PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

FERHAT ABBAS UNIVERSITY OF SETIF

Faculty of Sciences

Department of Computer Science

Dissertation submitted in partial fulfilment of the requirements for the degree of Master of Data Engineering and Web Technologies

Theme

Efficient Deep Self-Supervised Learning for Epileptic Seizures Detection Using EEG Signals

---

Presented by:

Zakarya BOUDRAF

Oussama houssem eddine TAMOURT

Supervisor:

Pr. Abdelouahab Moussaoui

June 2023

Acknowledgements

Praise be to the Almighty God who has given us faith, courage, and patience to carry out this work.

We want to express our deep gratitude to our supervisor Pr. Abdelouahab Moussaoui from Ferhat Abbas university, for the confidence he has placed in us, through his presence always with us, by his direction, his modesty, his advice, and constructive remarks for the good progress of this work.

We would like to thank everyone who helped us improve our work, and who gave us any remark that helped us to perfect this manuscript.

We express our deep gratitude to our parents, our brothers, our sisters, and our whole family for their encouragement and prayers that allowed us to achieve this modest job. We are very grateful for the confidence they have placed in us.

Finally, We express our gratitude to all those who have contributed in one way or another to the development of this work.

O Allah, send your blessings on your noble messenger, his family, and companions, and bless us in our lives.

Dedication

We dedicate this work to our parents:

May they find here the testimony of our deep gratitude and acknowledgment

To our brothers and our sisters, our grandparents and our family who give love and liveliness.

To all those who have helped us - directly or indirectly - and those who shared with us the emotional moments during the accomplishment of this work and who warmly supported and encouraged throughout our journey.

To all our friends who have always encouraged me, and to whom we wish more success.

Thanks!

Zakarya BOUDRAF & Oussama houssem eddine TAMOURT

Abstract

When dealing with epileptic seizures electroencephalogram's (EEG) can provide essential information about electrical brain activity. Patients with epilepsy produce an excess of electrical discharges, causing involuntary body movements along with other unpleasant symptoms. That information allows us to detect these seizures and help minimize the damage done. However, an EEG requires extensive knowledge of signal processing in order for medical practitioners to correctly diagnose a patient. That's why in recent years machine learning algorithms have been employed to automatically detect these seizures. But, in order to train these models, a large dataset of labeled data is needed which is both expensive and time consuming. In this paper, we propose three self-supervised learning models that make use of unlabeled data, while still providing accurate and efficient predictions. Our model performs competitively with previously published works by achieving an accuracy of 99.08%, sensitivity of 83.33%, and a FPR of 0.06.

Key words: *Self-supervised, epilepsy, EEG, deep learning, signal processing.*

ملخص

عند التعامل مع نوبات الصرع يمكن أن يوفر مخطط الدماغ الكهربائي (EEG) معلومات أساسية حول نشاط الدماغ الكهربائي. ينتج مرضى الصرع فائضا من الإفرازات الكهربائية ، مما يتسبب في حركات الجسم اللاإرادية إلى جانب أعراض أخرى. تسمح لنا هذه المعلومات باكتشاف هذه النوبات والمساعدة في تقليل الضرر الذي يحدث. ومع ذلك ، يتطلب تخطيط الدماغ معرفة واسعة بمعالجة الإشارات من قبل الممارسين الطبيين لتشخيص المريض بشكل صحيح. لهذا السبب تم استخدام خوارزميات التعلم الآلي في السنوات الأخيرة للكشف تلقائيا عن هذه النوبات. ولكن ، من أجل تدريب هذه النماذج ، هناك حاجة إلى مجموعة بيانات كبيرة من البيانات المصنفة والتي تكون باهظة الثمن وتستغرق وقتا طويلاً للتصنيف.

في هذا البحث ، نقترح ثلاثة نماذج تعليمية خاضعة للإشراف الذاتي تستخدم البيانات غير المصنفة ، مع الاستمرار في تقديم تنبؤات دقيقة وفعالة. يعطي نموذجنا نتائج تنافسية مع الأعمال المنشورة سابقا من خلال تحقيق دقة 99.08 % ، وحساسية 83.33 % ، و FPR 0.06.

كلمات مفتاحية: :تعلم عميق ، معالجة الإشارات، التعلم بالإشراف الذاتي، الصرع، النشاط الكهربائي الدماغي الحيوي.

Résumé

Lorsqu'il s'agit de crises d'épilepsie, l'électroencéphalogramme (EEG) peut fournir des informations essentielles sur l'activité électrique du cerveau. Les patients épileptiques produisent un excès de décharges électriques, provoquant des mouvements corporels involontaires ainsi que d'autres symptômes désagréables. Ces informations nous permettent de détecter ces crises et de minimiser les dommages causés. Cependant, un EEG nécessite une connaissance approfondie du traitement du signal afin que les médecins diagnostiquent correctement un patient. C'est pourquoi ces dernières années, des algorithmes d'apprentissage automatique ont été utilisés pour détecter automatiquement ces crises d'épilepsie. Mais, pour former ces modèles, un grand ensemble de données de données étiquetées est nécessaire, ce qui est à la fois coûteux et prend beaucoup de temps. Dans cette thèse, nous proposons trois modèles d'apprentissage auto-supervisés qui utilisent des données non étiquetées, tout en fournissant des prévisions précises et efficaces. Notre modèle fonctionne de manière compétitive avec les œuvres publiées précédemment en atteignant une précision de 99,08 %, une sensibilité de 83,33 % et un FPR de 0,06.

Mots clés :*Auto-supervisé, épilepsie, EEG, apprentissage en profondeur, traitement du signal.*

Contents

List of Figures

List of Tables

List of Abbreviations

EEG: Electroencephalography

ML: Machine Learning

AI: Artificial Intelligence

DL: Deep Learning

SVM: Support Vector Machine

ANN: Artificial Neural Network

PCA: Principal Component Analysis

SSL: Self-Supervised Learning

SimCLR: Simple Clear

MoCo: Momentum Contrast

BYOL: Bootstrap Your Own Latent

SimSiam: Simple Siamese

EDF: European Data Format

FPR: False Positive Rate

General introduction

Epilepsy is a neurological disorder that affects millions of people worldwide. One of the most challenging aspects of epilepsy is the unpredictability of seizures, which can lead to serious consequences for patients' safety and quality of life. In recent years, there has been a growing interest in developing predictive models for epileptic seizures using machine learning techniques. However, most existing approaches require a large amount of labeled data, which can be difficult to obtain in clinical settings.

In this paper, we propose a self-supervised learning methods for epileptic seizure detection that can be trained using unlabeled data and perform classification tasks. Our model integrates electroencephalogram (EEG) signals to capture the complex temporal dynamics of seizures. By leveraging self-supervised learning techniques, our model can learn meaningful representations from unlabeled data, which can improve its predictive performance.

We evaluate our model on a large dataset of EEG recordings from patients with epilepsy and demonstrate how it performs against existing state-of-the-art approaches. Our results suggest that self-supervised machine learning models have the potential to significantly improve epileptic seizure detection, paving the way for more effective personalized treatment and management of epilepsy.

Chapter 1

General notions about Epilepsy

1.1 Introduction

Epilepsy is a neurological disorder that affects millions of people worldwide. It affects the electrical brain activity of a person, and thus it can do a lot of damage to the patient. In this chapter we will go in depth about the history of this illness, the different types and symptoms for each one. We will also talk about the possible causes and treatments for epilepsy. Then we will define Electroencephalography and how we can collect EEG data from patients. By understanding the basics of this condition, we can better appreciate the importance of developing efficient methods for detecting epileptic seizures using EEG signals.

1.2 Definition of epilepsy

Epilepsy is a chronic noncommunicable disease of the brain that affects around 50 million people worldwide. It is characterized by recurrent seizures, which are brief episodes of involuntary movement that may involve a part of the body (partial) or the entire body (generalized) and are sometimes accompanied by loss of consciousness and control of bowel or bladder function.

Seizure episodes are a result of excessive electrical discharges in a group of brain cells. Different parts of the brain can be the site of such discharges. Seizures can vary from the briefest lapses of attention or muscle jerks to severe and prolonged convulsions. Seizures can also vary in frequency, from less than one per year to several per day.

One seizure does not signify epilepsy (up to 10% of people worldwide have one seizure during their lifetime). Epilepsy is defined as having two or more unprovoked seizures. Epilepsy is one of the world's oldest recognized conditions, with written records dating back to 4000 BCE. Fear, misunderstanding, discrimination and social stigma have surrounded epilepsy for centuries. This stigma continues in many countries today and can impact on the quality of life for people with the disease and their families.[9]

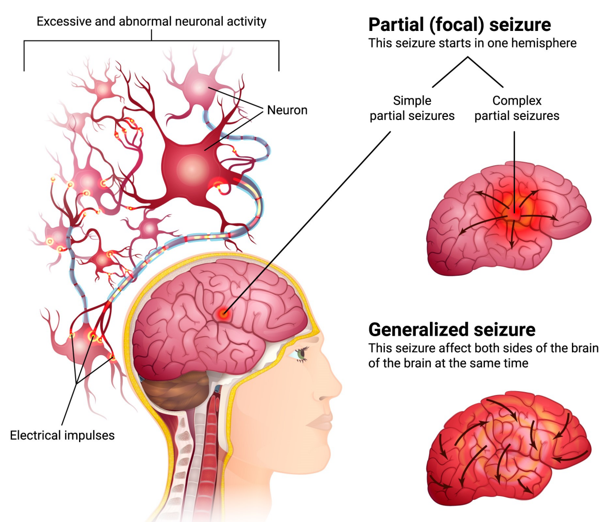

Figure 1.1: Abnormal Brain Activity During Epileptic Seizures.

1.3 History of epilepsy

During Antiquity (3000 BC - 500 AD)

An Assyrian-Babylonian text provided the first description of some seizure phenomena. Physicians in China and India were also familiar with epilepsy during this period. The word "epilepsy" is derived from the Greek verb "epilamvanein" meaning "to be seized" or "to be attacked," as Greeks believed that an individual having a seizure, usually believed as a punishment, was possessed by a god or a spirit. Although epilepsy was commonly thought to be a sacred disease, Hippocrates (c. 460-377 BCE) argued in his famous treatise "On the Sacred Disease" that it had nothing to do with spirits and demons. He suggested that seizures originated in the brain, but unfortunately, his work had a small influence on the general belief that epilepsy was caused by supernatural forces.[10]

During the Renaissance and Enlightenment (1400-1800)

Thomas Willis (1621-1675) suggested that epilepsy originated in the brain but in the form of "animal spirits" moving from the brain to peripheral nerves. He believed that a centripetal movement of an animal spirit could lead to an explosion in the brain resulting in a convulsive epileptic seizure. Further progress was based on the work of Luigi Galvani (1737-1798), who discovered that a frog muscle could be made to contract by electricity. In a long-term controversy, Alessandro Volta (1745-1827) disputed his interpretation of obtained results.[10]

During the 19th century (1800-1900)

The belief in supernatural forces faded out, and new theories were developed. Robert Bentley Todd (1809-1860) collaborated with Michael Faraday (1791-1867), an outstanding pioneer in electricity, and he firstly recognized the role of electrical discharges in epilepsy. Tremendous efforts were made by John Hughlings Jackson (1835-1911) in clinical observations. In 1870, he emphasized that "A convulsion is but a symptom, and implies only that there is an occasional, an excessive, and a disorderly discharge of nerve tissue on muscles." Furthermore, following his ideas about cerebral localization, the nervous system has a three-level hierarchical structure where each element of the lowest level represents a certain body part. The view of a localized representation of motor functions was supported by experiments of Fritsch and Hitzig, which were published in 1870. They found that stimulating motor cortex in dogs immediately resulted in motor responses, which muscles twitched depending on the placement of the stimulating electrodes. Especially, Richard Caton (1842-1926) observed in his animal experiments electrical activity of the brain and discovered that brain stimulation would lead to an electrical response of the brain, i.e. an evoked potential. With his results, he provided an important basis for the work of Hans Berger (1873-1941), the inventor of electroencephalography. The discovery of Berger, described in his famous publication in 1929, can be regarded as a historical breakthrough and an important step to modern clinical technology. It was a long winding road from myths and demonizing to a better understanding of epilepsy based on research.[10]

1.4 Types of epilepsy

1.4.1 Generalized Epilepsy

This type of epilepsy is characterized by seizures that affect the entire brain. Generalized epilepsy can be further classified into the following sub-types:

- Absence Epilepsy: This type of epilepsy is characterized by brief episodes of staring or inattention, which can last for a few seconds to a minute.
- Myoclonic Epilepsy: This type of epilepsy is characterized by brief jerking movements that can affect one or more parts of the body.
- Clonic Epilepsy: This type of epilepsy is characterized by rhythmic, repetitive movements that can affect one or more parts of the body.

- Tonic Epilepsy: This type of epilepsy is characterized by sustained muscle contractions that can cause the body to become rigid.
- Atonic Epilepsy: This type of epilepsy is characterized by sudden loss of muscle tone, which can cause the body to collapse or fall.
- Tonic-Clonic Epilepsy: This type of epilepsy is characterized by a combination of tonic and clonic seizures, which can cause loss of consciousness, convulsions, and other symptoms.

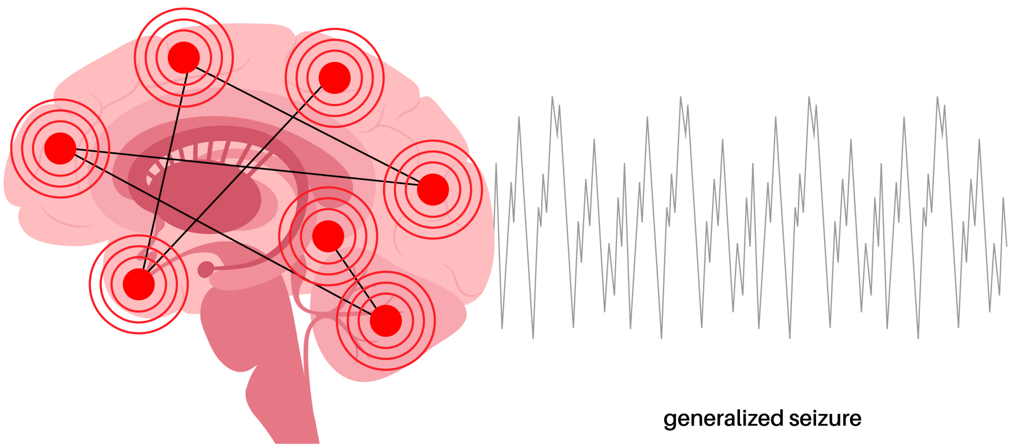

Figure 1.2: Generalized epilepsy.

1.4.2 Focal Epilepsy

This type of epilepsy is characterized by seizures that originate in a specific part of the brain. Focal epilepsy can be further classified into the following sub-types:

- Temporal Lobe Epilepsy: This type of epilepsy is characterized by seizures that originate in the temporal lobe of the brain, which can cause symptoms such as altered perception, memory loss, and emotional changes.
- Frontal Lobe Epilepsy: This type of epilepsy is characterized by seizures that originate in the frontal lobe of the brain, which can cause symptoms such as abnormal movements, loss of consciousness, and altered behavior.

- Occipital Lobe Epilepsy: This type of epilepsy is characterized by seizures that originate in the occipital lobe of the brain, which can cause symptoms such as visual hallucinations, flashing lights, and other visual disturbances.
- Parietal Lobe Epilepsy: This type of epilepsy is characterized by seizures that originate in the parietal lobe of the brain, which can cause symptoms such as altered sensation, numbness, and tingling.
- Multifocal Epilepsy: This type of epilepsy is characterized by seizures that originate in multiple areas of the brain, which can cause a variety of symptoms depending on the location and extent of the seizures.

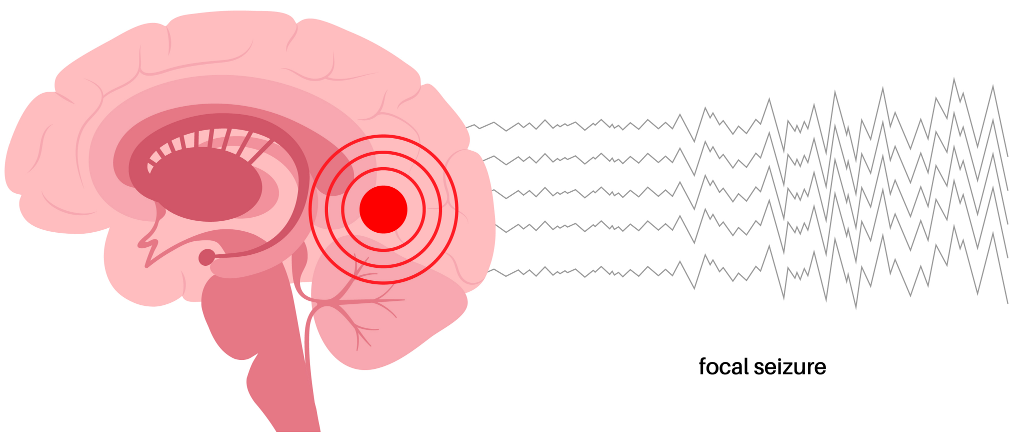

Figure 1.3: Focal epilepsy.

1.4.3 Unknown Epilepsy

Some cases of epilepsy cannot be classified into a specific type or sub-type due to incomplete or insufficient information about the seizures and their underlying causes.

1.5 Causes of epilepsy

Epilepsy is not contagious. Although many underlying disease mechanisms can lead to epilepsy, the cause of the disease is still unknown in about 50% of cases globally. The causes of epilepsy are divided into the following categories: structural, genetic, infectious, metabolic, immune and unknown. [9] Examples include:

- brain damage from prenatal or perinatal causes (e.g. a loss of oxygen or trauma during birth, low birth weight);
- congenital abnormalities or genetic conditions with associated brain malformations;
- a severe head injury;
- a stroke that restricts the amount of oxygen to the brain;
- an infection of the brain such as meningitis, encephalitis or neurocysticercosis;
- certain genetic syndromes; and
- a brain tumour.

1.6 Treatment of Epilepsy

Epilepsy can be managed with a variety of treatment options, including medication, surgery, and lifestyle modifications. In this section, we discuss the different ways to treat epilepsy.

Antiepileptic Drugs (AEDs)

AEDs are the most commonly used treatment option for epilepsy. They work by reducing the electrical activity in the brain, thus preventing seizures. AEDs are available in different formulations and dosages, and the choice of medication depends on several factors, including the patient's age, medical history, and the type of epilepsy. The most commonly prescribed AEDs include carbamazepine, phenytoin, valproic acid, and lamotrigine.

Ketogenic Diet

The ketogenic diet is a high-fat, low-carbohydrate diet that has been shown to be effective in managing epilepsy, particularly in children with refractory epilepsy. The diet works by inducing a state of ketosis in the body, which can reduce seizure activity. The exact mechanism of action of the ketogenic diet is not fully understood, but it is believed to involve changes in brain metabolism and neurotransmitter activity.

Vagus Nerve Stimulation (VNS)

VNS is a non-invasive treatment option for epilepsy that involves implanting a device in the chest that sends electrical impulses to the vagus nerve in the neck. The vagus nerve stimulation has been shown to reduce seizure frequency and severity in patients with refractory epilepsy.

Surgery

Surgery is an option for patients with epilepsy who do not respond to other treatment options. The surgical procedure involves removing the part of the brain that is responsible for the seizures, or disconnecting the nerve pathways that cause the seizures. The success of the surgical procedure depends on several factors, including the location of the seizures, the age of the patient, and the overall health of the patient.

Responsive Neurostimulation (RNS)

RNS is a newer treatment option for epilepsy that involves implanting a device in the brain that detects and responds to seizure activity. The device sends electrical impulses to the part of the brain that is responsible for the seizures, thus preventing them from occurring. RNS has been shown to be effective in reducing seizure frequency and severity in patients with refractory epilepsy.

1.7 Electroencephalography (EEG)

EEG is a method of brain exploration that measures the electrical activity of the brain through electrodes placed on the scalp, often shown as a tracing called an electroencephalogram. Comparable to the electrocardiogram which makes it possible to study the functioning of the heart, the EEG is a painless and non-invasive examination that provides information on the neurophysiological activity of the brain over time and in particular of the cerebral cortex, either for a diagnostic purpose in neurology or in cognitive neuroscience research. The electrical signal at the origin of the EEG is the result of the summation of synchronous post-synaptic potentials from a large number of neurons. EEG can also be referred to as intracranial (iEEG), subdural or stereotaxic electroencephalography (sEEG) to refer to measurements of the electrical activity of the brain made from electrodes implanted under the surface of the skull, either at the surface or at depth of brain tissue.

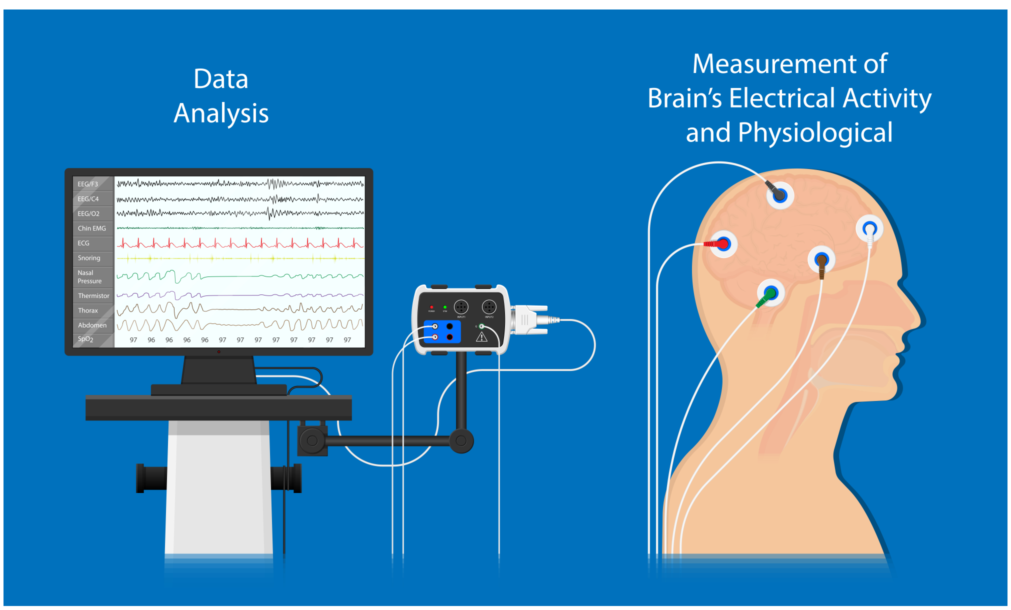

Figure 1.4: The process of capturing EEG signals.

EEG activity is quite small, measured in microvolts (µV) with the main frequencies of interest up to approximately 30 Hertz (Hz).[11]

1.7.1 Electrodes

Small metal discs called electrodes are placed on the scalp in special positions. These positions are identified by the recordist who measures the head using the International 10/20 System. This relies on taking measurements between certain fixed points on the head. The electrodes are then placed at points that are 10% and 20% of these distances.

Each electrode site is labelled with a letter and a number. The letter refers to the area of brain underlying the electrode [11]

- F - Frontal lobe
- T - Temporal lobe
- C - Central lobe
- P - Parietal lobe
- O - Occipital lobe
- Even numbers denote the right side of the head
- Odd numbers denote the left side of the head.

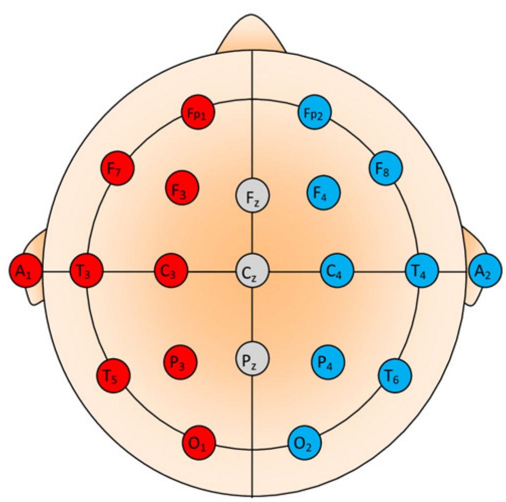

Figure 1.5: Top view of scalp zones.[1]

1.7.2 EEG rhythms

The EEG is the result of a potential difference measured between two points. The recording between two points is done using electrodes placed on the scalp. [12]

Rythme	**Fréquence**	**Amplitude**	**Localisation**	**Corrélats**
Delta	< 4 Hz	$> 30\ \mu$V	$> 30\ \mu$V	Sommeil lent profond
Theta	$4 - 7$ Hz	$20\ \mu$V	Centrotemporal	Sommeil léger
Alpha	$8 - 13$ Hz	$30\ \mu$V	Postérieur	Veille calme
Beta	$13 - 30$ Hz	$< 20\ \mu$V	Antérieur et moyen	Veille active

Table 1.1: Table of different cerebral rhythms.

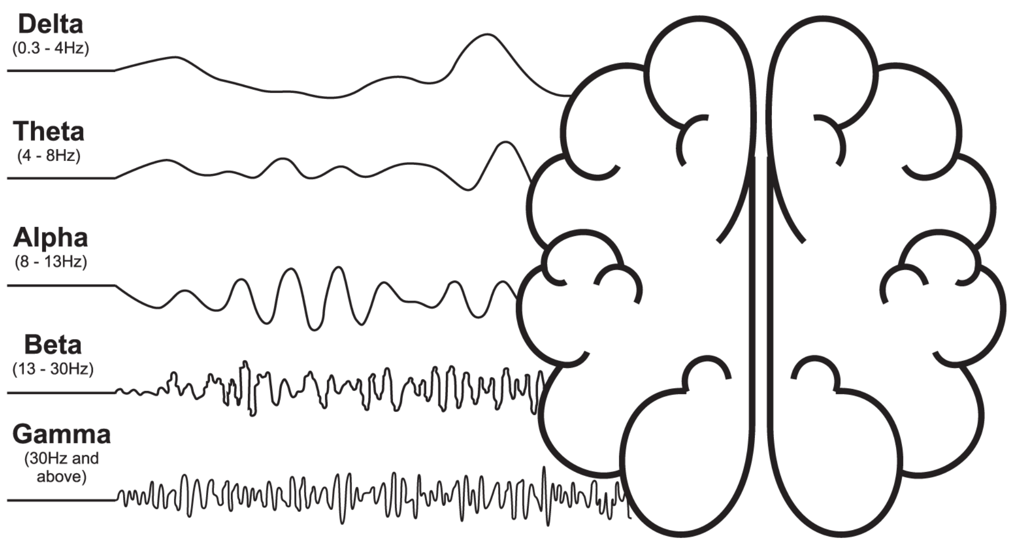

Figure 1.6: Visualization of different cerebral rhythms.

The alpha rhythm

The alpha rhythm is a band rhythm (or frequency) between 8 – 13Hz and 30 to 50μV amplitude. Its topography is more particularly posterior (behind the vertex) in the occipital region. It mostly appears with closed eyes.

Delta and theta rhythms

Delta and theta rhythms, also known as slow waves, are arbitrarily defined as signals whose frequency content is lower than that of the alpha band. These slow waves can testify to a lesional pathological process or underlying functionality. In partial epilepsies, they are frequent and often localized in the same region as the intercritical epileptic focus.

The beta rhythm

The beta rhythm, with a frequency greater than 13 Hz, occupies the middle regions of the two hemispheres often asynchronously. Of low amplitude (less than 20μV), these rhythms can be masked by alpha rhythms (more energetic).

The gamma rhythm

The gamma rhythm is of very low amplitude and of rarer occurrence. The detection of these rhythms can be used for the confirmation of certain pathologies.

1.7.3 EEG épileptique

The rhythms described above are physiological and correspond to the cyclical activities of the body which can be subdivided into 3 main categories: wakefulness, slow sleep, paradoxical sleep. Epilepsy goes through neuronal hyper synchronization and hyperexcitability, including cortical ones. [12]

The EEG of the epileptic patient has 3 different phases:

Inter-critical phase

This phase is characterized by transient EEG signals following:

- Peak: discharge peak whose duration varies between 20 and 70 ms.
- Slow peak: or discharge peak whose duration varies between 70 and 200 ms.
- Spike-wave: spike followed by a slow wave.
- Poly tip-wave: several successive spikes followed by a slow wave.

Several combinations of these elements can be found on the same EEG.

Precritical phase

This phase is the one that precedes the crisis. Its duration is not unanimous at the literature level. It can therefore vary from a few minutes up to approximately one hour. The physical behavior of EEG signals during this phase varies considerably depending on the type of crisis in question.

Critical phase

Epileptic seizures show patterns of EEG signals that are quite different depending on the type of crisis present. One can frequently distinguish one of the following items:

- Synchronization of EEG signals which begin to oscillate with high amplitudes.
- An accentuation of low frequencies (theta) around 5 Hz.
- An accentuation of high frequencies around 10 Hz.

1.8 Conclusion

In this chapter, we have provided an overview of epilepsy, including its definition, history, types, causes, and treatment, we have also defined EEG and some information regarding it. This information serves as a foundation for understanding the significance of developing efficient deep self-supervised learning methods for detecting epileptic seizures using EEG signals. In the following chapters, we will delve deeper into the technical aspects of this research.

Chapter 2

State-of-the-art

2.1 Introduction

In this chapter, we will review the state-of-the-art in epileptic seizure detection using EEG signals. We will provide a literature review of existing approaches and define the techniques they used. We will also compare these approaches and discuss self-supervised learning and the metrics used to evaluate performance.

2.2 Literature Review

Literature in this area demonstrated that even though the use of conventional methods yielded great results when working on epileptic seizure classification using EEG signals, they required the use of a large database of labeled data. The characterization step makes it possible to extract the relevant information from the EEG signals. A second step in the system for identifying epileptic seizures consists in assigning a class to the feature vector extracted previously. This class must represent a mental task, a psychic state, a crisis, etc. The classification is performed by an intelligent classifier using a training set. This set is able to classify vectors according to their memberships. Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN) and Support Vector Machines (SVM), are considered the most popular classifiers in the characterization of epileptic seizures. A brief introduction of these approaches is presented in this section.

Convolutional Neural Network (CNN)

CNNs are the most frequently used network architectures in automated seizure classification. A convolutional neural network, or CNN, is a deep learning neural network designed for processing structured arrays of data such as images. Convolutional neural networks are widely used in epileptic seizure detection as shown by multiple studies[13] [14].

Support Vector Machines (SVM)

The Support Vector Machine (SVM), generally translated as the Vast Margin Separator, belongs to the family of the most discriminating supervised learning algorithms. Its basic principle relies on the existence of a linear classifier called hyperplane, separating the data. SVM has been applied in solving various problems like regression, merging and classification. This classification method has been used in several medical imaging studies: the classification of MRI images. This approach has been applied in several other works [15] [16] in order to classify the critical states associated with an epileptic seizure and the inter-critical states.

K-means

K-Means, an unsupervised machine learning algorithm is a vector quantization method from signal processing used for clustering. It partitions the objects into k clusters such that each object in the dataset belongs to the cluster. K stands for number of clusters. The value of k should be defined initially. Objects in the dataset are assigned to the cluster with nearest mean. Nearest mean is found based on Euclidian distance between two data points. Some works used K-means in seizure detection[17].

Artificial Neural Networks (ANN)

Artificial neural networks are computer models inspired by the functioning of the human brain. They are used to solve complex problems such as pattern recognition, prediction and natural language processing. These models are built from layers of interconnected neurons that process inputs and produce outputs. The weights and biases of each connection are adjusted during training to optimize network performance.

They are composed of three layers (input layer, hidden layer, output layer). The layers are made up of interconnected neurons. ANNs have been used in several fields such as prediction, classification, approximation.

Several types of RNA have been applied in order to detect electrical discharge peaks associated with epileptic seizures such as: Recurrent Neural Network (RNR), Probabilistic Neural Network, Radial Based Neural Network (RBNN), Odelet Network [18].

For an ANN with back-propagation (Feed-Forward), as shown in the image above, all the layers are connected to the previous layers and to the following layers with a connection weight. The hidden layer neurons also called processing unit, are controlled by an activation function.

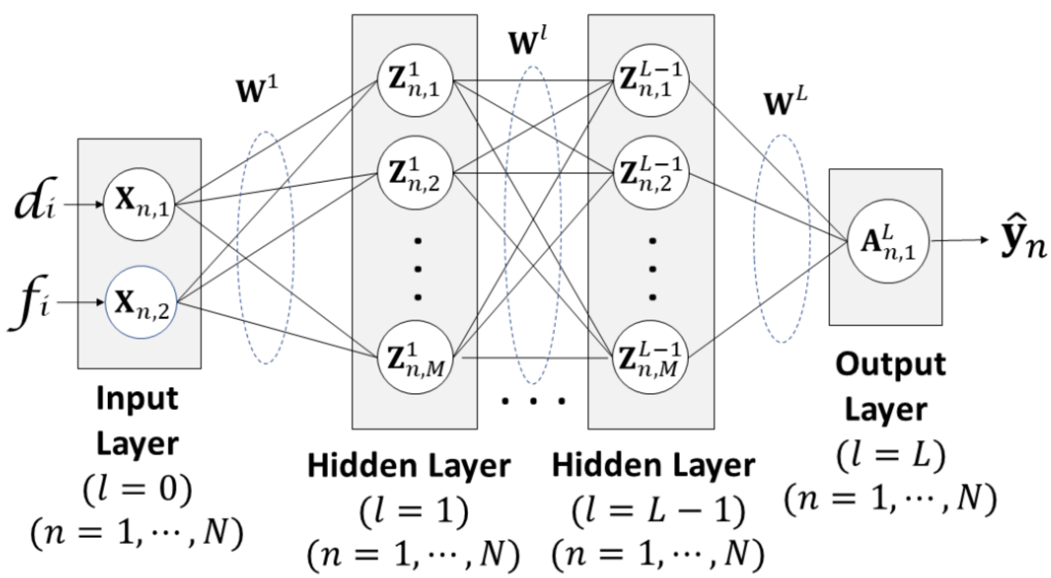

Figure 2.1: Block diagram of multilayer perceptron neural network(MLP-NN).[2]

With j as the index of input layer neurons, p is the index of hidden layer neurons, w_{pj} is the weight weight (hidden layer-input layer), k is the index of neurons of the output layer, n_h is the number of neurons in the hidden layer, d is the dimension of the i^{th} input sample.

Another classification method is the hybrid classification, which combines both supervised and unsupervised approaches to improve the accuracy of the classification called self-supervised that we will use in this topic.

Multivariate statistical process control (MSPC)

MSPC is a powerful tool used in modern manufacturing processes to monitor and improve product quality. It involves the analysis of multiple variables simultaneously, allowing for a more comprehensive understanding of the production process. MSPC is important because it enables manufacturers to detect and correct problems before they result in defects or other quality issues. By identifying patterns and trends in data, MSPC helps manufacturers make informed decisions about process improvements and adjustments. This has been used for epileptic seizure prediction by using ECG signals to predict seizure before they occur[19].

Short-Time Fourier Transform (STFT)

Short-time Fourier transform (STFT) is a sequence of Fourier transforms of a windowed signal. STFT provides the time-localized frequency information for situations in which frequency components of a signal vary over time, whereas the standard Fourier transform provides the frequency information averaged over the entire signal time interval.[20]

2.3 Comparison between state-of-the-art approaches

In the table below we can see a list of previous works about seizure detection and prediction. We notice that there is a variety of methods used in this field. Most of the results show a sensitivity of over 80%.

Authors	Methods and algorithms	Sensitivity (%)	FPR	Data	Source
Kharbouch, Alaa et al. (2011)[15]	SVM	97	0.6	ECG + Scalp EEG CHB-MIT data-base	Link
Williamson et al. (2011)[21]	SVM	90.8	0.094	Freiburg EEG database	Link
Hunyadi et al. (2012)[16]	LS-SVM	100	0.11	Scalp EEG CHB-MIT data-base	Link
Hocepied et al. (2013)[22]	Self-regressive modeling extraction of parameters frequency	96	0.14	SEEG+ECOG	Link
Dhulekar et al.(2014)[17]	K-means	88.24	-	SEEG+MRI	Link
Fu et al. (2015)[23]	HMS analysis and SVM	98.72	-	Cranial EEG	Link
Rabbi et al. (2013)[24]	Correlation dimension and Neural networks	80	0.14	IEEG	Link
Fujiwara et al. (2019)[19]	Multivariate statistical process control (MSPC)	91	0.7	ECG, heart rate variability (HRV)	Link
Antoniades et al., (2016)[13]	CNN	87.51	-	Clinical	Link
Tian et al. (2019)[14]	CNN	96.66	-	CHB-MIT	Link

Table 2.1: Some state-of-the-art approaches to seizure detection and prediction.

2.4 Self-Supervised Learning

Self-supervised learning (SSL) is a subset of unsupervised learning in machine learning, where a model learns to identify and extract useful features from unlabeled data without the need for manual annotations or labels. Self-supervised learning has gained significant attention in recent years due to its success in various domains, such as computer vision, natural language processing, and speech recognition.

In self-supervised learning, the model learns from the inherent structure of the data by creating a pretext task or auxiliary task. The pretext task is a supervised learning problem created from the input data, but without using human-labeled annotations. This pretext task is used to generate a supervised signal, which is then used to train the model.

For example, in computer vision, a pretext task could be to predict the relative position of two randomly cropped patches from the same image. In natural language processing, a pretext task could be to predict the missing word in a sentence or to predict the next sentence in a document. By solving these pretext tasks, the model learns to extract relevant features that are useful for downstream tasks.

2.5 Metrics

In order to precisely measure the performance of seizure detection we employed both sensitivity and false positive rate (per 24 hours) which are important metrics for evaluating the performance of diagnostic tests, as they provide information about the accuracy and reliability of the test in correctly identifying individuals with and without the condition being tested for.

To calculate the accuracy, sensitivity and FPR we need values from the confusion matrix as seen in the next sections.

Confusion Matrix

A confusion matrix represents the prediction summary in matrix form. It shows how many prediction are correct and incorrect per class. It helps in understanding the classes that are being confused by model as other class.[25]

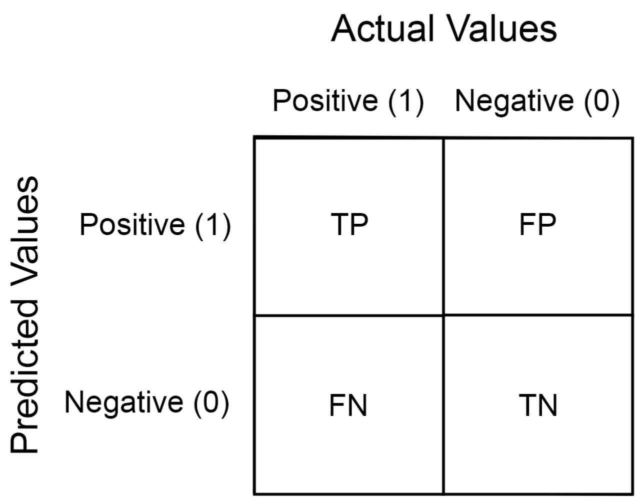

Figure 2.2: Confusion Matrix.

Accuracy

The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

accuracy = (true positives + true negatives) / (true positives + false positives + true negatives + false negatives) [26]

Sensitivity

In the context of a diagnostic test, sensitivity refers to the proportion of individuals with the condition being tested for (i.e., true positives) who are correctly identified as positive by the test. In other words, sensitivity measures the ability of the test to correctly identify individuals who actually have the condition. Mathematically, sensitivity is calculated as:
sensitivity = true positives / (true positives + false negatives)

False Positive Rate

Also known as type I error rate, false positive rate is the proportion of individuals without the condition being tested for (i.e., true negatives) who are incorrectly identified as positive by the test. In other words, false positive rate measures the rate of false alarms or incorrect positive identifications made by the test. Mathematically, false positive rate is calculated as:
false positive rate = false positives / (false positives + true negatives)

2.6 Conclusion

In this chapter, we have reviewed the state-of-the-art in epileptic seizure detection. We have also provided a literature review of existing approaches, including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM). We have also compared these approaches and discussed self-supervised learning and the metrics used to evaluate performance. This information provides a foundation for understanding the current state of research in this field and the potential for further advancements.

Chapter 3

Proposition of a new self-supervised model for epileptic seizure detection

3.1 Introduction

In this chapter, we will propose a new self-supervised model for epileptic seizure detection using EEG signals. We will describe the CHB-MIT Database and the implementation frameworks and tools used. We will also discuss the proposed methods, including SimCLR (Simple Clear), MoCo (momentum contrast), and BYOL (Bootstrap Your Own Latent). Additionally, we will outline our seizure prediction methodology and pretext tasks.

3.2 Description of the CHB-MIT Database

A collection of brain activity recordings from 22 patients (5 males, ages 3–22; and 17 females, ages 1.5–19) with uncontrollable seizures. These patients were monitored for several days after their anti-seizure medication was stopped to better understand their seizures and see if surgery could help them. In total, the start and end times of 182 seizures were recorded. Each subject has a set of files, labeled chb01, chb02, and so on. These files contain continuous data recorded from the subject. Due to hardware limitations, there are small gaps between the files where no data was recorded. Most of these gaps are 10 seconds or less, but some can be longer.

The privacy of the subjects is protected. Usually, .edf files have an hour of digitized EEG signals. But for case chb10, they're two hours long. For cases chb04, chb06, chb07, chb09, and chb23, they're four hours long. Sometimes, files with seizures recorded are shorter.

All the signals were recorded at a rate of 256 samples every second and with a high level of detail using 16-bit resolution. Most of the files have 23 EEG signals, but some have 24 or 26. In some records, other types of signals were also recorded. For example, an ECG signal was recorded in the last 36 files for case chb04 and a VNS signal was recorded in the last 18 files for case chb09.

In some cases, up to 5 "dummy" signals were added among the EEG signals to make the display easier to read. These dummy signals can be ignored.

The RECORDS file has a list of all 664 .edf files in this collection. The RECORDS-WITH-SEIZURES file lists the 129 files that have one or more seizures. In total, these records have 185 seizures. The start and end of each seizure are marked in the .seizure annotation files that come with each file listed in RECORDS-WITH-SEIZURES.

The chbnn-summary.txt files have information about the montage used for each recording and the time in seconds from the start of each .edf file to the start and end of each seizure in it.[27] [28]

Subject	Gender	Age	# of Seizures	Total Ictal Time (seconds)	Duration (hours)
chb01/chb21	F	11,13	11	641	73 : 22 : 57
chb02	M	11	3	172	35 : 15 : 59
chb03	F	14	7	402	38 : 00 : 06
chb04	M	22	4	378	156 : 03 : 54
chb05	F	7	5	558	39 : 00 : 10
chb06	F	1.5	10	153	66 : 44 : 06
chb07	F	14.5	3	325	67 : 03 : 08
chb08	M	3.5	5	919	20 : 00 : 23
chb09	F	10	4	276	67 : 52 : 18
chb10	M	3	7	447	34 : 01 : 24
chb11	F	12	3	806	20 : 41 : 47
chb12	F	2	27	989	33 : 00 : 00
chb13	F	3	12	535	26 : 00 : 00
chb14	F	9	8	169	40 : 00 : 36
chb15	M	16	20	1992	19 : 00 : 00
chb16	F	7	10	84	21 : 00 : 24
chb17	F	12	3	293	35 : 38 : 05
chb18	F	18	6	317	29 : 55 : 46
chb19	F	19	3	236	31 : 00 : 11
chb20	F	6	8	294	26 : 33 : 30
chb22	F	9	3	204	21 : 17 : 47
chb23	F	6	7	424	**979 : 56 : 07**
chb24	-	-	16	511	
TOTAL	-	-	**185**	**11125**	

Table 3.1: A table showing the recording of various information about the CHB-MIT dataset (patient , gender, age, number of seizures, duration of EEG recordings).[8]

There are 664 files total from 22 patients in the EEG dataset. Working with such enormous amounts of data would require significant computational resources, which could slow down research by requiring more time to process the data rather than modifying and fine-tuning the model for optimal results. As such, the proposed research only focuses on EEG files containing seizures. Which cuts down the total time from 979 hours to around 100 hours

3.3 Implementation frameworks and tools

PyTorch

PyTorch is an optimized tensor library for deep learning using GPUs and CPUs. It's an open-source machine learning framework based on the Torch library, used for applications such as computer vision and natural language processing. It was originally developed by Meta AI and is now part of the Linux Foundation umbrella. PyTorch provides a way to build neural networks simply and train them efficiently, which has led to its popularity in research and industry.[29]

Jupyter notebook

The notebook extends the console-based approach to interactive computing in a qualitatively new direction, providing a web-based application suitable for capturing the whole computation process: developing, documenting, and executing code, as well as communicating the results. The Jupyter notebook combines two components:

A web application: a browser-based tool for interactive authoring of documents which combine explanatory text, mathematics, computations and their rich media output.

Notebook documents: a representation of all content visible in the web application, including inputs and outputs of the computations, explanatory text, mathematics, images, and rich media representations of objects.[30]

Kaggle

Kaggle is an online community of data scientists and machine learning practitioners that is a subsidiary of Google LLC. Kaggle enables users to find and publish datasets, explore and build models in a web-based data science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges 1. Kaggle provides a platform for users to share their work and collaborate with others, making it a valuable resource for those interested in machine learning and data science.[31]

Sickit-learn

Scikit-learn is an open source machine learning library that supports supervised and unsupervised learning. It also provides various tools for model fitting, data preprocessing, model selection, model evaluation, and many other utilities.[?]

MNE

In order to read data from the raw recording EDF files we used a package called MNE, which is an open-source Python package for exploring, visualizing, and analyzing human neurophysiological data: MEG, EEG, sEEG, ECoG, NIRS.[32]

This allowed us to visualize and interpret the data and made it easier to use and process the data during developement.

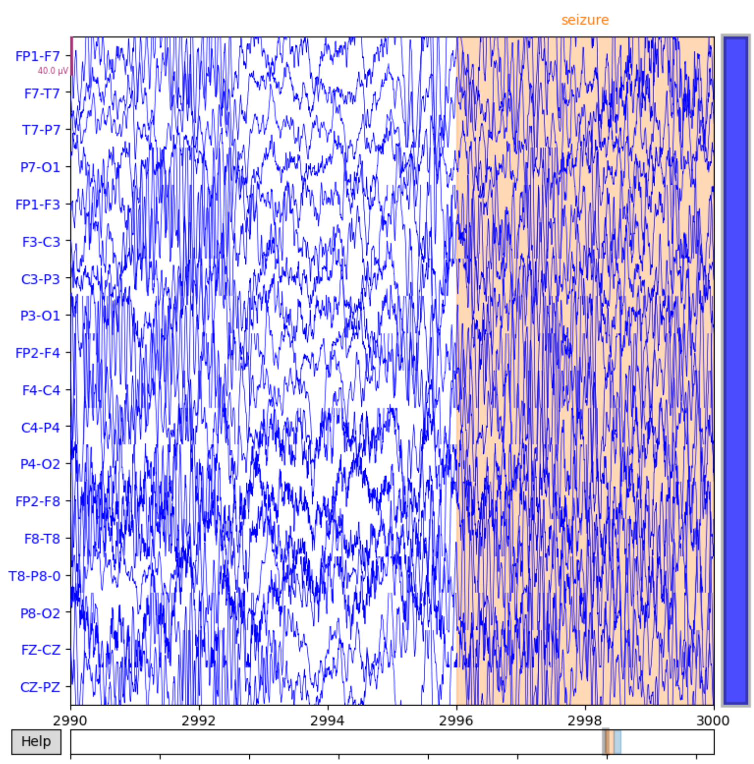

Figure 3.1: Visualizing the recording of a seizure using MNE.

3.4 Proposed methods

MoCo, SimCLR, and BYOL are a set of self-supervised learning methods that make use of unlabeled data.

MoCo and SimCLR employ contrastive learning by comparing two different views of the same data point while distinguishing it from other data points.

On the other hand, BYOL apply non-contrastive techniques to achieve remarkable performance without negative pairs by using Siamese networks with dual pairs along with an extra learnable predictor and stop-gradient operation.

3.4.1 SimCLR (Simple Clear)

SimCLR is a well-known computer vision technique that assists computers in identifying images. Specifically, SimCLR uses multiple variations of the same image to train the computer in recognizing identical patterns by utilizing contrastive loss formula.

SimCLR is a powerful module that does wonders when it comes to augmenting data. The SimCLR algorithm creates two interrelated versions, known as positive pairs, by modifying the original data in various ways. This manipulation involves three simple techniques - resizing and cropping an image, changing colors effectively and adding blur, which altogether result in getting splendid outcomes. Through extensive research done by leading experts, they discovered that the most significant factors for achieving accurate results are changes made through cropping and color modification.

The framework developed by the authors utilizes a neural network-based encoder f(x) to extract representation vectors from augmented data examples. This approach offers flexibility in selecting the network architecture, and ResNet is chosen due to its simplicity $h_i = f(X_i) = ResNet(X_i)$ where $h_i \epsilon R^d$ is the output after the average pooling layer.

A small neural network projection head g(·) that maps representations to the space where contrastive loss is applied. Authors use a MLP with one hidden layer to obtain

$z_i = g(h_i) = W^{(}2))\partial(W^{(}1))h_i)$ where ∂ is a ReLU non-linearity. The authors find it beneficial to define the contrastive loss on z_i's rather than h_i's.

A contrastive loss function defined for a contrastive prediction task. Given a set X_k including a positive pair of examples Xi and Xj , the contrastive prediction task aims to identify Xj in Xk k $\neq$ i for a given Xi

A minibatch of N examples is randomly sampled and the contrastive prediction task is defined on pairs of augmented examples derived from the minibatch, resulting in 2N data points. Negative examples are not sampled explicitly. Instead, given a positive pair, the other 2(N-1) augmented examples within a minibatch are treated as negative examples. [3]

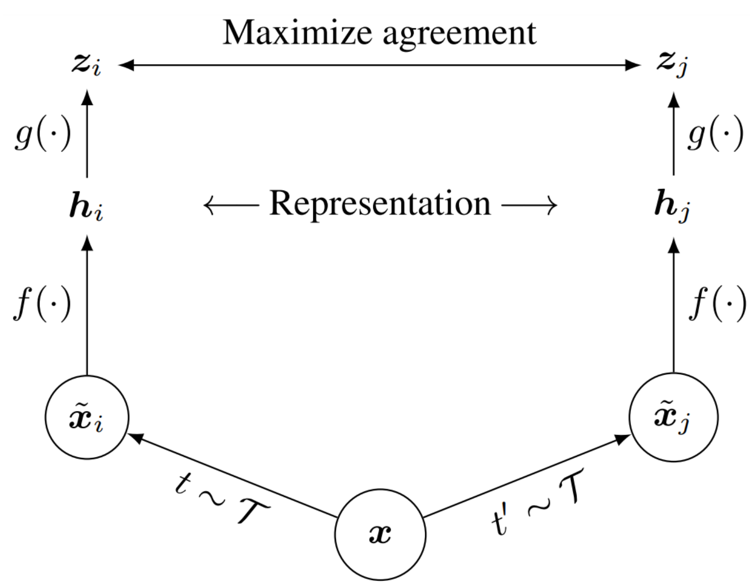

Figure 3.2: A simple framework for contrastive learning of visual representations. [3]

3.4.2 MoCo (momentum contrast)

First, the model uses two encoders: a query (online) encoder and a key (target) encoder. The query encoder is updated during each training iteration, while the key encoder is a slower-moving copy of the query encoder that is used to compute the negative samples for contrastive learning.

Next, the MoCo model uses a queue structure to store a large number of negative samples, which are used to compute the contrastive loss. This helps the model to learn more diverse and representative representations.

The MoCo model also employs a momentum updating mechanism for the key encoder, which helps to stabilize the training process and avoid overfitting.

Like the SimCLR model, the MoCo model uses contrastive loss and data augmentation functions to encourage the model to learn invariant and discriminative representations.

Finally, the MoCo model often includes fully connected layers at the end of the encoder network to generate an embedding representation for downstream tasks.[4]

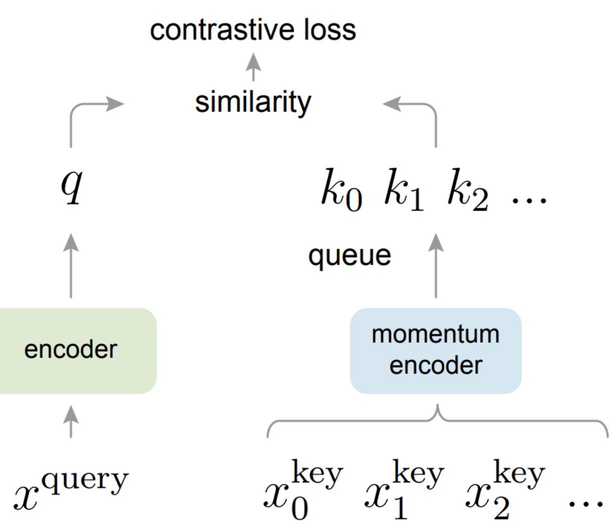

Figure 3.3: Momentum Contrast (MoCo) trains a visual representation encoder by matching an encoded query q to a dictionary of encoded keys using a contrastive loss. [4]

3.4.3 BYOL (Bootstrap Your Own Latent)

The BYOL (Bootstrap Your Own Latent) model architecture is similar to the SimCLR and MoCo models in that it also consists of several key components.

First, the BYOL model uses a neural network encoder function to encode the input data. Next, the model employs a "predictor" network with additional fully connected layers to predict the latent code of the encoded image, which is compared to the target latent code to compute the contrastive loss.

Unlike SimCLR and MoCo, BYOL does not use negative pairs in calculating the contrastive loss, instead, it only compares the prediction to a "target" representation that is generated by the same neural network during the training process. This makes the training process more computationally efficient.

Another key feature of the BYOL model is the use of "online" and "target" networks, where the online network parameterizes the encoder and predictor network, while the target network is a slower-moving copy of the online network that is updated at a slower rate via an exponential moving average.

Like SimCLR and MoCo, BYOL also uses data augmentation functions to enhance the model's ability to learn robust and discriminative representations.

Finally, the BYOL model includes a projection head, similar to SimCLR.[5]

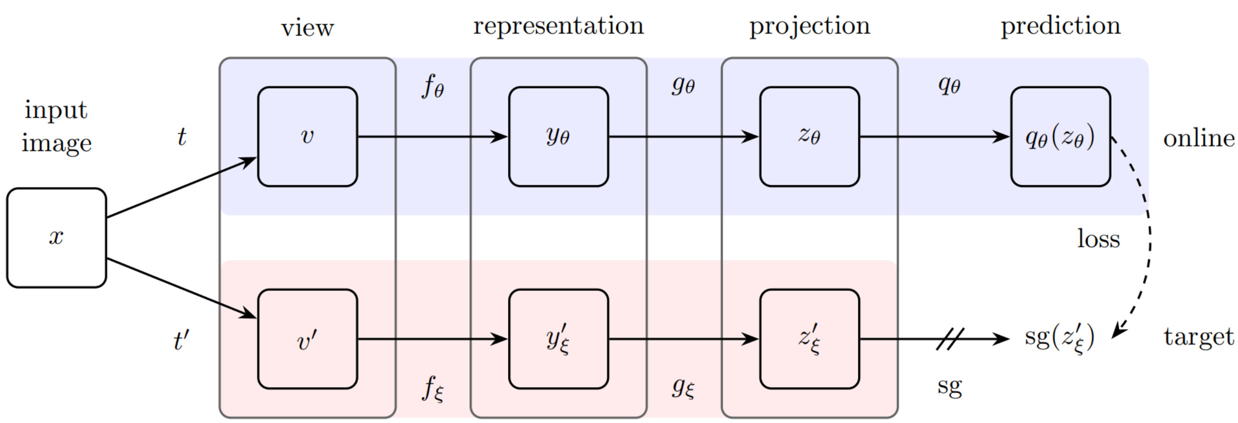

Figure 3.4: BYOL's architecture. [5]

3.5 Seizure Prediction Methodology

Due to the large size of data in the CHB-MIT dataset, as mentioned above, it would be impractical and computationally expensive to process all of it, that's why in this work we only focused on recordings containing epileptic seizures.

Each recording is stored in an ".edf" file, which are divided into three separate folders prior to processing:

80% of these files are put in the pretext folder, followed by 15% in the train folder and the final 5% in the test folder.

Then, we segmented each recording into 30 second segments and labeled each segment "1" or "0" depending on whether the segment contained a seizure or not. The labels are only used in the testing phase to evaluate the performance of the models.

These segments are then stored as pickle (.pkl) binary files which contain the data of the 30 seconds "X" and the label "Y".

Each of the 30 second segments contains 18 channels of data which would make the shape of each segment 18x7680.

When loading the data to train our model these segments which are stored in binary files are loaded and converted back to a dictionary with 2 items "X" and "Y" which contain the data and label respectively.

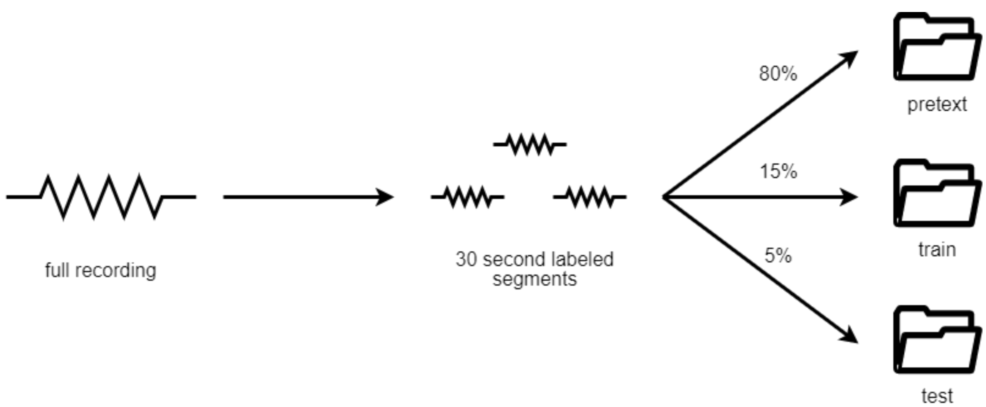

Figure 3.5: Processing and distributing data.

3.6 Pretext tasks

Pretext tasks are extra tasks that aid in the training of self-supervised models. Pretext tasks are used to turn an unsupervised learning problem into a supervised one. Designing a pretext task that is straightforward to complete with the available data and forces the model to learn useful features that it can apply to other tasks is the goal.

Predicting how an image will rotate, for instance, could be a pretext task in computer vision. The model is trained to forecast the angle at which a randomly rotated image will appear. The data itself makes it simple to complete this task, but the model must also learn useful features like edges and corners that can be applied to other tasks like object detection or image classification.

Pretext tasks are used as support tasks for self-supervised model training. They require the model to learn useful features that can be used for other tasks and are used to turn an unsupervised learning problem into a supervised learning problem.

In signal processing, a pretext transformation could be to **add noise** to a signal. The model is trained to predict the original signal from the noisy signal. This task is easy to solve using the data itself, but it also requires the model to learn useful features such as edges and corners that can be used for other tasks such as speech recognition or audio classification.

Other examples of pretext transformations we used are **removing noise** from a signal, **cropping a signal**, and **inverting channels**.[33] These transformations are used to create a supervised learning problem from an unsupervised one and require the model to learn useful features that can be used for other tasks.

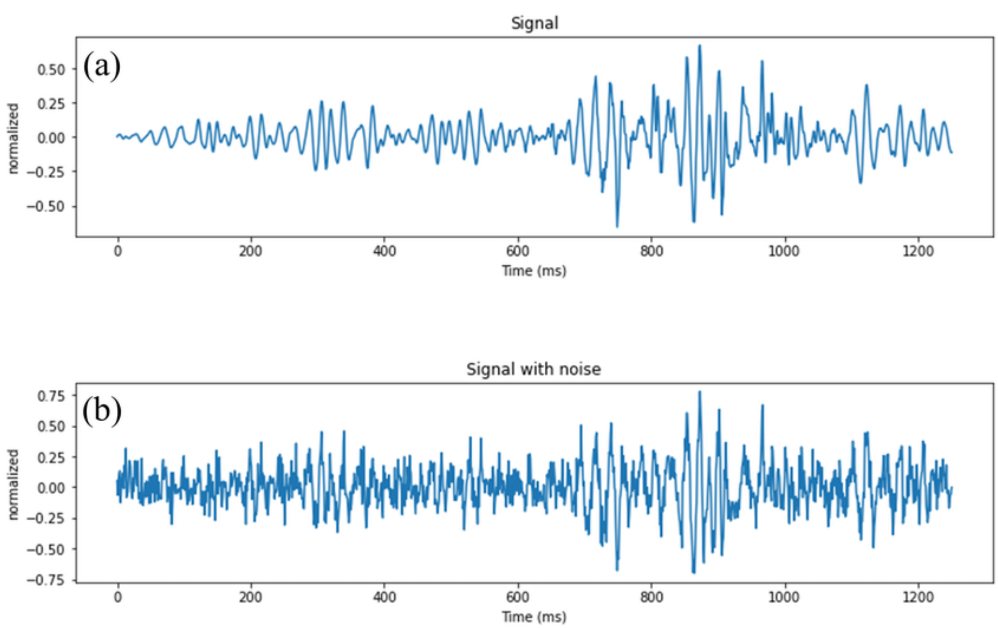

Figure 3.6: Adding noise to a signal.[6]

In our project we apply these transformations randomly, so multiple tasks are solved at the same time which is called **multi-task** learning. This helps save time by allowing us to complete multiple tasks concurrently, and improves the learning efficiency and prediction accuracy of our model.

3.7 Proposed Solution

In order to classify an EEG segment as containing an epileptic seizure or not, we first used the segmented data with the pretext task to extract important features from the data. We use the same pretext task with all our self-supervised loss functions that way we have a controlled environment we can use to compare our results. When using contrastive learning methods we train two encoders, named the query and key encoder, we use both the encoders to get a vector representation from the data and help us learn that the query is similar to its key data point while being dissimilar to other key data points. In our implementation we have also used a scheduler and an optimizer to adjust the learning rate and the weights of the model, and to minimize the loss. The encoders are trained for a determined number of epochs and the model is evaluated after each of these epochs. We have also used backpropagation to update the weights based on the loss.

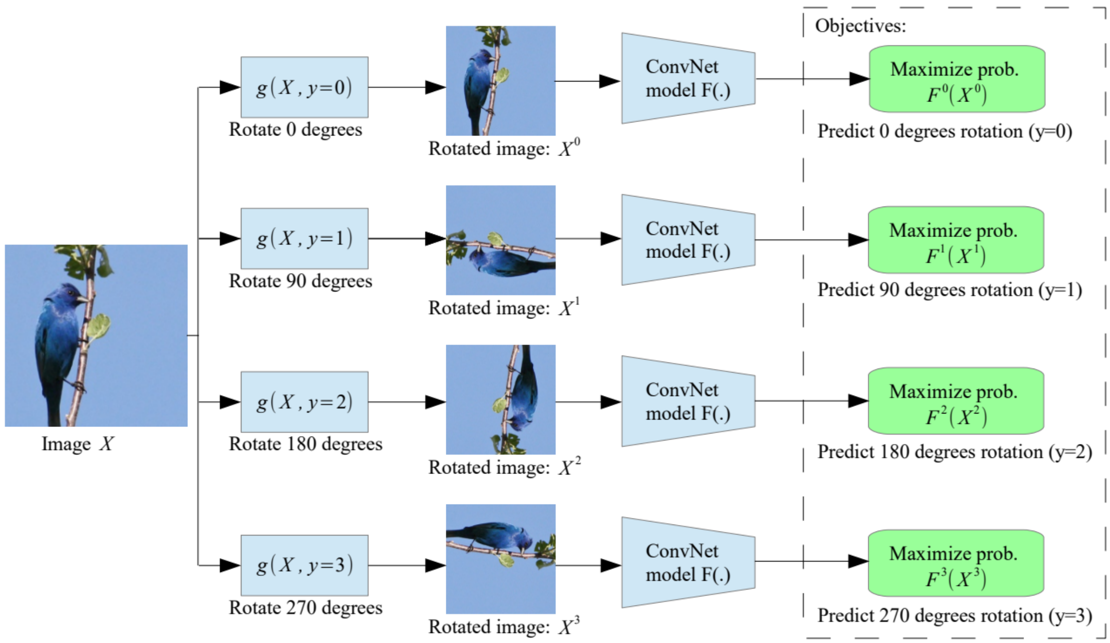

Figure 3.7: Illustration of a self-supervised task for semantic feature learning.[7]

Similar to the figure above transformations are applied but in our case on signal data instead of images. Finally, using the evaluation function mentioned above gives us the confusion matrix which we can use to calculate the accuracy, sensitivity and the false positive rate of the model.

3.8 Conclusion

In this chapter, we have proposed a new self-supervised model for epileptic seizure detection using EEG signals. We have described the CHB-MIT Database and the implementation frameworks and tools used. We have also discussed the proposed methods, including SimCLR (Simple Clear), MoCo (momentum contrast), and BYOL (Bootstrap Your Own Latent). Additionally, we have outlined our seizure prediction methodology and pretext tasks. This information provides a detailed overview of our proposed solution for efficient deep self-supervised learning for epileptic seizure detection using EEG signals.

Chapter 4

Analysis of the obtained results

4.1 Introduction

In this chapter, we will discuss the evaluation of the self-supervised learning models that we trained for epileptic seizure detection using EEG signals. We will describe our approach to evaluating the performance of each model, including the use of a confusion matrix to calculate accuracy, sensitivity, and false positive rate (FPR) per 24 hours. We will also present graphical representations of the results and discuss our initial approach and revised solution.

4.2 Evaluating the models

After training the self-supervised learning models, we had to evaluate the performance of each model and compare the results. To conduct these evaluations we defined a function that would evaluate each epoch and give us the confusion matrix, using the confusion matrix we calculated the accuracy, sensitivity and false positive rate (per 24 hours), we then used a plot to graphically represent the results.

In the context of evaluating a self-supervised model, we used logistic regression to assess the performance of the model by comparing its predictions to the true labels of the data.

For example, if the self-supervised model generates representations for a dataset, these representations are used as input features for a logistic regression model. The logistic regression model is then trained to predict the binary labels of the data using these features. The performance of the logistic regression model, as measured by metrics such as accuracy, sensitivity and false positive rate, would provide an indication of how well the self-supervised model is able to generate useful representations for the task at hand.

4.2.1 Initial approach

On our initial attempt we used the raw data as is, the unbalanced data affected our models by having a very small amount of positive values opposed to a large set of negatives, this made it hard to attempt to detect the seizures without raising the FPR.

In the first iteration of the experiment we used 30 epochs to train the models with data which was unbalanced with a ratio of $1:500$ positive to negative segments.

SimCLR

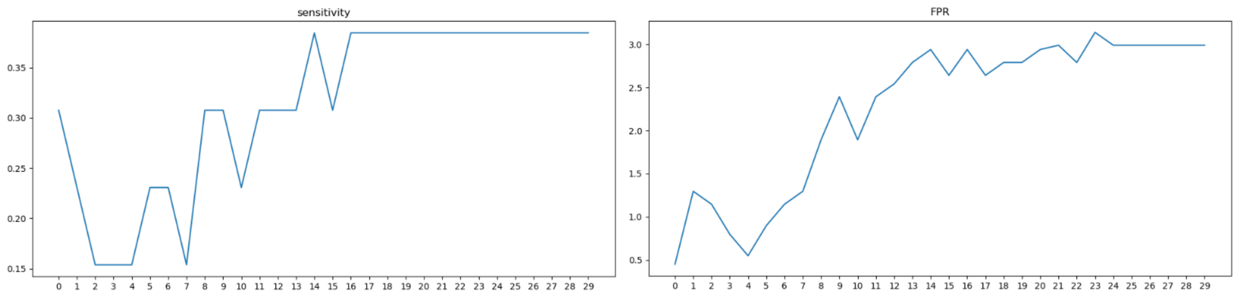

Figure 4.1: Sensitivity and FPR graphs for our SimCLR model.

BYOL

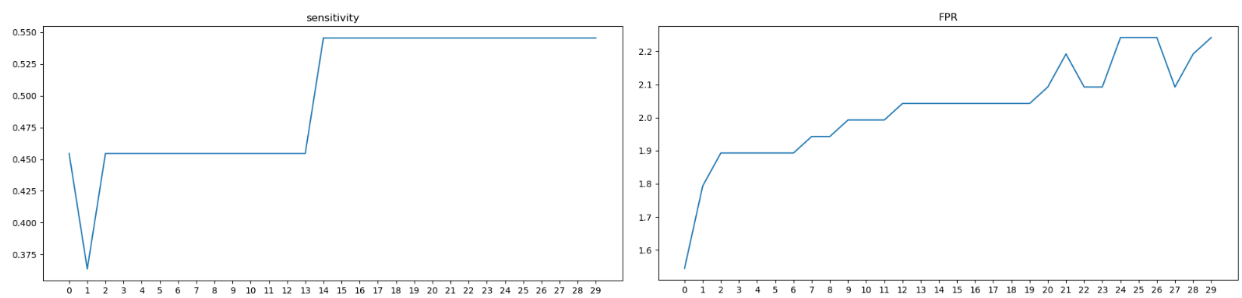

Figure 4.2: Sensitivity and FPR graphs for our BYOL model.

MoCo

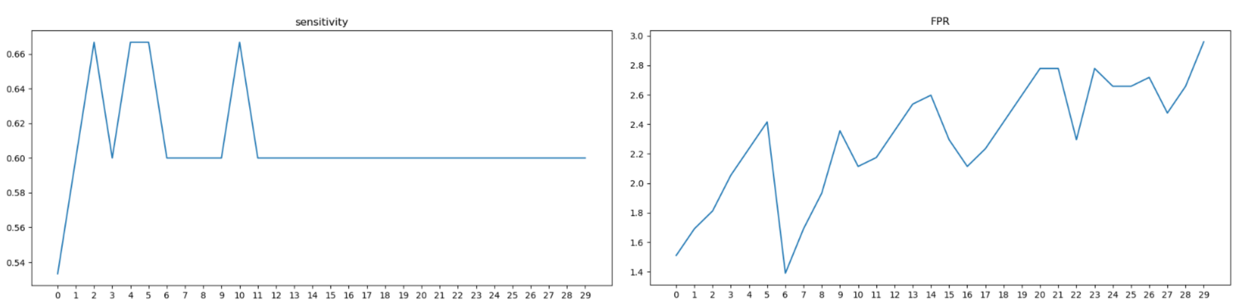

Figure 4.3: Sensitivity and FPR graphs for our MoCo model.

4.2.2 Revised Solution

After reviewing the results from the initial attempt we tried balancing the data by removing some of the negative labeled segments, this helped balance the ratio of positive and negative segments, thus making it easier to detect epileptic seizures without increasing the FPR.

For the second iteration we used 50 epochs, and removed 50% of the negative segments which gave us a new ratio of 1 : 250 positive to negative segments.

SimCLR

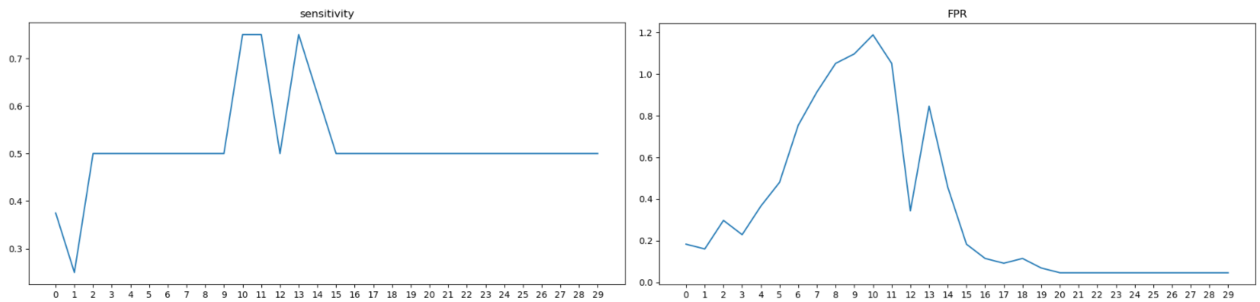

Figure 4.4: Sensitivity and FPR graphs for our SimCLR model.

BYOL

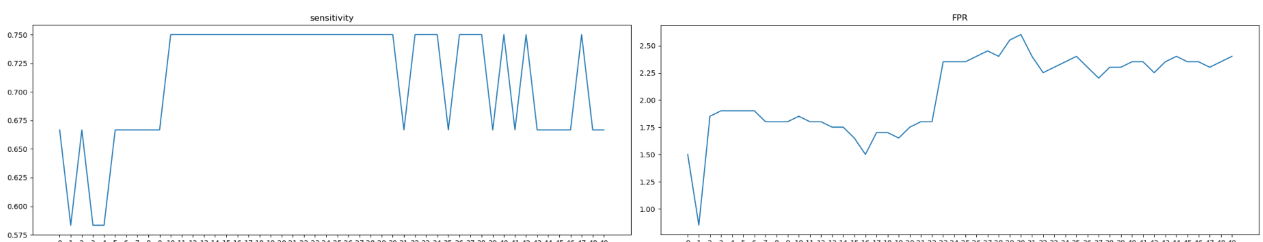

Figure 4.5: Sensitivity and FPR graphs for our BYOL model.

MoCo

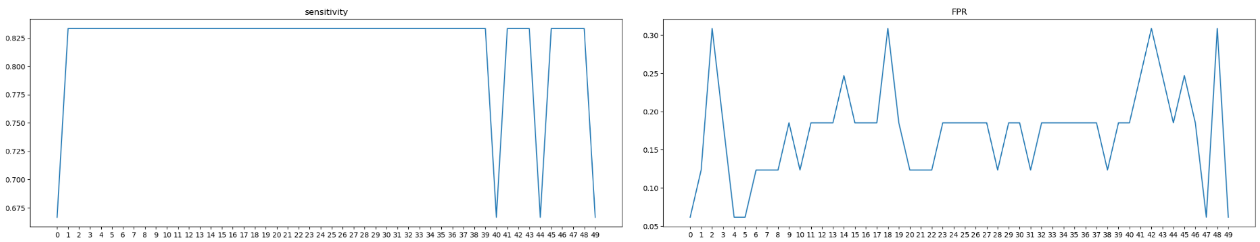

Figure 4.6: Sensitivity and FPR graphs for our MoCo model.

Summary

After looking at the plots we notice that at first the FPR starts at 0 but the sensitivity also starts at a low value, this can be explained by the model not predicting any epileptic seizures, and since it does not output any positive values there are no false positives, and as we train the model we see it attempt to predict more and more positive values, thus increasing both the FPR and the sensitivity.

After revising our models and retraining them we got a much better outcome especially with the MoCo model which has a noticeably better result than our other models.

Model	Accuracy	Sensitivity	FPR (per 24h)
MoCo 1	82.30%	66.66%	2.11
BYOL 1	80.89%	54.54%	2.09
SimCLR 1	74.08%	38.46%	2.79
MoCo 2	**99.08%**	**83.33%**	**0.06**
BYOL 2	84.14%	75%	1.80
SimCLR 2	86.63%	75%	1.05

Table 4.1: Summary of the results obtained using our Self-Supervised models

As we can note from the results the best scores were obtained using the revised MoCo model with an accuracy of 99.08%, sensitivity of 83.33% and a FPR of 0.06.

4.3 Discussion

Due to the unbalanced nature of the data, since an epileptic seizure occurs for a brief period of time in each recording as most last for 30 seconds to two minutes, this makes it particularly challenging to train a model to recognize when a seizure occurs. The full duration of the data is 980 hours, only around 3 hours of that are ictal data, this does not mean the quality of data is bad, the issue with ML models in classification tasks is that by having an imbalanced dataset, this means there is more data of one class than there is of the other class, which when training can make the model become biased towards one class, which for this case can be particularly shown in the sensitivity metric. We have only used recordings containing epileptic seizure in an attempt to remedy the balance problem, this cuts down the duration of data down to approximately 80 hours.

In our revision of the models we tried to balance the data even more by randomly selecting and removing negative labeled segments, this helped us achieve better scores.

Another issue we ran into while working on this project is that because of the big amount of data we had to work with, doing segmenting and pretext tasks often caused memory issues, this would require us to restart the whole process. In order to avoid resetting the execution of code we implemented a checkpoint system which would save the model after each epoch, this helped us continue where we left off and even run our evaluation code after each step.

4.4 Conclusion

In this chapter, we have evaluated the performance of our self-supervised learning models for epileptic seizure detection using EEG signals. We have described our approach to evaluating the models, including the use of a confusion matrix to calculate accuracy, sensitivity, and FPR per 24 hours. We have also presented graphical representations of the results and discussed our initial approach and revised solution. Our results show that the revised MoCo model performed the best, with an accuracy of 99.08%, sensitivity of 83.33%, and a FPR of 0.06. These results demonstrate the potential of self-supervised learning for epileptic seizure detection using EEG signals.

General Conclusion

The goal of this thesis was to implement self-supervised models to detect epileptic seizures, and see how they perform against previously published papers.

To achieve this we experimented with a variety of self-supervised learning methods on the CHB-MIT EEG database.

As mentioned in the last chapter, the results of our self-supervised models are competitive with other approaches, and that's without even using the labeled data, but instead using only the raw input from the EEG recordings. This proves that self-supervised learning can not only achieve promising results, it can also do so without the need for labeling and annotations.

This promising result leads us to believe that there are endless possibilities to use self-supervised learning, especially with data that's particularly difficult to label. We could also fine-tune and improve our models so they can be used in real applications of epileptic seizure detection. Which can help advance our understanding of epilepsy and find better solutions in the future.

Bibliography

[1] Benito Núñez and Iván Manuel. Eeg artifact detection. 2011.

[2] Chanshin Park, Daniel K. Tettey, and Han-Shin Jo. Artificial neural network modeling for path loss prediction in urban environments. *CoRR*, abs/1904.02383, 2019.

[3] Chen et al. A simple framework for contrastive learning of visual representations. 2020.

[4] He et al. Momentum contrast for unsupervised visual representation learning. 2019.

[5] Grill et al. Bootstrap your own latent - a new approach to self-supervised learning. In *Advances in Neural Information Processing Systems 33*, 2020.

[6] Ahmad Ahmad and Takeshi Tsuji. Traffic monitoring system based on deep learning and seismometer data. *Applied Sciences*, 11:4590, 05 2021.

[7] Nikos Komodakis Spyros Gidaris, Praveer Singh. Unsupervised representation learning by predicting image rotations. 2018.

[8] Enrique Posada Lozano. Analysis and classification of raw electroencephalograms for epileptic seizure prediction using long-short term memory networks. Business Solution Development Capstone Project, Ingeniería en Sistemas Computacionales, 2021. Advisor: Dr. José Antonio Cantoral Ceballos.

[9] World Health Organization. Epilepsy Fact Sheet. `https://www.who.int/news-room/fact-sheets/detail/epilepsy`. [Online; accessed March 28, 2023].

[10] Ronald Tetzlaff and Vanessa Senger. The seizure prediction problem in epilepsy: Cellular nonlinear networks. *IEEE Circuits and Systems Magazine*, 12(4):8–20, 2012.

[11] EBME. Introduction to eeg. *EBME*, 2022.

[12] HADDOUCHE Bilal and MEGAIZ Nassima Jamila. Classification de la crise épileptique par réseau de neurones (lvq) et acp. 2015/2016.

[13] Andreas Antoniades, Loukianos Spyrou, Clive Cheong Took, and Saeid Sanei. Deep learning for epileptic intracranial eeg data. pages 1–6, 09 2016.

[14] Tian et al. Deep multi-view feature learning for eeg-based epileptic seizure detection. 2019.

[15] Kharbouch et al. An algorithm for seizure onset detection using intracranial eeg. 2012.

[16] Hunyadi et al. Incorporating structural information from the multichannel eeg improves patient-specific seizure detection. *Journal of Process Control*, 22(9):1738–1746, 2012.

[17] Dhulekar et al. Seizure prediction by graph mining, transfer learning, and transformation learning. 2014.

[18] Thanaraj et al. Implementation of deep neural networks to classify eeg signals using gramian angular summation field for epilepsy diagnosis. 2020.

[19] Koichi Fujiwara, Miho Miyajima, Toshitaka Yamakawa, Erika Abe, Yoko Suzuki, Yuriko Sawada, Manabu Kano, Taketoshi Maehara, Katsuya Ohta, Taeko Sasai-Sakuma, Tetsuo Sasano, Masato Matsuura, and Eisuke Matsushima. Epileptic seizure prediction based on multivariate statistical process control of heart rate variability features. *IEEE Transactions on Biomedical Engineering*, 63(6):1321–1332, 2016.

[20] Nasser Kehtarnavaz. Chapter 7 - frequency domain processing. In Nasser Kehtarnavaz, editor, *Digital Signal Processing System Design (Second Edition)*, pages 175–196. Academic Press, Burlington, second edition edition, 2008.

[21] James R. Williamson, Daniel W. Bliss, and David W. Browne. Epileptic seizure prediction using the spatiotemporal correlation structure of intracranial eeg. In *2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 665–668, 2011.

[22] Gatien Hocepied, Benjamin Legros, Patrick Van Bogaert, Francis Grenez, and Antoine Nonclercq. Early detection of epileptic seizures based on parameter identification of neural mass model. *Computers in biology and medicine*, 43:1773–82, 11 2013.

[23] Kai Fu, Jianfeng Qu, Yi Chai, and Tao Zou. Hilbert marginal spectrum analysis for automatic seizure detection in eeg signals. *Biomedical Signal Processing and Control*, 18:179–185, 2015.

[24] Ahmed F. Rabbi, Leila Azinfar, and Reza Fazel-Rezai. Seizure prediction using adaptive neuro-fuzzy inference system. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 2100–2103, 2013.

[25] Ashish Tiwari. Chapter 2 - supervised learning: From theory to applications. In Rajiv Pandey, Sunil Kumar Khatri, Neeraj kumar Singh, and Parul Verma, editors, *Artificial Intelligence and Machine Learning for EDGE Computing*, pages 23–32. Academic Press, 2022.

[26] A. Baratloo, M. Hosseini, A. Negida, and G. El Ashal. Part 1: Simple definition and calculation of accuracy, sensitivity and specificity. *Emergency (Tehran, Iran)*, 3(2):48–49, 2015.

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

[28] A. Goldberger, L. Amaral, L. Glass, J. Hausdorff, P.C. Ivanov, R. Mark, J.E. Mietus, G.B. Moody, C.K. Peng, and H.E. Stanley. Physiobank, physiotoolkit, and physionet:

Components of a new research resource for complex physiologic signals. *Circulation*, 101(23):e215–e220, 2000.

[29] Pytorch. https://pytorch.org. [Online; accessed March 30, 2023].

[30] Project jupyter. https://jupyter.org. [Online; accessed March 30, 2023].

[31] Kaggle. https://www.kaggle.com. [Online; accessed March 30, 2023].

[32] Alexandre Gramfort, Martin Luessi, Eric Larson, Denis A. Engemann, Daniel Strohmeier, Christian Brodbeck, Roman Goj, Mainak Jas, Teon Brooks, Lauri Parkkonen, and Matti S. Hämäläinen. MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7(267):1–13, 2013.

[33] Chaoqi Yang, Danica Xiao, M. Brandon Westover, and Jimeng Sun. Self-supervised eeg representation learning for automatic sleep staging, 2023.

[34] AHMED KHODJA Imane and DERMOUCHE Rokia. Détection/classification de crises d'épilepsie chez les nouveaux nés en utilisant des signaux eeg. 2017/2018.

[35] LAIFA Haroune and CHIKOUCHE HAMINA Abdelhaq. Étude de signaux eeg quantifie. 2021/2022.

[36] Y. Filali Zegzouti M. Bouachrine H. Zaki1, .M. Benlyas. Méthodologie générale d'une étude acp : Généralités, concepts et exemples. 2016.

[37] Scikit-learn. https://scikit-learn.org. [Online; accessed March 30, 2023].