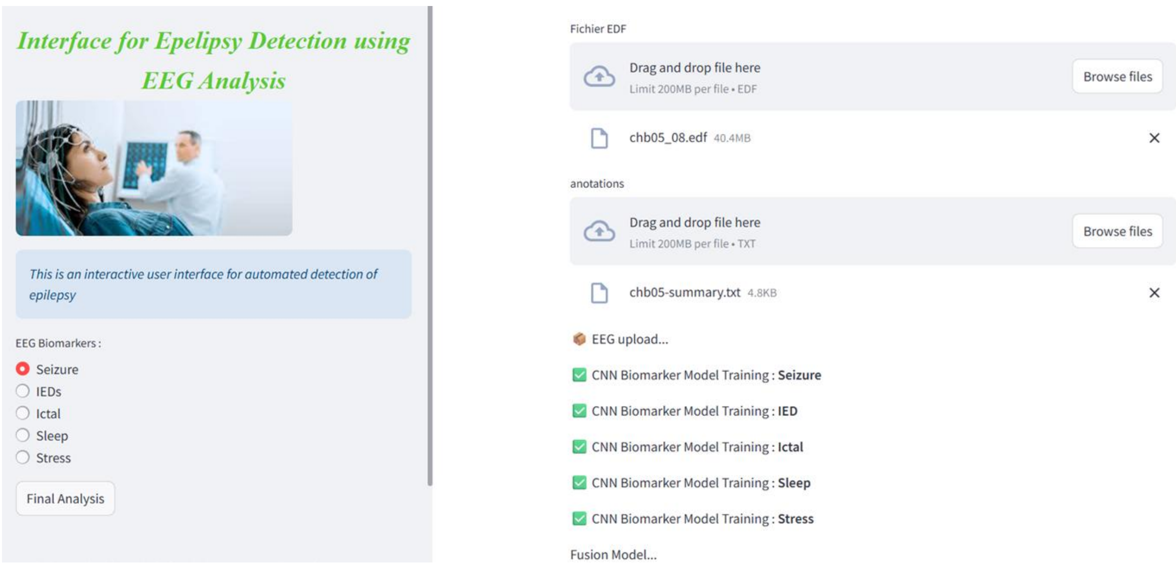

Figure IV-39.Streamlit UI in use

IV .10 . Conclusion

In conclusion, this chapter has presented the development and evaluation of a CNN-based model for automated epilepsy detection from EEG signals. The system integrates five specialized classifiers, each targeting a distinct neurological biomarker: stress, sleep quality, epileptic seizures, interictal epileptiform discharges and ictal states of the patient. The individual models achieved promising performance, with the stress classifier reaching an accuracy of (79%), the sleep model achieving the impressive accuracy of (95%), and analysis of ictal states' performance accuracy of (95%). The model used for seizure detection also impressively achieved (98%) accuracy, (99%) AUC and the precision of (97%). Lastly, for the interictal epileptiform discharges (IEDs), the model achieved (87%) in training accuracy and rose to a promising (90%) accuracy. These results indicate that each classifier provides meaningful contributions toward assessing brain states.

To make a final decision, two fusion strategies were applied at the decision level: one based on a late fusion technique using an intelligent model, and the other using a weighted fusion approach. Unlike direct classification from raw EEG signals, this method leverages the probabilistic outputs of several specialized models, each focused on a particular biomarker (stress, sleep, IED, ictal activity, or seizure detection). Each model provides complementary information on the patient's brain state. The late fusion approach allows this heterogeneous information to be combined during the decision-making process, either through weighted averaging or model stacking, to produce a more robust final prediction. This strategy reduces uncertainty arising from individual sub-model errors, enhances generalization, and improves interpretability by highlighting the relative impact of each biomarker on the final diagnosis. This is especially important in clinical scenarios, where seizures may appear in diverse forms influenced by multiple physiological factors.

The weighted fusion method, in particular, helps boost the final model's performance by downplaying the influence of weaker classifiers and giving more weight to the most reliable signals. Although the current accuracy of the fusion model is promising (86.11% overall accuracy and 86% recall), its performance could likely be improved by training on a larger and more diverse dataset. Unfortunately, due to time constraints, such data expansion could not be carried out during this project.

These results establish a strong foundation for future work. For future work, we will focus on reducing false positives through expanded training datasets, improved feature engineering, and model optimization. Clinical validation will also be essential to confirm the system's performance in real-world medical settings. Overall, the proposed approach represents a significant step toward reliable, automated EEG analysis and holds considerable potential for enhancing diagnostic efficiency in neurological practice.

GENERAL CONCLUSION

GENERAL CONCLUSION

This project presented a comprehensive study on the detection of epilepsy using EEG signals through the application of deep learning techniques with the integration of biomarkers. Beginning with an overview of epilepsy and the challenges associated with its diagnosis, the work emphasized the critical role of EEG as a non-invasive and reliable tool for capturing brain activity. The study then explored the principles of machine learning and deep learning, highlighting how neural networks—particularly convolutional architectures—can effectively extract complex patterns in EEG data without the need for manual feature engineering.

A deep learning-based model was proposed, trained, and evaluated using real EEG datasets, demonstrating promising performance in classifying seizure and non-seizure states. The model achieves clinically relevant performance with the stress classifier reaching an accuracy of (79%), the sleep model achieving the impressive accuracy of (95%), and analysis of ictal states' performance accuracy of (95%). The model used for seizure detection also impressively achieved (98%) accuracy, (99%) AUC and the precision of (97%). Lastly, for the interictal epileptiform discharges (IEDs), the model achieved (87%) in training accuracy and rose to a promising (90%) accuracy. The final fusion model for epileptic seizure detector obtained an overall accuracy of (86.11%) and a precision and recall of (86)% for seizure detection and this supports the potential of AI-assisted systems to enhance the accuracy and speed of epilepsy diagnosis, particularly in clinical environments where rapid and reliable decision-making is crucial.

While the results are encouraging, certain limitations such as the need for large, well-annotated datasets and the challenge of generalizing across patients remain. Future work could focus on improving model robustness, incorporating transfer learning, or exploring real-time implementation in wearable devices.

In conclusion, this work contributes to the growing field of intelligent biomedical systems and demonstrates the value of deep learning in addressing real-world healthcare challenges. In addition, it also represents a step toward more efficient, accessible, and automated diagnostic tools for epilepsy and other neurological disorders.

REFERENCES

References

[1] Mallick,S and Bats,V. Novel deep learning framework for detection of epileptic seizure using EEG signals, 2024

[2] World Health Organization. (n.d.). *Epilepsy*. World Health Organization. Retrieved April 20, 2025, from https://www.who.int/health-topics/epilepsy

[3] The Editors of Encyclopaedia Britannica. "brain". Encyclopedia Britannica, 29 Apr. 2025, https://www.britannica.com/science/brain. Retrieved May 6 2025

[4] Stewart, S. (2023, October 30). Lobes of the brain: Structure and function. Kenhub. Retrieved April 1, 2025 from https://www.kenhub.com/en/library/anatomy/lobes-of-the-brain

[5] National Institute of Neurological Disorders and Stroke. (2024, March). Epilepsy and seizures. U.S. Department of Health and Human Services, National Institutes of Health. Retrieved 3, May 2025 from https://www.ninds.nih.gov/health-information/disorders/epilepsy-and-seizures

[6] Scientific Research Publishing. (2025). *Epilepsy: Overview and recent advances*. Retrieved April 1, 2025 from https://www.scirp.org/pdf/samplechapter_2025033108510112.pdf

[7] CURE Epilepsy. (n.d.). *Types of seizures*. Retrieved 7 May, 2025 from https://www.cureepilepsy.org/understanding-epilepsy/epilepsy-basics/types-of-seizures/

[8[Mayo Clinic Staff. (2023, October 14). Epilepsy care at Mayo Clinic. Retrieved on 7 May 2025 from https://www.mayoclinic.org/diseases-conditions/epilepsy/symptoms-causes/syc-20350093

[9] Tao, J X., Yung, I., & Fish, D.R. (2020). Epileptic seizures. *Discoveries*, 8(2), e108. https://doi.org/10.15190/d.2020.9

[10] Anwar, H., Khan, Q. U., Nadeem, N., Pervaiz, I., Ali, M., & Cheema, F.F. (2020). Epileptic seizures. *Discoveries*, 8(2), e110. https://doi.org/10.15190/d.2020.7

[11] Biasiucchi, A., Franceschiello, B., & Murray, M. M (2019). Electroencephalography. *Current Biology*, 29(3), R80-85. https://doi.org/10.1016/j.cub.2018.11.052

[12] Hasan, T. F., & Tatum, W. O. (2021). When should we obtain a routine EEG while managing people with epilepsy?. *Epilepsy & behavior reports*, *16*, 100454. https://doi.org/10.1016/j.ebr.2021.100454

[13] Acharya, J.N., Hani, A., Cheek, J., Thirumula, P., &Tsuchida, T.N (2016). American Clinical Neurophysiology Society guideline 2: Guidelines for standard electrode position nomenclature. Journal of Clinical Neurophysiology, 33(4), 308-311. https://doi.org/10.1097/WNP.0000000000000316

[14] Mir WA, Anjum M, Izharuddin, Shahab S. Deep-EEG: An Optimized and Robust Framework and Method for EEG-Based Diagnosis of Epileptic Seizure. Diagnostics (Basel). 2023 Feb 17;13(4):773. doi: 10.3390/diagnostics13040773. PMID: 36832260; PMCID: PMC9954819.

[15] iMotions. (n.d). *EEG (Electroencephalography): The complete Pocket Guide. iMotions.* Retrieved 19 May 2025 https://imotions.com/blog/learning/best-practice/eeg/

REFERENCES

[16] Phutela N, Relan D, Gabrani G, Kumaraguru P, Samuel M. Stress Classification Using Brain Signals Based on LSTM Network. Comput Intell Neurosci. 2022 Apr 28;2022:7607592. doi: 10.1155/2022/7607592. PMID: 35528348; PMCID: PMC9071939.

[17] Janmohamed M, Nhu D, Kuhlmann L, Gilligan A, Tan CW, Perucca P, O'Brien TJ, Kwan P. Moving the field forward: detection of epileptiform abnormalities on scalp electroencephalography using deep learning-clinical application perspectives. Brain Commun. 2022 Aug 29;4(5):fcac218. doi: 10.1093/braincomms/fcac218. PMID: 36092304; PMCID: PMC9453433.

[18] Gotman, J., Ives, J., & Gloor, P. (1979). Automatic recognition of inter-ictal epileptic activity in prolonged EEG recordings. Electroencephalography and clinical neurophysiology, 46(5), 510-520.

[19] Subasi, 2007; Tzallas et al., 2009

[20] Abdulhamit Subasi, EEG signal classification using wavelet feature extraction and a mixture of expert model. Expert Systems with Applications, 32(4), 1084–1093, (2007).

[21] Huang, X., Sun, X., Zhang, L., Zhu, T., Yang, H., Xiong, Q., & Feng, L. . A Novel Epilepsy Detection Method Based on Feature Extraction by Deep Autoencoder on EEG Signal. *International Journal of Environmental Research and Public Health*, *19*(22), (2009).

[22] Tzallas, A. T., Tsipouras, M. G., & Fotiadis, D. I. Epileptic seizure detection in EEGs using time–frequency analysis. IEEE Transactions on Information Technology in Biomedicine, 13(5), 703–710, (2009).

[23] Ling Guo, Daniel Rivero, Alejandro Pazos. Epileptic seizure detection using multiwavelet transform-based approximate entropy and artificial neural networks. Journal of Neuroscience Methods, 193(1), 156–163, (2010).

[24] Poomipat Boonyakitanont, Apiwat Lek-uthai, Krisnachai Chomtho, Jitkomut Songsiri. A review of feature extraction and performance evaluation in epileptic seizure detection using EEG. Biomedical Signal Processing and Control, Vol.57, (2020).

[25] Cherifi Dalila, Falkoun Noussaiba, Ouakouak Ferial, Boubchir Larbi, Nait-Ali Amine. EEG Signal Feature Extraction and Classification for Epilepsy Detection. Informatica, 45(3), 377–386,(2022).

[26] Yongqiang Yu. Review of epileptic EEG feature extraction methods. Frontiers in Computing and Intelligent Systems, 1(3), 5-7, (2022).

[27] Dehua Zhang, Tong Wang. Feature Extraction Method of Epileptic EEG Signal based on Wavelet Packet and Improved Fuzzy Entropy, Scientific Journal of Technology, 4(6), 2022.

[28] Ihsan Ullah, Muhammad Hussain, Emad-ul-Haq Qazi, Hatim Aboalsamh. An automated system for epilepsy detection using EEG brain signals based on deep learning approach, Expert Systems with Applications, Volume 107, (2018)

[29] Y. Yuan, G. Xun, K. Jia and A. Zhang, "A Multi-View Deep Learning Framework for EEG Seizure Detection," in *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 1, pp. 83-94, Jan. 2019

REFERENCES

[30] T. Dissanayake, T. Fernando, S. Denman, S. Sridharan and C. Fookes, "Deep Learning for Patient-Independent Epileptic Seizure Prediction Using Scalp EEG Signals," in *IEEE Sensors Journal*, vol. 21, no. 7, pp. 9377-9388, (2021)

[31] Mohammed Alsuwaiket. Extraction of EEG Signals for Seizure Detection Using Machine Learning Algorithms. Engineering, Technology & Applied Science Research, 12(5), 9247–9251,(2022).

[32] Jie Xu, Kuiting Yan, Zengqian Deng, Yankai Yang, Jin-Xing Liu, Juan Wang, Shasha Yuan. EEG-based epileptic seizure detection using deep learning techniques: A survey, Neurocomputing,Vol 610, (2024)

[33] Siadati, S. (2017, November). *Just a moment with machine learning* [Presentation slides]. ResearchGate. DOI: 10.1118/06.2.1.37161.3080

[34] IBM. (22 September 2021). *What is machine learning?* IBM Think. Retrieved [25 May 2025], from https://www.ibm.com/think/topics/machine-learning

[35] Besse, P. (n.d.). *RNN & deep learning*. Institut de Mathématiques de Toulouse. Retrieved from https://www.math.univ-toulouse.fr/~besse/Wikistat/pdf/st-m-hdstat-rnn-deep-learning.pdf

[36] Sharma, A. (2023). *Artificial neural networks: An overview*. ResearchGate. https://www.researchgate.net/publication/373700317_Artificial_Neural_Networks_An_Overview

[37] GeeksforGeeks. (n.d.). *Activation functions in neural networks*. Retrieved [27 May, 2025], from https://www.geeksforgeeks.org/activation-functions-neural-networks/

[38] V7 Labs. (2023, May 3). *Activation functions in neural networks: All you need to know!* https://www.v7labs.com/blog/neural-networks-activation-functions

[39] Crest Infotech. (2025, January 29). *Exploring reinforcement learning: How machines learn through trial and error* [Post]. LinkedIn. https://www.linkedin.com/pulse/exploring-reinforcement-learning-how-machines-learn-through-ibenf

[40] Ratan, P**.** (2025, May 1). *What is the convolutional neural network architecture?* Analytics Vidhya. https://www.analyticsvidhya.com/blog/2020/10/what-is-the-convolutional-neural-network-architecture/

[41] AS_3107**.** (2024, May 21). *Convolutional neural networks* [Blog post]. Medium. https://medium.com/@maliashwin3107/convolutional-neural-networks-6cc280618ad1

[42] Mienye, I. D., Swart, T. G., & Obaido, G. (2024). Recurrent Neural Networks: A Comprehensive Review of Architectures, Variants, and Applications. *Information*, *15*(9), 517. https://doi.org/10.3390/info15090517

[43] Official Web site of GoogleColab : https://colab.google/

REFERENCES

[44] Shimanto, H. (2021). *Epileptic seizure recognition dataset* [Data set]. Kaggle. https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure-recognition

[45] Tibrewal, A. (2024). *EEG features dataset for stress classification* [Data set]. Kaggle. https://www.kaggle.com/datasets/ayushtibrewal/eeg-features-dataset-for-stress-classification/data

[46] Guttag, J. (2010). CHB-MIT Scalp EEG Database (version 1.0.0). *PhysioNet*. RRID:SCR_007345. https://doi.org/10.13026/C2K01R

[47] Ali Shoeb. Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, Massachusetts Institute of Technology, September 2009.

[48] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220. RRID:SCR_007345

[49] Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience, 7*, 267. https://doi.org/10.3389/fnins.2013.00267

[50] Microsoft. (n.d.). *Visual Studio Code - Code Editing. Redefined*. Visual Studio. Retrieved 20 May, 2025, from https://visualstudio.microsoft.com/#vscode-section

[51] Python-Bloggers. (2023, June). *A tutorial guide: How to install Anaconda for Python*. Python-Bloggers. Retrieved 25 May, 2025, from https://python-bloggers.com/2023/06/a-tutorial-guide-how-to-install-anaconda-for-python-2/

[52] Sanei, S., & Chambers, J. A. (2007). *EEG signal processing*. Wiley.

[53] Miah, M. O., Khan, S. S., Shatabda, S., Mamun, K. A. A., & Farid, D. M. (2019, June). *Different frequency bands inside the brain (ϑ, α, low β, high β)* [Figure]. In **Real-Time EEG Classification of Voluntary Hand Movement Directions using Brain-Machine Interface**. IEEE Region 10 Symposium (TENSYMP), Kolkata, India. Retrieved from https://www.researchgate.net/figure/Different-frequency-bands-inside-the-brain-a-theta-b-alpha-c-low-beta-d-high_fig2_338947608

[54] Acharya, U. R., Sree, S. V., Swapna, G., Martis, R. J., & Suri, J. S. (2013). Automated EEG analysis of epilepsy: A review. *Knowledge-Based Systems*, *45*, 147–165. https://doi.org/10.1016/j.knosys.2013.02.014
(Figure retrieved from https://www.researchgate.net/figure/An-exemplary-of-raw-normal-seizure-free-and-epileptic-seizure-of-EEG-signals_fig1_270523871)

[55] Sinha, S. R. (n.d.). *EEG instrumentation*. In *NeupsyKey*. Retrieved June 19, 2025, from https://neupsykey.com/eeg-instrumentation/

REFERENCES

[56] Acharya, U. R., Sree, S. V., Swapna, G., Martis, R. J., & Suri, J. S**.** (2013). EEG machine schematic diagram [Figure]. In *Automated diagnosis of epileptic EEG using entropies*. *Expert Systems with Applications, 41*(5), 1825–1834. https://doi.org/10.1016/j.eswa.2013.08.041 *Retrieved from https://www.researchgate.net/figure/EEG-machine-schematic-diagram_fig11_263581341*

[57] Singh, A. K**.** (2021, December 28). *Architecture of artificial neural network*. NashTech Global. https://blog.nashtechglobal.com/architecture-of-artificial-neural-network/

[58] Tilinda**, S.** (2024, April 24). *Deep learning (Part 4): Recurrent neural network (RNN)*. Medium. https://medium.com/@sumbatilinda/deep-learning-part4-recurrent-neural-network-rnn-0714e0852581