UNIVERSIDADE
BEIRA INTERIOR

Epileptic seizure prediction using machine learning techniques

Versão Final após defesa

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Disertação para obtenção do grau de Mestre em Bioengenharia.
Bioengenharia
(2º Ciclo de Estudos)

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Julho de 2023.

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Dedication

Dedico esta tese à minha família, que sempre esteve pronta para me ajudar.

” Não deves deixar ninguém definir
os teus limites por causa de onde vens.
O teu único limite é a tua alma.”

-Ratatouille

Acknowledgements

Ao terminar este meu percurso, quero deixar aqui os meus sinceros agradecimentos a todos aqueles que me apoiaram ao longo destes anos. Não só na realização desta dissertação, mas ao longo deste percurso.
Quero agradecer, em primeiro lugar, ao meu orientador e coorientadores, Professor Doutor Nuno Garcia, Faculdade de Ciências da Universidade de Lisboa, à Doutora Virginie Felizardo, Instituto de Telecomunicações, e ao Doutor Mehran Pourvahab, Universidade da Beira interior. Agradeço todo o apoio, disponibilidade e valiosas contribuições feitas ao longo destes anos.
Quero também expressar a minha gratidão aos meus amigos por todo o apoio, noites de estudo e momentos compartilhados ao longo destes 5 anos. Sem eles, esses 5 anos teriam sido um pouco mais difíceis.
Por fim, mas não menos importante, quero agradecer à minha família pelo apoio, compreensão e palavras de incentivo quando mais precisei. Sem eles, eu não estaria aqui.

Resumo

Crises epiléticas afetam cerca de 1% da população mundial, tornando-a assim a quarta doença neurológica mais comum. Esta é considerada uma doença caracterizada pela atividade anormal do cérebro.
Parte da população que sofre desta condição não consegue recorrer a qualquer tratamento, pois este não apresenta qualquer efeito benéfico no paciente.
Uma das principais preocupações associadas com este problema são os danos causados pelas convulsões imprevisíveis. Estes danos não afetam somente o próprio paciente, como também as pessoas que o rodeiam. Com esta situação em mente, o objetivo desta dissertação consiste em, através de métodos de *Machine Learning*, criar um algoritmo capaz de prever as crises epiléticas antes da sua ocorrência.
Para proceder à previsão destas convulsões, será utilizado o eletroencefalograma (EEG), uma vez que é o método mais usado para o diagnóstico de epilepsia. Serão utilizados apenas 8 dos 23 canais disponíveis, devido à sua localização.
Quando ocorre uma crise, além das alterações visíveis no sinal EEG, não só no momento da crise, são também notáveis alterações antes e após a convulsão. A estas fases a literatura nomeou:

- Pre-ictal: momento anterior à crise epilética;
- Ictal: momento da convulsão;
- Pós-ictal: momento posterior à crise;
- Interictal: espaço de tempo entre convulsões.

O objetivo do algoritmo preditivo será fazer a classificação das diferentes classes e o estudo de diferentes problemas de classificação, através do uso de técnicas de *machine learning*, mais precisamente um classificador. Ao realizar esta classificação, quando forem detetados indícios de que uma possível crise epilética irá ocorrer, o paciente será então avisado, podendo assim preparar-se para esta.

Palavras-chave

EEG, Previsão de Crises, Epilepsia, *Machine Learning*

Resumo alargado

0.1 Introdução

Nesta secção, é apresentado um resumo detalhado do tema abordado ao longo desta dissertação intitulada "Previsão de crises epiléticas através de métodos de *machine learning*"(Epileptic seizure prediction using machine learning techniques).
Este resumo alargado está organizado da seguinte forma: primeiro, é feita uma introdução ao tema da tese, onde são apresentados os objectivos desta dissertação. De seguida, é feita uma revisão geral dos diferentes tópicos relacionados com a previsão de crises epilépticas e o estado da arte. É também efectuada uma revisão sistemática da literatura de forma a verificar quais as técnicas mais utilizadas na predição de crises epilépticas. Posteriormente, é apresentada a abordagem proposta, onde são introduzidos os resultados obtidos, seguidos de uma discussão dos mesmos. Por fim, apresenta-se a conclusão e possíveis trabalhos futuros.

0.2 Objetivos e contexto

A epilepsia é uma doença neurológica que afeta aproximadamente 1% da população mundial, sendo mais comum em pessoas de idade pediátrica. Uma grande parte dos indivíduos que sofrem desta doença é tratada com medicação adequada ou através de cirurgia. No entanto, cerca de 30% dos pacientes não respondem a nenhum tipo de tratamento.
A imprevisibilidade das convulsões pode levar a quedas e lesões graves, especialmente em crianças na sua vida diária, devido à natureza ativa das suas vidas. A possibilidade de prever as convulsões é uma solução que permite às pessoas prepararem-se para uma convulsão, afastando-se de uma possível situação de perigo para si e para as pessoas que as rodeiam. Tendo isto em consideração, o principal objetivo desta dissertação é prever crises epilépticas através de métodos de
Ao criar a abordagem proposta nesta dissertação, foram consideradas as seguintes questões:

- Se é possível prever convulsões através do uso de apenas canais periféricos de EEG? (relevante para um contexto do dia a dia).
- Quais os canais e características do sinal que mais contribuem para a previsão?
- Qual é a janela temporal óptima para definir o período pré-ictal, 10 minutos ou 20 minutos?

Tendo isto em consideração, os objetivos desta dissertação podem ser resumidos em quatro pontos:

- Realizar uma análise dos desafios existentes no atual estado da arte para a previsão de crises epiléticas;

- Investigar e avaliar a viabilidade de utilizar apenas canais periféricos na abordagem proposta;
- Identificar os canais e características que mais contribuem para a previsão.
- Avaliar e comparar o desempenho utilizando diferentes períodos pre-ictais.

Com base nestes quatro objectivos, esta dissertação irá contribuir através da realização de uma revisão sistemática das abordagens existentes para a predição da epilepsia. Será desenvolvida uma abordagem que utiliza exclusivamente canais periféricos. Além disso, será realizado um estudo sobre a importância dos canais e das características na predição individual, bem como uma comparação entre dois períodos pré-ictais, 10 e 20 minutos, a fim de avaliar o desempenho da abordagem proposta.

0.3 Estado da Arte

De forma a compreender o tema abordado nesta tese, no capítulo 2 é realizada uma breve introdução aos diferentes tópicos relacionados com a epilepsia e os algoritmos preditivos, tais como o cérebro humano, a eletroencefalografia, a doença da epilepsia e a abordagem convencional para a predição de eventos epilépticos. É efectuado um estudo sobre o processo geralmente utilizado pela literatura para a previsão de eventos epilépticos, que consiste em três passos:

1. Pré-processamento: Nesta etapa, os dados do sinal são pré-processados para remover artefatos, filtrar sinais indesejados e preparar os dados para as etapas seguintes.
2. Extração e seleção de características: Nesta fase, as características relevantes são extraídas dos dados pré-processados e, em seguida, selecionadas as mais importantes para a previsão dos eventos epilépticos.
3. Classificação: Nesta fase, um modelo de classificação é treinado usando as características selecionadas, com o objetivo de classificar os dados em eventos epilépticos e não epilépticos.

Posteriormente, também são abordadas as diferentes técnicas de avaliação do desempenho do algoritmo.
Com o objetivo de compreender quais os métodos mais utilizados na previsão de crises, quais as melhores combinações de características, os melhores métodos de classificação e as técnicas mais utilizadas para avaliar o desempenho, é efectuada uma revisão sistemática. Esta revisão sistemática abrange um período de 10 anos (2012-2022) e resultou num total de 621 artigos únicos. Após a filtragem destes artigos através da leitura dos resumos e dos textos completos, foi analisado um total de 81 artigos. A partir desses artigos, foi definida a abordagem aplicada para a classificação do sinal.

0.4 Abordagem à Previsão de crises epilépticas

A abordagem proposta é aplicada em um conjunto de dados de livre acesso do repositório Physionet. Este conjunto de dados é constituído por 23 pacientes pediátricos, de ambos os géneros, com idades compreendidas entre 1,5 e 22 anos. Todos os pacientes foram incluídos no estudo. A aquisição dos dados foi efetuada com uma taxa de amostragem de 256Hz e uma resolução de 16 bits.
O sinal de EEG foi adquirido utilizando 23 elétrodos do escalpe, no entanto, nesta dissertação, apenas 8 elétrodos periféricos foram considerados para análise.
Para filtrar e segmentar o sinal, são aplicadas técnicas de pré-processamento. De seguida, foram selecionadas 6 características do domínio do tempo, espaço e frequência com base na revisão sistemática realizada no capítulo 2. Essas características foram extraídas de um intervalo pré-ictal de 20 minutos.
Por fim, foram efetuados testes para determinar qual o classificador que, juntamente com as características selecionadas, obtém os melhores resultados. Neste caso, o classificador utilizado foi o Bagging Tree.

0.5 Resultados e Discussão

Este capítulo descreve os resultados da aplicação do processo descrito no capítulo 3.
Em primeiro lugar, são apresentados os resultados para a população em geral e para cada doente, para cada um dos cenários propostos (0-10 minutos, 10-20 minutos e 0-20 minutos). Estes resultados mostram que a aplicação do processo utilizando apenas canais periféricos é viável, especialmente quando se utiliza o método de validação *Hold-out 75/25*.
Para além de confirmar a viabilidade da utilização apenas dos canais periféricos, foi também realizado um estudo para determinar a melhor janela temporal para a classificação dos eventos epilépticos. Através deste estudo, verificou-se que a janela temporal ótima para cada caso (população geral ou cada doente individual) é a mesma, que abrange o período de 0 a 20 minutos.
No entanto, contrariamente aos resultados obtidos a partir dos dados gerais, ao comparar a janela de tempo entre 10 e 20 minutos, o resultado para cada paciente foi dividido, ou seja, houve bons resultados para cada uma das janelas de tempo. Isso significa que os padrões pré-ictais são reconhecidos para 0-10 e 10-20 minutos.
Posteriormente, foi efetuada uma validação do algoritmo utilizando o método *Leave One Patient Out* para a população. Os resultados obtidos não são favoráveis e podem ser tiradas algumas conclusões sobre a incapacidade de generalização do algoritmo sem a utilização do próprio doente e para a aplicação do algoritmo no mundo real.
Estes resultados indicam que o algoritmo desenvolvido pode não ter uma capacidade de generalização robusta para além dos dados específicos dos doentes utilizados para a formação. Isto significa que o desempenho do algoritmo pode ser limitado quando aplicado a outros doentes com características diferentes ou a cenários do mundo real que podem

variar em relação aos dados de treino.
Para colmatar esta lacuna de informação, optámos por aplicar uma técnica de seleção de características, mais concretamente o algoritmo de máxima relevância e mínima redundância (mRMR), com o objetivo de perceber quais os canais e características que mais contribuem para as classificações.
Através dos resultados obtidos, foi possível observar uma clara discrepância entre a caraterística Dimensão Fractal Petrosiana e todas as outras características, o que indica que esta caraterística tem uma grande influência no algoritmo de classificação. Além disso, o parâmetro de complexidade Hjorth e o número de intersecções de zero também apresentaram altos valores de relevância. Portanto, podemos concluir que utilizar apenas essas características para a classificação poderia tornar o algoritmo menos redundante e mais eficiente.
Outra análise realizada foi a importância dos canais e características para cada paciente, conforme apresentado no Apêndice A.7, A.8, A.9. A partir desses resultados, podemos fazer algumas considerações a respeito do tipo de canal e caraterística mais adequada para cada paciente, possibilitando assim a criação de um algoritmo personalizado para cada paciente individualmente.
Estes resultados indicam a possibilidade de desenvolver estratégias de personalização do algoritmo, tendo em conta as características específicas de cada doente, o que pode levar a uma melhoria significativa do desempenho e da capacidade de generalização do algoritmo de previsão de eventos epilépticos.

0.6 Conclusão e Trabalhos Futuros

Ao longo desta dissertação, apresentamos uma abordagem para a previsão de convulsões epiléticas utilizando técnicas de *Machine Learning* e EEG.
Após revisão da literatura existente, observamos que abordagens semelhantes já foram aplicadas, porém não são adequadas para pacientes em situações do dia a dia. Portanto, a criação de uma abordagem que inclua o uso de canais periféricos contribui significativamente para o desenvolvimento de uma solução que auxilie os pacientes e os prestadores de cuidados no manejo da epilepsia. Para fundamentar esta dissertação, foram alcançados quatro objetivos principais:

- Análise dos desafios existentes no atual estado da arte da previsão de convulsões epilépticas.
- Conceber e investigar a viabilidade da utilização de canais periféricos de EEG para a abordagem de previsão de crises epilépticas
- Identificar os canais e as características que mais contribuem para a previsão.
- Avaliar e comparar o desempenho utilizando diferentes períodos pré-ictais.

A investigação realizada nesta dissertação trouxe contribuições significativas para os objetivos estabelecidos.

A revisão sistemática da literatura (SLR), apresentada no Capítulo 2, foi uma importante contribuição para o primeiro objetivo. Através desta revisão, foi possível verificar que poucos autores exploram a redução de canais e que este tema não tem sido discutido em profundidade na literatura existente. Esta constatação revela uma lacuna no conhecimento atual e realça a relevância da abordagem proposta nesta dissertação.

O segundo objetivo foi abordado em duas partes ao longo do Capítulo 3, onde apresentamos uma estratégia para a conceção e implementação da abordagem proposta para a previsão de crises epiléticas. Os resultados obtidos no Capítulo 3 demonstraram que é possível realizar a classificação utilizando apenas os canais periféricos do EEG. No entanto, observamos que os modelos não generalizam bem sem o uso dos dados do próprio paciente. Essa constatação ressalta a importância de considerar a individualidade de cada paciente na construção de algoritmos personalizados.

O terceiro objetivo, apresentado no Capítulo 4, foi abordado através da aplicação do algoritmo de seleção de características mRMR. Os resultados obtidos neste capítulo revelam as características e os canais que mais contribuem para a classificação. Verificou-se que diferentes doentes têm canais específicos que produzem melhores resultados de classificação. Além disso, foi possível identificar três características que apresentam uma contribuição significativa para a classificação.

O quarto objetivo foi abordado no Capítulo 3, onde foram realizados testes para determinar a melhor janela pré-ictal para a classificação, utilizando o conjunto de características selecionadas. Os resultados obtidos nesse capítulo indicam que a melhor janela pré-ictal para classificação, considerando as características utilizadas, foi de 0 a 20 minutos. Esta janela abrange um período de tempo mais amplo em comparação com as janelas de 0-10 minutos e de 10-20 minutos, e apresentou resultados mais favoráveis para a classificação.

Ao cumprir estes quatro objetivos, foi possível responder às questões apresentadas no Capítulo 1.

Relativamente a trabalhos futuros, existem várias questões e possibilidades de investigação que podem ser exploradas com base nos resultados e lacunas identificadas durante a realização desta dissertação.

Uma das possibilidades é a realização de análises estatísticas para investigar a influência de variáveis como o género e a idade nos resultados obtidos. Isto poderia fornecer informações sobre possíveis diferenças na previsão de convulsões entre diferentes grupos populacionais.

Outra linha de investigação interessante seria explorar o efeito da aplicação de técnicas de seleção de características nos resultados obtidos. Ao aplicar algoritmos de seleção de características mais avançados, é possível identificar um subconjunto ainda mais otimizado de características que contribuem significativamente para a classificação, melhorando assim o desempenho do algoritmo.

Além disso, seria interessante investigar a possibilidade de utilizar outros biossinais além do EEG, como o ECG (eletrocardiograma), para complementar a previsão de crises epiléticas.

Uma abordagem mais específica para pacientes individuais também pode ser explorada. Em vez de deixar um paciente inteiro de fora durante a validação do algoritmo, poder-se-ia deixar apenas um ficheiro de dados do doente e utilizar o resto dos dados do doente para treino.
Outra possibilidade seria investigar a capacidade de identificar a zona epileptogénica, que é a região do cérebro responsável pela geração das crises epiléticas. A localização e a compreensão desta região poderiam ser benéficas para melhorar os resultados obtidos na previsão de convulsões.
Por último, pode ser explorada a aplicação de filtros passa-banda para diferenciar as diferentes frequências de onda do EEG e distinguir atividades específicas do doente, como o sono. Isto poderia fornecer informações adicionais sobre os padrões e características do EEG que estão correlacionados com as crises epilépticas, melhorando assim a precisão da previsão.

Abstract

Epileptic seizures affect about 1% of the world's population, thus making it the fourth most common neurological disease, this disease is considered a neurological disorder characterized by the abnormal activity of the brain.
Part of the population suffering from this disease is unable to avail themselves of any treatment, as this treatment has no beneficial effect on the patient.
One of the main concerns associated with this disease is the damage caused by uncontrollable seizures. This damage affects not only the patient himself but also the people around him. With this situation in mind, the goal of this thesis is, through methods of Machine Learning, to create an algorithm that can predict epileptic seizures before they occur.
To predict these seizures, the electroencephalogram (EEG) will be employed, since it is the most commonly used method for diagnosing epilepsy. Of the total 23 channels available, only 8 will be used, due to their location.
When a seizure occurs, besides the visible changes in the EEG signal, at the moment of the seizure, the alterations before and after the epileptic seizure are also noticeable. These stages have been named in the literature:

- Preictal: the moment before the epileptic seizure;
- Ictal: the moment of the seizure;
- Postictal: the moment after the seizure;
- Interictal: space of time between seizures.

The goal of the predictive algorithm will be to classify the different classes and study different classification problems by using supervised learning techniques, more precisely a classifier. By performing this classification when indications are detected that a possible epileptic seizure will occur, the patient will then be warned so that he can prepare for the seizure.

Keywords

EEG, Seizure Prediction, Epilepsy, Machine Learning

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Acronyms and Abbreviations

EEG	Electroencephalogram
iEEG	intracranial Electroencephalogram
AP	Action Potential
AED	Antiepileptic Drug
EZ	Epileptogenic Zone
fMRI	functional Magnetic Resonance Imaging
MEG	Magneto Encephalogram
ANN	Artificial Neural Network
SVM	Support Vector Machine
RF	Random Forest
MLP	Multilayer Percepton
K-NN	K-Nearest Neighbour
SLR	Systematic Literature Review
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
CHB-MIT	Children's Hospital Boston-Massachusetts Institute of Technology
FIR	Finite Impulse Response
CNN	Convolutional Neural Network
LSTM	Long short-term memory
CRA	Characteristic Response Analysis
ILAE	International League Against Epilepsy
LOO	Leave One Out
ECG	Electrocardiogram

Chapter 1

Introduction

This chapter presents an introduction to the dissertation entitled "Epileptic seizure prediction using machine learning techniques.". This dissertation addresses research on epileptic seizure prediction using EEG peripheral channels and machine learning techniques. The remaining chapter presents the following topics:

- the context and motivation of this study;
- the problem definition and objectives of the research;
- the main contributions of this study, and,
- the thesis organization.

1.1 Context and Motivation

Epilepsy is a neurological disease that affects about 1% of the world's population, in which, about 30% don't react to treatment[1]. Due to the unpredictability of the associated seizures, it can lead to an increase in the risk of sudden death or morbidity [2].
This disease is characterized by the neurons firing in a self-sustained and hiper-synchronized fashion in the cerebral cortex [3].
Usually, the cause of this disease is associated with a brain injury or a chemical imbalance in the brain [4], however, in most cases, there is no known cause for the appearance of this disease.
Through electroencephalography (EEG), a physician can identify the moment when a seizure takes place. However, this process is made manually through visual inspection of the EEG, which is time-consuming [5]. By making this process automatic it would make it easier and faster to detect and predict when a seizure will occur.
The signal from the patient that suffers from this neurological disease can be divided into 4 stages:

- Preictal is the exact moment before the seizure;
- Ictal is the state in which the patient is during the seizure;
- Postictal is the moment after the seizure;
- Interictal is considered the time in between seizures.

Due to the electrical nature of the brain and the disease, these different phases can be visible in the EEG, thus making it possible to identify each.

1.2 Problem Statement and objectives

Intractable seizures can cause a limitation on the independence and mobility of an adult, and as a consequence, they can cause social isolation and economic deprivation. One of the most problematic consequences of refractory seizures is the increase in the probability of the patient experiencing falls, and injuries such as burns lacerations, and skull fractures, among others.
The possibility of being able to predict seizures is a possible solution, so the patients can prepare themselves for a seizure and warn families and friends. The alarm given for the occurrence of a seizure can also be important in the case of children so that the parents can be warned and protect the child from a potentially dangerous situation. The focus of this dissertation includes the design and development of an approach for epileptic seizure prediction. There are several open research questions involved in the development of the proposed approach:

- Whether it is possible to predict events using only peripheral EEG channels? (relevant for a free-living context);
- Which channels and features contribute the most to prediction?
- What is the ideal temporal window to define the pre-ictal period, 10 minutes or 20 minutes? (possibility of extending to 30 and 40 minutes windows)

These goals were translated into four objectives:

- Analyze the existing open challenges in the current State-of-the-art for epileptic seizure prediction;
- Design and investigate the feasibility of using EEG peripheral channels for the epileptic seizure prediction approach;
- Identify the channels and features that contribute most to prediction;
- Evaluate and compare the performance using different pre-ictal periods.

These objectives will help the research to address the main objective by providing a comprehensive evaluation of the use of peripheral channels for the predictions, and by comparing its effectiveness using different pre-ictal windows.

1.3 Main Contibutions

The achievement of the four objectives of this dissertation resulted in the following main contributions:

- a systematic literature review addressing the existing approaches for epileptic seizure prediction;

- an approach using only EEG peripheral channels for the epileptic seizure prediction;
- a study about the importance of some channels and features in individual predictions;
- a comparative study of performances achieved using two pre-ictal periods, 10 and 20 minutes.
- an article entitled ”Epileptic seizure prediction using EEG peripheral channels”, accepted in a IEEE conference.

1.4 Dissertation organization

This last section of the chapter 1 will outline this dissertation and will give a brief discussion of each chapter.

- Chapter 1: a brief introduction is made to the topic that will be discussed, the theme is contextualized and the motivations for the discussion of said theme. It is also presented the main contribution and the organization of the dissertation.
- Chapter2: presents the state of the art. It also is presented the Systematic Literature Review method used for the research, the results obtained, and a discussion of said results.
- Chapter3: the approach for the seizure prediction is presented;
- Chapter4: the approach is implemented and a discussion of the results obtained is made;
- Chapter5: it will be presented some conclusions that can be taken from the previous chapters and future work.

Chapter 2

State-of-the-Art

The chapter presents and discusses concepts of the state-of-the-art of epileptic seizure prediction giving a background about the topic and a systematic literature review covering the approaches and methods in this field.

2.1 Background Knowledge

2.1.1 Human Brain

To understand Epilepsy is important to understand the brain and its physiology.
The human brain is composed of three main sections the cerebrum, the cerebellum, which regulates the information of other cerebral systems and makes them more precise, and the brain stem, where the nucleus that presides over the homeostatic mechanisms is located. The cerebrum is divided into two hemispheres, these hemispheres are composed of an outer layer called the cortex (gray matter), which presents a large number of neurons, and the inner layer (white matter) [6], each of these hemispheres can be divided into four lobes, the frontal lobe, the parietal lobe, the occipital lobe and at last, the temporal lobe (Figure 1).

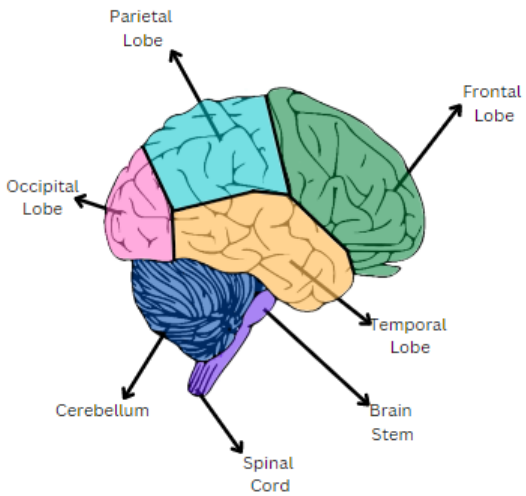


Figure 1: Cortex Lobes

On a smaller scale, the brain is composed of an uncountable number of neurons, these neurons are composed of three main components: the axons, dendrites, and cellular bodies, Figure 2.

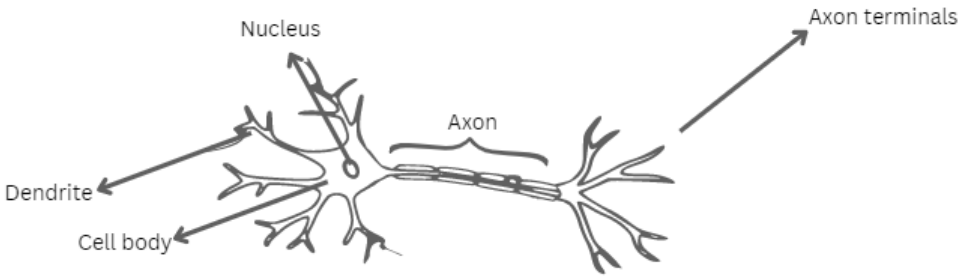


Figure 2: Neurons

When a stimulus occurs, the information is transmitted in the brain through the neurons via an action potential (AP). This AP is transmitted from dendrites to axons or dendrites from other neurons, that receive and transmits the AP [5].
In a normal state, the cellular membrane presents a positive charge in the extracellular medium and a negative charge in the interior. However when a stimulus occurs the potassium and sodium bombs will change their morphology, and alter the charge of the cells so that the interior will become positively charged and the exterior negatively charged, this process is fast, 1-2 milliseconds, and it spreads through the neurons forming a time-varying electrical current. After the AP, the cell membrane is repolarized, returning to the resting potential [5].
When the electrical current travel through the neurons, it can be read with the EEG. Then they can be divided into 5 five frequency bands, the Delta (up to 4 Hz), which is associated with deep sleep, Theta (4–8Hz) is associated with the appearance of consciousness (drowsiness), Alpha (8–12 Hz), connected with the occipital region, it indicated a relaxed awareness without attention, Beta (12–26 Hz), which correlates with deep thought and focus, and Gamma (26–100 Hz), which represents the binding of different population of neurons, this means the cognitive phenomena such as working memory.

2.1.2 Electroencephalography (EEG)

Electroencephalography is a clinical equipment that measures the electrical potential generated by the neural activity in the brain. This fact makes the EEG the ideal equipment to identify and predict seizures.
The EEG is a non-stationary and non-Gaussian signal, that is, there are changes in the signal over time and the noise distribution cannot follow a Gaussian distribution. To be able to make an accurate prediction of an epileptic seizure, the recordings of the EEG need to be of longer duration, which means several days, weeks, or even months [3].
The measuring of an EEG may be made through scalp EEG or intracranial EEG (iEEG). Scalp EEG is a non-invasive method of recording, however, the signal obtained from this method will have more noise due to the interference of the hair, and the long distance between neurons and the electrodes. The other method, iEEG, is an invasive method,

where the electrodes are placed in the exposed surface of the brain, the signal through this method will have less noise, however, it is a more harmful technique for the patient. There are two types of scalp electrodes, they can be dry and wet, the latter are more resistant to movement associated artifacts, and can be the soft gel-based or saline solution. A soft gel-based electrode uses a conductive gel that is applied into the pocket of each electrode, while a saline solution electrode is applied to each electrode. The dry electrodes do not apply any kind of substance to the scalp which makes it easier to record EEG data [7]. The recording of the signal can be made through a bipolar montage or a monopolar/ unipolar montage. In a bipolar montage, the electrodes are placed in an electrically active region, where will be measured the difference between the different voltages. In a monopolar/ unipolar montage, there will be a reference where there is no electrical activity, and the other in an electrical active area. The signal will be the difference between the reference and the electrical active area [3].
There are multiple configurations available for the placement of the electrodes, there is the 10-20 System, visible in Figure 3, with approximately 21 channels, the 10-10 with 64 and 85 channels, and 10-5 for high-density caps with more than 300 channels. The values 5,10, and 20 refer to the distance between electrodes in relation to the total cap size[8]. The placement of each electrode must be precise, for a precise reading. In the case of using the EEG, the usual configuration for signal acquisition is the 10-20 System.

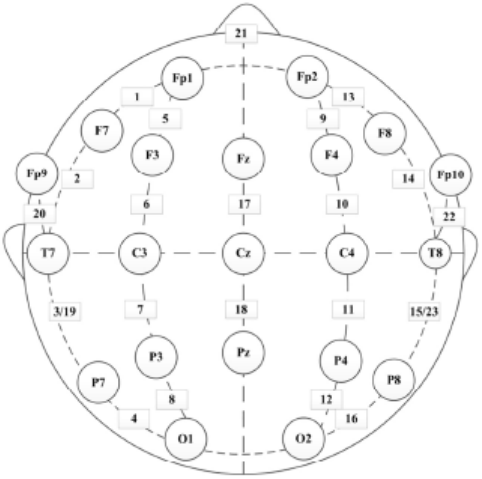


Figure 3: International System 10-20 [9].

2.1.3 Epilepsy

Epilepsy affects around 70 million people worldwide, the fourth most common neurological disorder, it is defined as the continuous occurrence of unprovoked convulsions resulting from the excessive, hyper-synchronized discharge of neurons in the brain [10], this is caused by a neurological proceeding called *"epileptogenesis"* [3].
Epileptogenesis is the development and extension of tissue capable of spontaneously causing seizures, resulting in the development of an epileptic state and/or progression of epilepsy after it is established.

In most cases, around 70-80%, this neurological disease can be controlled through anti-epileptic medication, and the other 20-30% do not respond to the drug or the surgical treatment [2]. According to [10], 75% of the cases develop in childhood, mirroring the increased susceptibility of the developing brain to seizures [10]. Epilepsy in which the patients do not respond to the use of antiepileptic drugs (AED) is referred to as refractory epilepsy, and in this case, the patient is referred for presurgical evaluation, where specialized people will evaluate through EEG and other techniques whether the patient should be submitted to surgery [11].

The main symptom that characterizes this disorder is the unpredictability of the seizures. However, it can also lead to migraines, strokes, and Alzheimer's disease [3]. This ailment is caused by brain injuries or a chemical imbalance of the brain, although at least 50% of the reported cases have no apparent cause of origin [4]. It can also develop due to a genetic mutation in the mechanism in charge of neural behavior, migration, and organization, this mutation can be inherited from a parent [12].

Epilepsy can be divided into three categories according to the International League Against Epilepsy (ILAE), depending on the point of origin of the seizure. If the electrical discharge is general and involves the totality of the brain, then we have a generalized seizure [10]. If the discharge occurs in a specific lobe of the brain, such as the temporal, frontal, occipital, or parietal, then it is called a partial seizure. The area of the cortex that is responsible for a partial seizure is referred to as the epileptogenic zone (EZ) [11]. A seizure can begin focally and later become a generalized seizure. At last, a seizure can also be an epileptic spasm, this kind of seizure does not have a certain known origin, however, it is manifested through a sudden extension or flexion of the extremities [10].

Generalized seizures can be classified into various types, including absence, generalized tonic-clonic, myoclonic, and atonic seizures. Absence seizures are characterized by a lack of responsiveness to external verbal stimuli. Generalized tonic-clonic seizures are marked by symmetrical convulsive movements, starting with stiffening and followed by jerking. Myoclonic seizures can occur either in a generalized or focal manner and are characterized by sudden, brief movements that typically do not cause a loss of consciousness. Lastly, atonic seizures affect body tone, potentially leading to a fall.[10].

Seizures can be divided into four phases. Preictal, right before the seizure, ictal, when the seizure occurs, postictal, right after the seizure, and interictal, in between seizures. According to [13], 50% of the patients involved in a study conducted in the United States display an aura before a seizure of which around 42% exhibit this aura 5 or more minutes before. This aura is associated with the preictal state, through the characterization of this phase, it is possible to predict a seizure, which will allow an improvement in the quality of life of epileptic patients[14].

Multiple techniques have been proposed to address epilepsy, such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and EEG. However, the EEG offers multiple advantages above the others, such as high temporal resolution, low cost, and a system that is capable of long-term and portable monitoring.

2.1.4 Epilepstic Seizure Prediction

The first texts mentioning the prediction of epileptic seizures occurred in 1975, by Viglione and Walsh, in which the authors looked for visible and reproducible patterns in the EEG, enabling the potential prediction of epileptic seizures [15].
Later, other authors mentioned changes in the preictal stage between 6-60 seconds before the seizure onset through the use of autoregressive models [2]. Many other studies from the 1970s reported the importance of spikes, which are transient signals with a distinguishable pointed peak. According to [2] when a spike presents itself in the preictal state, it suggests that the interictal-ictal transition results from a process that affects the interictal activity, creating the conditions for the occurrence of a seizure.
In this day and age, with the technology available, it is possible to create algorithms able to make predictions up to 50 min [14], the most used algorithms use machine learning techniques. This prediction algorithm consists of a 3 phase process:

- Preprocessing: the filtering and removing of the noise from the EEG signal;
- Feature Extraction/ selection: selection of critical characteristics in the various domains, from this the most relevant features are selected;
- Classification: use of machine learning classifiers to label the seizures.

2.1.4.1 Preprocessing

This first step of the prediction process focuses mainly on the signal acquisition, noise removal, averaging, segmentation, etc [5]. There are multiple types of techniques for this process, such as the application of bandpass filters, wavelet filters, and finite impulse response, among others. This step is also used to normalize the data and allow the comparison among patients [3].
The most used techniques in this stage are the segmentation of the signal into moving windows, and the application of bandpass filters as we can see in [9], and [1]. Some of the other techniques that can be applied such as smoothing, resampling, and detrending.

2.1.4.2 Feature Extraction/ Selection

After the preprocessing of the EEG signal, the features are extracted through the use of different domains, such as the time domain, the frequency domain, and the time-frequency domain. The frequency domains are usually associated with behavioral patterns [5].
They can also be qualified as linear or non-linear, and univariate (one channel) or multivariate (multiple channels) [2].
The extraction of the features is a crucial step in a prediction, due to the fact that no good classification can be made without features that can correlate with the different stages of the convulsions (preictal, ictal, interictal). This process aims to represent the data in a more compact and meaningful way, making it easier for machine learning algorithms to process and make decisions based on these features.

Dimension Reduction is a technique used to convert a high-dimensional data representation into a low-dimensional representation. Thus, feature extraction is a Dimension Reduction Technique that consists of reducing variables by transforming a certain number of attributes, thereby converting a large number of attributes into a reduced number of features[16].
Some of the most used features in the literature are non-linear and time domain. These features have the objective of obtaining non-redundant and objective results. Such as:

- Statistical Features: Mean, Variance, Skewness, Kurtosis, etc.;
- Non-Linear: Approximate Entropy, Spectral Entropy;
- Time/Frequency: Hjorth Parameters, Petrosian Fractal Dimension, Katz Fractal Dimension.

Feature Selection is defined as the selection process of the most relevant features. This is a very important step in the classification due to the reduction of the high-dimensional feature space into a lower-dimensional subspace [17].
The aim of Feature Selection is to understand the data, reducing the effect of the excess of features or variables in a dataset, thus improving the predictor performance [18].
[18] divides the feature selection methods into three different categories:

- Filter methods: use a ranking method to select the more relevant features, highly ranking features are selected while low ranking techniques are eliminated;
- Wrapper methods: evaluates subsets of features by training and testing a model using different combinations of features, the subset of features that presents a higher performance is selected;
- Embedded methods: takes into account the features during the model training process, and selects the most informative features.

Another possible approach is to select features that incorporate biological importance. These features are selected with the purpose of capturing underlying biological systems that are relevant. This approach has never been applied in epileptic seizure prediction, however, it has been applied in [19].

2.1.4.3 Classification

Machine learning is a branch of artificial intelligence in which the algorithm employs statistical methods to recognize patterns in a big data collection [3].
Machine Learning can be divided into various techniques, such as [3]:

- **Supervised Learning**: this technique of machine learning consists in assigning labels to the training data, and feeding it to the learning algorithm, so that the algorithm may identify the relationship between them and use this relation to classify the rest of the data.

- **Unsupervised Learning**: in this technique, the machine learning algorithm identifies patterns in new information and feeds this information without labels to the algorithm.

- **Reinforced Learning**: is a technique in which the objective is to develop a policy to maximize the rewards and minimize any undesirable interaction between the agent and its environment, this is done by a reward/punishment system, by rewarding positive interactions and penalizing the opposite.

Supervised Learning can be split into two more categories, classification, and regression. In regression, the output variable assumes continuous values while in classification, the output variable assumes class labels, the most used techniques in classification are the Decision Tree, Random Forest, Bayesian Networks, K-Nearest Neighbor, and Support Vector Machines [20].

For epileptic seizure prediction, supervised learning is most used, more precisely classification. Although this method is very useful, especially for predicting models, it can have issues, such as missing values, which can lead to problems when training the algorithm. This problem can be overcome by ignoring omitted data, exchanging entire omitted values with a constant global individual, exchanging an omitted value with its average characteristic for the class in question, manually observing samples with omitted values, and inserting a feasible or probable value [20].

Classification is made through the use of the extracted/selected features a classifier can differentiate between different stages of the seizure [2], it can be classified into two classes, for example preictal, and interictal, that is to say, biclass, or into multiple classes, and in this case multiclass.

To be able to make the correct classification, firstly the signal must be divided into two or three parts, one part is used for the training of the algorithm, the other for validation, and, the last one is used for the testing [5].

According to [15] usually, there are two machine learning algorithms used in seizure prediction, artificial neural networks (ANN), and support vector machines (SVM).

Support Vector Machines was introduced by Vapnik in 1995, this classifier is very popular for making predictions because it minimizes structural risks and switches between training error and complications of modeling [4] [2].

However there are other techniques used by the community, such as the random forest (RF), multilayer perceptron (MLP), and K-nearest neighbor (K-NN), used by [21], which also yields good results.

Random Forest, is an algorithm proposed by Breiman. This algorithm is fast, presents a high accuracy, and is noise resistant. RF is the combination of bagging and random feature selection, where every tree in the forest is influenced by the values of a random vector sampled separately and presents a similar distribution on any other tree in the forest. [21].

2.1.4.4 Performance

With the objective of analyzing the performance of the algorithm, different metrics have been proposed throughout Epileptic Seizure prediction.
Such as:

- **Sensitivity/ Recall/ True Positive Rate (TPR)** is defined as a measure of the ratio of corrected predicted seizures in relation to all of the seizures[3]. It is calculated through the following formula:

$$Sensitivity = \frac{TruePositives}{(TruePositives + FalseNegatives)} \quad (2.1)$$

- **Specificity/True Negative Rate (TNR)** it is the ratio of real non-seizure cases correctly predicted by the model [3]. It is calculated through the following formula:

$$Specificity = \frac{TrueNegatives}{(TrueNegatives + FalsePositives)} \quad (2.2)$$

- **Accuracy** is the quantification of the overall correctness of the model [3]. It is calculated through the following formula:

$$Accuracy = \frac{(TruePositives + TrueNegatives)}{(TotalCases)} \quad (2.3)$$

- **Precision** is the quantity of actual positive predictions that are really true positives [3]. It is calculated through the following formula:

$$Precision = \frac{TruePositives}{(TruePositives + FalsePositives)} \quad (2.4)$$

- **F1 Score** provides a balance between sensitivity and precision, especially in cases of class imbalance [3]. It is the harmonic mean of precision. It is calculated through the following formula:

$$F1Score = 2 * \frac{(Precision * Sensitivity)}{(Precision + Sensitivity)} \quad (2.5)$$

Where:

- True positive (TP) is the number of correctly predicted ES.
- False Negative (FN) is the number of ES that are incorrectly predicted as not seizures.
- True negative (TN) is the number of correctly predicted no-seizure.
- False Negative (FP) is the number of non-ES that are incorrectly predicted as seizures.

When making the evaluation of the model performance, it is very important to have into account the metrics in conjunction with the domain and specific requirements to be able to determine the model effectiveness, when evaluating epileptic seizure prediction models, it is crucial to consider these metrics in conjunction with domain knowledge and specific requirements to determine the model's effectiveness and feasibility for practical implementation [3].
Another performance metric is a seizure occurrence period (SOP), the time duration in which there is a possibility of seizure and the seizure prediction horizon (SPH), the duration of time between the alarm and the inception of SOP. At last the Receiver Operator Characteristic (ROC) curve. This diagnostic method evaluates the true positive rate against the false positive rate during the interictal and pre-ictal states. It is a plot used to exhibit the diagnostic efficacy of classifiers. The area under the ROC curve (AUC) is also used for performance evaluation of ES predicting algorithms [3].

2.2 Systematic Literature Review

This chapter addresses the Systematic Literature Review (SLR) component of this dissertation. The systematic review proposed is made based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) scheme [22].
To be able to perform the SLR, first, it must be verified that there are no SLR about the theme. This first approach is very important, as these reviews are often used as a starting point for other research development and are also often used for consultation of existing work in a particular research area.

2.3 Method

This section will be explaining the methodology used to make the SLR, and the obtained results.

2.3.1 Research Strategy

When making a systematic review the databases used are very important. These databases must be multidisciplinary such as ACM Library, Scopus, ScienceDirect, and IEEE Xplore to be able to obtain a wide range of articles.
For the research made in January 2023, it was used different keywords for different databases. This research is focused on titles, keywords, and abstracts, and it covers the years 2012 to 2022. The chosen keywords for the research were the following:

- Scopus, IEEE Xplore, ACM Library: (prediction) AND (epileptic seizures) AND (EEG);
- ScienceDirect: (prediction) AND (machine learning OR deep learning) AND (epileptic seizures) AND (EEG)

2.3.2 Article Selection

From the total of the obtained articles, duplicated articles were eliminated, and articles that don't make EEG signal processing and don't make epileptic seizure prediction.
After this initial filtering based solely on the abstract reading, the articles that remain are subject to a comprehensive reading. Then according to a set of criteria, they are selected to be used on the SLR or are eliminated.
The criteria proposed for this Systematic Review are, the number of participants and whether the data acquisition is done in a clinical/hospital setting. Regarding signal processing, the signal preprocessing method, the variable extraction technique, the technique used for classification or regression, the type of prediction, and the performance of the algorithm were analyzed. After this selection, the resulting PRISMA scheme can be seen in Figure 4.

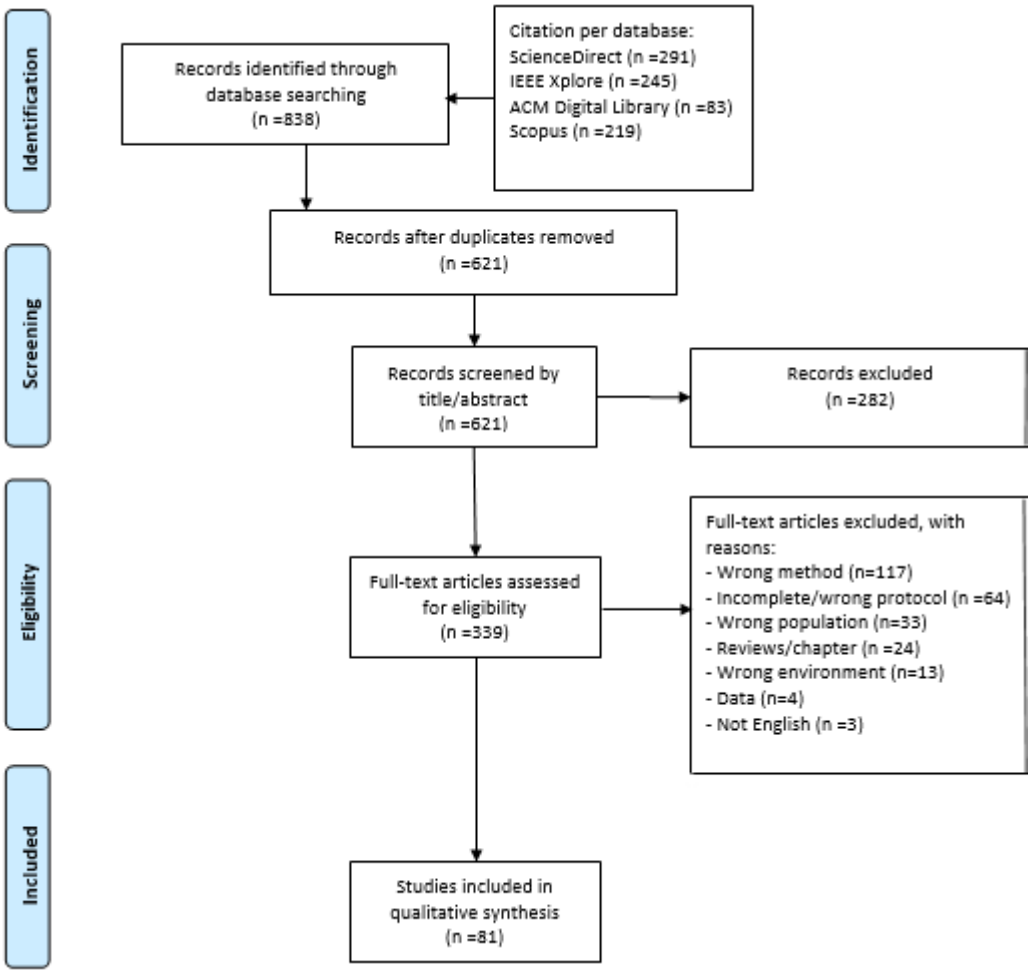


Figure 4: PRISMA scheme.

From the scheme, it may be verified that the initial research yielded a total of 621 unique articles. After the review of the title and abstracts, 282 articles were excluded, therefore 339 full-text publications were studied, and from these 258 were excluded. The records excluded are described as follows:

1. one-hundred and seventeen article report research on epilepsy, but does not apply the pretended method;
2. sixty-four studies apply detection models instead of the pretended prediction, or do not present enough information on the experimental method;
3. thirty-three studies use animals in their protocol;
4. twenty-four studies were review studies or book chapters;
5. thirteen studies either do not make the acquisition on the clinical environment or do not mention where the acquisition is made;
6. four studies use different signals;
7. three studies were not in English;
8. one study presents a wrong outcome.

The final selection of articles resulted in 81 articles that can be seen in the tables below.

Table 1: Related works.

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[23]	2012	Freiburg	19	128	Segmentation (5s, no overlap), Decomposition (5 subands), FIR	AIE, AIF	SVM	Preictal (50min)/ Intericatl	5-fold cross-validation	Sensitivity: 95.2% FAR: 0.130 h^{-1} SPH: 50min	Average
[24]	2012	Epilepsiae	12	6	Segmentation (5s)	Normalized Spectral Power, Relative Normalized Spectral Power	SVM	Preictal(10, 20, 30, and 40 min)/ Non-preictal	Firing Power, 56/44 testing	mDAD: Sensitivity: 76.09% FPR: 0.15^{-1}	Average
[25]	2012	Beijing Xuanwu Hospital	7	23	Segmentation (5s)	CSP	SVM	Preictal(10 min)/ Interictal		Prediction time: 2-20min	Average
[4]	2013	European Database	10	6	Segmentation (5s), IIR, forward-backward Butterworth, Notch filter, FFT, MA, outlier	Spectral Power, Statistical moments, Hjorth parameter, Long-term Energy, Autoregressive error, Decorrelation Time, Wavelet Coefficients	SVM	Preictal (10, 20, 30, and 40 min) / non-preictal	100 testing/iteration; Regularization	Sensitivity: 68.7% FPR: 0.33 h^{-1}	Average
[26]	2014	Freiburg	21	6	Segmentation (4s- non-overlap), Chebyshev bandpass filter (0.5-30Hz)	Higuchi Fractal Dimension	BLDA	Preictal (50min)/ Interictal	training/testing	Sensitivity: 89.33% FPR: $0.2h^{-1}$ Prediction time: 39.39 min	Average
[15]	2014	European Epilepsy Database	278	6	Segmentation (5s), Notch filter	Hjorth mobility and complexity, Relative Power, Spectral Edge, Mean, Variance, Skewness, Kurtosis, Wavelet Coefficient	ANN, SVM	4 class (Interictal, Preictal (10, 20, 30, and 40 min), ictal, postictal (10 min))	2/3 seizures training/ rest for test	Sensitivity: 73.55% FPR: 0.28 h^{-1}	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[27]	2015	SCTIM-AST	6	33-96	Notch filtering, bandpass filter, band stop filtering	MCC, PLV, MLE	SVM	Preictal (5-60min)/ Interictal/ Ictal/ IED/ Electrographic Seizures	Training (2min preictal)	Sensitivity:100%, FAR: 0.03 h^{-1}	2 patients
[28]	2015	CHB-MIT	22	23	Segmentation (15s non-overlap), FIR (0.5-100Hz), Notch Filter (60Hz)	EMD, FPGA, Hilbert Transform	LSSVM	Preictal (5min)/ Interictal		AuC: 1.0	child:21
[29]	2015	Freiburg	19	6	Segmentation (5s non-overlap), Decomposition, Multiband Demodulation	AIE, AIF	SVM	Preictal (50min)/ Interictal	leave-one-record-out cross-validation	Sensitivity: 98.8% FAR: 0.054 h^{-1}	Average
[30]	2015	European Epilepsy Database	24	6	Segmentation (5s), IIR, Butterworth, and Notch Filter	Spectral Power, Relative Spectral Power, mRMR	SVM	Preictal/ non-preictal	Moving Average Regulizer, First 3 for training/ last one for testing	Sensitivity: 73.98% FPR: 0.06 h^{-1}	Average of scalp patients
[31]	2016	Freiburg	17			N-Gram	Random Forest	Preictal/ Interictal	Training/ Testing	Accuracy: 93.83% Sensitivity: 96.12% FAR: 8.44%	Average
[32]	2016	MGH	1		Butterworth (50Hz), Segmentation	Power Spectrum of each LFP channel	CNN	Interictal/ Preictal	Leave-one-seizure-out	Sensitivity: 80%	Specific
[33]	2017	CHB-MIT, SNUH	16	1	Segmentation (20s, overlap)		FFT			Sensitivity: 86.67% FPR: 0.367 h^{-1}	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[34]	2017	CHB-MIT	10	23	Sliding window(10s)		Cross-correlation	Normal/ Pre-seizure		Sensitivity: 84% Specificity: 63% Prediction Horizon: 1h	Average
[35]	2017	Freiburg	21	6	Segmentation (4s, non-overlap), Wavelet Transform	Diffusion Distance	BLDA	Preictal/ Interictal	2 seizure training/ testing, MAF Smoothing and Thresholding	SOP(30min): 85.1% SOP(50min): 93.61% Sensitivity: 93.62% FPR: 0.08h^{-1}	Average
[36]	2018	Epilepsae	103	22-37	Segmentation (5s, non-overlap)	Mean, Variance, Skewness, Kurtosis, Energy, SEF, SEP, Decorrelation Time, Hjorth mobility and complexity	Stacked Auto-Encoders (SA)	Preictal/ non-preictal	2 seizure training; 2 seizure optimization/ at least one seizure testing	iEEG: FPR:0.27h^{-1} Sensitivity: 16.05% EEG: FPR:0.88h^{-1} Sensitivity: 17.49% SOP 10, 20, 30, and 40 min	Average
[37]	2018	CHB-MIT	14	23	Segmentation (10s), STFT	CNN	LSTM	Preictal/ Interictal	From 10 predictions if at least 8 are preictal, for the next 30 min there will be no prediction	Sensitivity: 98.21% FPR: 0.13h^{-1} Mean prediction time: 44.74 min	Average
[38]	2018	CHB-MIT	12	23	Segmentation (4s)		2D Convolutional Autoencoder, Bi-LSTM	Preictal/ Interictal	Training (2 random patients); Cross-validation	Sensitivity: 94.6% FPR:0.04h^{-1}	Average
[39]	2018	CHB-MIT	8	23	Segmentation (5s)		DCNN, Bi-LSTM	Preictal/ Interictal	Leave-one-out cross-validation	Accuracy: 99.66% Sensitivity: 99.72% Specificity: 99.6% FAR: 0.004h^{-1}	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[21]	2018	Freiburg, CHB-MIT	21+23	128;23	MSPCA, EMD, DWT, WPD	Mean Coefficients, absolute power, Standard Deviation, Ratio, skewness, and kurtosis	RF, SVM, MLP (ANN), k-NN	Interictal/ Preictal	10-fold cross-validation	CHB-MIT: Accuracy: 99.5% Sensitivity: 99.92% Specificity: 99.17%	Average
[40]	2018	CHB-MIT	23	18	Segmentation (5s, non-overlap)	Mean, Variance, Skewness, Kurtosis, Std Deviation, Zero Crossing, Peak-to-Peak Voltage, FFT, PSD, Total Signal Area, DWT, Cross-Correlation, Autocorrelation, Local and Global measures	LSTM	Preictal/ Interictal	Cross-validation	Preictal window: 120min: Sensitivity: 99.84% Specificity: 99.86% FPR: $0.02h^{-1}$	Average
[41]	2019	Freiburg	21	6	Signal Entropy, WT, Nonlinear System Dynamics, SSM, SBP, SEF	Accumulated energy, Energy level, STE, LTE, Correlation Dimension, Max Lyapunov Exponent	ANN, KNN, MC-SVM, MC-SVM	Preictal/ Interictal	1-against-1 and 1-against-all; 70 training/30 test	Prediction(30min): Accuracy: 98.04% Sensitivity: 98.85% Specificity: 97.27% S1-score: 98.05%	Average
[42]	2019	CHB-MIT	23	23	Segmentation (10s)	Standard Deviation, Mean, Variance, Median, Kurtosis, Skewness, Entropy, Moment, Maximum and Minimum of the EEG, and Power of the EEG	SVM, KNN, Decision Tree, Ensemble, and Logistic Regression	Seizure/ Normal	50 samples training/ 30 samples test	The best result was for SVM: Accuracy: 88.00% Sensitivity: 100% Specificity: 90.91% FPR:$0.0909h^{-1}$	Average
[43]	2019	Epilepsy Ecosystem	3	16	Segmentation (10min), Down-sampling (Factor 5)	Standard Deviation, Number of Zero Crossing, Kurtosis, Skewness, Normalized and Totally Summed Energy, Maximum Entropy	SVM, RF, Extra Trees, AdaBoost, XG Boost	Preictal/ Interictal		XG Boost (Lasting Features): Accuracy: 90.41%	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[44]	2019	Freiburg	8	6	Normalization using Z-score, FIR filters, Segmentation in frequency Bands	Hjorth parameters (complexity and mobility), Average Power, Mean of the Power Spectrum, Accumulate Energy	SVM	Seizure/ non-seizure	70% for training / 30% for testing. 10-fold cross-validation	Sensitivity: 68% Specificity: 100%	Average
[45]	2019	Benchmark Dataset	80	18	Bandpass filter (0.5-15Hz), Segmentation (1s)	CRA (Characteristic Response Analysis)	SVM	Preictal/ Interictal	30 train UML-DA/ 50 train SVM/ 20 test	AUC: 0.87	Average
[46]	2019	Hospital Xinjiang	15	10	Bandpass filter (1-35Hz), Segmentation (10s)		LRCN	Preictal (30min) / Interictal	10-fold cross-validation	Accuracy: 93.40% Sensitivity: 91.88% Specificity: 86.13%	Average
[5]	2020	Bonn University	5+5	23	Wavelet Transform, Fourier transform, Butterworth filter	Mean, Variance, Skewness, Kurtosis	KNN, SVM	Bi-class (A/E; B/E; C/E; D/E; ABCD/E; AB/CD)		SVM: Accuracy: 100% Sensitivity: 100% Specificity: 100% KNN: Accuracy: 99.5% Sensitivity: 99% Specificity: 100%	Average
[47]	2020	CHB-MIT	23	23	FIR filtering, Differentiating, Hilbert Transformation, Segmentation	Synchronization measures and graph model	ODLN	Preictal/ Interictal	Trained with categorical cross-entropy	EBE (120min): Sensitivity: 100% FPR: $0.02083h^{-1}$ SBE (120min): Sensitivity: 99.87% Specificity: 99.94%	Average
[48]	2020	CHB-MIT	6	Channels with best results	Segmentation	Fractal Dimension, Fluctuation Index, Variation Coefficient, Kurtosis	SVM	Ictal/ Non-ictal	70/30	Accuracy: 96.2% Sensitivity: 95.7%	Average
[49]	2020	CHB-MIT	24	2,13,23	Segmentation (5s)		CNN	Seizure/ non-seizure	Training/ Validation/ Testing (63:27:10)	Accuracy: 99%	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[50]	2020	Freiburg	19	6	Notch filter (50Hz), Segmentation (10s)	MVAR, DTF	CNN	Preictal/ Interictal	20/80; Cross-validation	FPR: 0.08h^{-1} Sensitivity: 90.8%	Average
[51]	2020	CHB-MIT	8	Algorithm to make channel selection	Segmentation (5s, non-overlap)		DCN	Preictal/ Interictal	Leave-one-out cross-validation	Accuracy: 96.1% Sensitivity: 97.41% Specificity: 94.8%	Average
[52]	2020	CHB-MIT	23	18	Segmentation (5s)		LSTM	Preictal (15 min)/ Interictal	10 fold cross-validation	Accuracy: 88.89% Sensitivity: 84.6% Specificity: 90.16% FPR:0.27h^{-1}	Average
[53]	2020	CHB-MIT	15	1	Segmentation	Whole series, Intervals, Shapelets, Dictionary and Spectral	HIVE-COTE	Preictal (15, 30, and 60 min)/ Interictal	Leave-one-out cross-validation/ 10-fold	Sensitivity: 87.4% AUC:0.859	Average
[54]	2020	CHB-MIT	23	23	FIR bandpass, Segmentation (4s)	Wavelet Transform, Power Spectral Density, UMLDA	SVM	Preictal/ Interictal	30 train UML-DA/ 50 train SVM/ 20 test	Accuracy: 95% F1-Measure: 94% Kappa: 90%	Average
[55]	2020	CHB-MIT	22	23	Non-overlapping window selection, Bandpass filter, STFT	CNN	SVM	Preictal/ Interictal		Sensitivity: 92.7% Specificity: 90.8%	Average
[1]	2020	Samsung Medical Center	12		Butterworth bandpass filter (0.5-50Hz), PSD, STF		AnoGAN	ictal/ non-ictal	100 epoch training	AUROC: 0.9372 Sensitivity: 96.6% FAR: 0.14h-1	Average
[13]	2020	CHB-MIT	6	23	Segmentation (8s), Wavelet based bandpass filter (0.4-4 Hz)	NPDC, FBN	ELM	Preictal/ Interictal		Accuracy: 89.2% Prediction Time: 1356.5 s	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[56]	2021	CHB-MIT	23	22	13 Filter Banks	MFCC	Siamese networks, CNN	Preictal/ Interictal	Leave One Patient Out	Siamese networks: Accuracy: 91.54% Sensitivity: 92.45% Specificity: 89.94% ROC-AUC score: 0.9694	Average
[57]	2021	CHB-MIT	13	23	Segmentation (5s), Window Time Choice	M-SampEn, SampEn	Bi-LSTM	Ictal/ non-ictal		Accuracy: 80.09% Recall: 86.67% Specificity: 74.11% FPR: 0.26h^{-1}	Average
[58]	2021	CHB-MIT	17	18	Bandstop filters (57–63 Hz and 117–123 Hz), Segmentation (1.5s)	STFT	CADCNN	Preictal/ Interictal	2 seizures train / one seizure test, leave-one-out	Sensitivity: 97.1% Specificity: 95.1% FPR: 0.029h^{-1}	Average
[59]	2021	CHB-MIT	13	18			1D-CNN	Preictal/ Interictal	5-fold cross-validation, 80% training/ 20% testing	Sensitivity: 96.95% Specificity: 97.87% Accuracy: 97.41% Precision: 97.78%	Average
[60]	2021	CHB-MIT	10	18	Segmentation (1s, non-overlapping)	DCT, DWT	LS-SVM	Preictal and Ictal/ Interictal	hold-out cross-validation, 80% training/ 20% testing	FPR: 0.19h^{-1} Accuracy: 96.38% Prediction time: 26.1 min	Average
[61]	2021	CHB-MIT	22	23	EMD, GAN, STFT, Segmentation (29s)	CNN	LSTM	Preictal/ Interictal	k-fold cross validation	Sensitivity: 93% Specificity: 92.5% Prediction time: 32 min	Average
[62]	2021	CHB-MIT	7	23	ICA	Variance, SUM, Power, ZCR, Mean, COV, RMS, Kurtosis, PSD	ANFIS, FNN, Fuzzy and anti-colony	Preictal/ Interictal/ Ictal		Sensitivity: 94.44% Specificity: 94.5% Accuracy: 96.02% FPR: 3.52%	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[63]	2021	CHB-MIT	23	Algorithm for channel reduction	Segmentation (1-8s)		CNN	Preictal/ Interictal		Sensitivity: 97.83% Specificity: 92.36% Accuracy: 99.47%	Average
[64]	2021	CHB-MIT	4	23	band-pass filter (0.5–64 Hz), Segmentation (4s)	WPT	Bi-LSTM	Preictal/ Interictal	leave-one-out cross-validation, moving average filter	Sensitivity: 99.34% Specificity: 99.6% Accuracy: 99.47%	Average
[65]	2021	CHB-MIT	5	22	STFT, Segmentation, Band reject filter (57–63 Hz, 117–123 Hz, and >114Hz)		MDLS	Preictal/ Interictal	5-fold cross-validation	Sensitivity: 54.72% AUROC: 0.5 Accuracy: 96.33% FPR:20.6h^{-1}	Patient 19
[66]	2021	CHB-MIT	10	22	Segmentation (2s, with 1s overlap), bandpass filter (0.5–50 Hz), PSD	GPT	Lightgbm classifier	Preictal/ Interictal	80 training/20 validation	For 10 min: Sensitivity: 94% Accuracy: 97% Specificity: 89%	Average
[67]	2021	CHB-MIT	14	21	Segmentation (5s)	Mean, Standard Deviation, Variance, Sub-band Powers, Zero-cross rate, Hjorth parameters (mobility, complexity), Renyi entropy, Shannon entropy, and Autoregressive coefficients	LDA	Preictal/ Ictal/ Normal	cross-validation	Accuracy: 100%	Patient 1
[68]	2021	Epilepsy-Ecosystem and CHB-MIT	13+3	22+16	Segmentation (1min), Butterworth IIR	DSTFT	SVM, CNN, CESP		10-fold cross-validation	Sensitivity: 62.87% FPR: 0.15h^{-1}	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[69]	2021	CHB-MIT	7	22	Segmentation (30s, with 8s overlap)	STFT	CNN	Preictal/ Interictal	leave-one-out cross-validation	Sensitivity: 85.8% Accuracy: 80.5% Specificity: 75.1%	Average
[70]	2021	CHB-MIT, NINC, SRM medical hospital	116	3	SART		ECNN	Preictal/ Interictal	70 training/30 test, Leave-One-Subject-Out Cross-Validation	Sensitivity: 93.26% Accuracy: 97.01% Specificity: 89.53% Selectivity: 90.33%	Average
[71]	2021	CHB-MIT	13	22	Segmentation (5s, 15s, and 30s), Band reject filter (57-63 Hz and 117-123 Hz)	STFT	ResNet, CNN, RADNet and a Dual Self-Attention Mechanism	Preictal/ Interictal	75 training/25 test,leave-one-out cross-validation	Sensitivity: 89.25% Accuracy: 92.07% Specificity: 92.67% AUC: 91.30%	Average
[72]	2021	Bonn University, Germany	Groups A and B sets-healthy volunteers; C, D and E epileptic sets			STFT, WPD, and KPCA	CDC-KUM, SVM, RBFNN, LM-PROJ, DAM, STSVM-GP	Positive class/ Negative class		Accuracy: 95.9%	Dataset D2
[73]	2021	NECFAH-SYU and FAHXMU	14+5	22	Segmentation (10s)	BNLSTM	CASA	Interictal/ Preictal/ Ictal	70% training/30% test, back-propagation with a batch size of 100	Accuracy: 95.6% AUC: 98.6% Sensitivity 94.2% Specificity: 96.8 %	Average
[74]	2021	CHB-MIT	5	23	Segmentation (20s), Butterworth bandpass filter	Mean, Variance, Skewness, and Kurtosis, Hjorth parameters, Long-term Energy, Standard Deviation, Entropy, and Lyapunov exponents	SVM, Decision Tree, KNN, Logistic Regression, LDA, Ensemble RUS Boosted Trees	Preictal/ Interictal		Sensitivity: 92.5% Accuracy: 93.3% Specificity: 87.73%	Average
[75]	2021	CHB-MIT	23	Algorithm for channel selection	Band-pass Butterworth filter (2.5-40 Hz)	EMD, SFS	MAML	Preictal/ Interictal	10-fold cross-validation	Sensitivity: 91% Specificity: 90% FPR: 0.26h^{-1}	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[76]	2021	CHB-MIT	23	18	Segmentation (5s, 2.5 overlapp), Butterworth filter band-passing (0.5 and 30 Hz)	Mean, Skewness, Kurtosis, Peak-to-Peak Amplitude, Coefficient of variation, Approximate Entropy, Sample Entropy, Singular Value Decomposition Entropy, Hurst Exponent, Higuchi Fractal Dimension, Hjorth parameters	SVM	Preictal/ Interictal	Leave-one-out cross-validation	Sensitivity: 90.2% AUC: 94.9% FPR: 0.096h^{-1}	Average
[77]	2021	CHB-MIT	21	22	Segmentation (5s), Band-reject Butterworth filter (58-61, and >120 Hz)	SPLV	Fully Connected Neural Network	Preictal/ Interictal	leave-one-seizure-out cross-validation, training 70/ validation 30	Sensitivity: 85% Specificity: 85% Precision: 88% FAR: 0.07h^{-1}	Average
[78]	2021	CHB-MIT	4	22	Wavelet Transform	Mean, Variance, Median, Derivative, Amplitude, Entropy	PDF	Preictal/ Normal	training 70/ validation 30	PH (90min): Sensitivity: 92.8% FPR: 0.05h^{-1}	Average
[79]	2021	CHB-MIT	23	All	Segmentation (10s), FIR filter (3–100 Hz)	Hilbert Transform (Mean, Variance, Instantaneous Median, Derivative, Amplitude)	PDF	Preictal/ Interictal		prediction time: 60.159 min Predicted seizures: 96.46% FA: 0.028077h^{-1}	Average
[80]	2021	Epilepsae	19	All	Bandpass filter (0.1-120Hz), Notch filter (50 HZ), Segmentation (5s, non-overlapping)	Band waves, Average Power, Normalized medium frequency, Amplitude,	Genetic Algorithm (GA)	Preictal/ Interictal	60 training/ 40 testing	Sensitivity: 0.78 FPR: 0.35h^{-1}	Patient 53402
[17]	2021	CHB-MIT	23	23	Segmentation (1s)	Wavelet Transform and reconstruction, mRMR	BP Neural Network	Preictal/ Interictal	80 training/ 20 Validation	Specificity: 95.61%, Sensitivity: 82%, Accuracy: 95.41%	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[81]	2022	CHB-MIT	10	23	Band-reject filter (57-63, and 117-123 Hz), Segmentation (1s)	Wavelet Transform, STFT, PLV, SBP	MAAE, MASF, MMDAAE, SAN	Preictal/ Interictal	leave-one-out cross-validation, 60 training/ 40 testing	AUC: 84%, FPR: $0.13h^{-1}$, Sensitivity: 95.27%, Accuracy: 84%	Average
[82]	2022	CHB-MIT	23	CAtt-MLP	STFT, Bandpass filter, Segmentation	CNN	GRNN	Preictal/ Interictal	leave-one-out cross-validation, 75 training/ 25 testing	Recall: 78.9%, FPR: $0.35h^{-1}$, F1-score: 76.13%, Precision: 75.81%, Accuracy: 71.91%	Average
[83]	2022	University of Bonn Dataset, CHB-MIT	23	All	LCADC, MASA, DWT	Signal Power Spectrum, Skewness, Mean Absolute Value, Standard Deviation, Kurtosis, Mean Ratio, Zero Crossings, Entropy, PPV, ppi, pnv, pni, snv, spi, sni	MLP, K-NN, SVM, RF, BG	Ictal/ Epileptic zone interictal/ Nonepileptic zone interictal/ Normal with eyes open/ Normal with eyes close	One-vs-All	NMI: 0.93 Accuracy: 0.992 F1: 0.988 Kappa: 0.982 Specificity: 1.00	Class 2
[84]	2022	Peking University People's Hospital	10	14	Bandpass Filter (0.5-35 Hz)	Absolute Sum, Second Order Norm, Third Order Norm, Fourth-Order Norm, Infinity Norm, Maximum Value, Minimum Value, Variance, Mean Value, and Root Mean Squared	VWCNN	seizure-free, preseizure, and seizure)	5-fold cross-validation, 80 training/ 20 testing	Accuracy: 91.67%	Average
[85]	2022	CHB-MIT	12	18	Segmentation (30s)	Mean, Variance, Skewness, Kurtosis, Spectral Band Power, Hjorth Parameters	SVM, CNN, and Transformer	Preictal/ Interictal	leave-one-out cross-validation	AUC: 0.939, Sensitivity: 94.6%, FPR: $0.06h^{-1}$	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[81]	2022	CHB-MIT	16	23	segmentation (1s), Power line noise removal	DCAAE	SVM	Preictal/ Interictal	leave-one-out cross-validation	AUC: 0.86 Sensitivity: 84% FPR: $0.12h^{-1}$ Accuracy: 87%	Average
[86]	2022	University of Siena	13	19	Segmentation (5s), Bandpass filtering (1-80 Hz) and Power Frequency Notch (50 Hz)	DTF, Clustering Coefficient and Global Efficiency	SVM	Preictal/ Interictal	7 patients training/ 3 patients validation/ 4 patients test	Accuracy: 99.8% Prediction Time: 50 min	Average
[87]	2022	CHB-MIT	23	22	Segmentation (10s), Bandpass filtering (1-80 Hz) and Power Frequency Notch (50 Hz)	MFCC	SPCNN	Preictal/ Interictal	70% patients training/ 15% patients validation/ 15% patients test	Accuracy: 93% Sensitivity: 91% F1-score: 0.83	Average
[88]	2022	CHB-MIT	23	22	Segmentation (5s), Bbandpass filtering (0.5-70 Hz) and Power Frequency Notch (50 Hz)		FBCSP+CNN	Preictal/ Interictal	5-fold stratified cross-validation test	Accuracy: 90.9% Sensitivity: 96.1% Specificity:84.6% F1-score: 91.3% FPR: $0.04h^{-1}$	Average
[89]	2022	CHB-MIT	23	Algorithm for channel selection	DWT	Zero crossings, Maximum, Minimum, and the Difference Between the Highest and Lowest Amplitude	K-NN	Preictal/ Normal	holdout cross-validation	Accuracy: 98.27% Sensitivity: 100% Specificity: 96.66%	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[90]	2022	CHB-MIT	6		Segmentation (5s), 50 Hz Notch filter, Divided into 5 sub-bands	Minimum, Maximum, Median, Variance, RenyiEntropy, logEnergyEntropy, Shannon and Tsallis Entropy, Mean Teager Energy, Mean Energy and Curve Length, First and Second Difference, Kurtosis, Skewness, Hjorth Parameters, CTGAN, ...	Auto-ML	Preictal/ Interictal		Accuracy: 99% Precision: 99% Specificity: 97% F1-score: 99% Recall: 99% FPR: 0.001h^{-1}	Average
[91]	2022	CHB-MIT + Hospital EEG data	10	22	Segmentation (10s)		DeepCNN	Preictal/ Interictal	9 data sets training/ 1 data set test	Accuracy: 94% Sensitivity: 88.47% Specificity: 89.75%	Average
[92]	2022	CHB-MIT	12	22	Segmentation (5s, 50% overlap), Z-score, Notch filter (57-63 Hz, 117-123 Hz)	RCVAE	Bi-LSTM+ MLP	Preictal/ Interictal	70% training/ 20% verification/ 10% test, 10-fold cross-validation	Accuracy: 96.17% Sensitivity: 95.75% FPR: 0.019h^{-1} AUC: 96.16%	Average
[93]	2022	CHB-MIT + Siena EEG	23+15	22	Segmentation (10s, 50% overlap:CHB-MIT; 2s, 40% overlap: Siena EEG)	MFCC	C-GNN + GSN	Preictal/ Interictal	10-fold cross-validation	Accuracy: 95.02% Sensitivity: 95.94% Specificity: 93.52% AUC: 0.98	Average
[94]	2022	CHB-MIT	16	22	Segmentation (4s, 50% overlap)	Skewness, Variance, Kurtosis, Hjorth Parameters	*r*-ELM	Preictal/ Interictal		Sensitivity: 85% FPR: 0.096h^{-1}	Average

Table 1: Related works(continued).

Study	Year	Data			Algorithm					Performance	
		Dataset	Participants	Channels	Preprocessing	Feature Extraction	Classification			Results	Type
							Classifier	Class	Validation		
[95]	2022	CHB-MIT	14	22	Segmentation (30s, 50% overlap)	STFT	ViT	Preictal/ Interictal	4 training: 1 validation: 1 test	Accuracy: 94.6% Recall: 98.6% Specificity: 89.8% Precision: 90.5% AUC: 0.989	chb21
[96]	2022	CHB-MIT + SWEC-ETHZ	8 + 6	22	Segmentation (64s), Butterworth Bandpass filter (0.5-150 Hz)	Mean, Variance, Skewness, Kurtosis, Coefficient of Variation, MADA, RMSA, Shannon Entropy, and SVD	CNN	Preictal/ Ictal/ Interictal	80:20 train validation, 5-fold cross-validation	Accuracy: 99.01% Sensitivity: 99.24% Specificity: 98.68% FPR: 0.47h^{-1}	Average
[97]	2022	CHB-MIT	13	5	Segmentation (1s)	AE	SVM	Preictal/ Interictal	Leave-One-Out, 10-fold cross-validation	Accuracy: 98.5% Sensitivity: 98.9% Specificity: 98% AUC: 99.0%	Average

2.3.3 Discussion of the SLR

2.3.3.1 Dataset

From the analyses of Table 1, it is possible to verify that the dataset most used in the literature is the CHB-MIT (Children's Hospital Boston-Massachusetts Institute of Technology), with 57 out of the 81 articles using this dataset, which is of public access in the following link: https://physionet.org/content/chbmit/1.0.0/.
This dataset is composed of the EEG recording of pediatric patients with epileptic seizures. In these 24 cases studied, 23 patients were monitored for multiple days after ceasing the antiepileptic medication to be able to characterize their seizures. The dataset comprises 24 cases, collected from 23 participants, 5 males with ages ranging from 2 to 22 years old, 17 females with ages from 1.5 to 19 years, and one other person about whom we have no information of any sort. Later it was added the 24 case, which as no data available about the patient.
Another dataset mentioned multiple times in Table 1 is the European database on Epilepsy, or Epilapsiae, available at http://www.epilepsy-database.eu/, the data available on this dataset was collected from multiple hospitals and clinical environments. This dataset is available to be bought through two different packages one with 30 scalp EEG and another with 30 iEEG. The European Database comprises 278 patients in total, 149 males, and 129 females, with ages between 1 and 67 years old.
The Freiburg EEG database features 10 participants, 8 males and 2 females with ages between 15 and 57 years, which is also used in multiple articles, this dataset is available upon request to the authors.
Every dataset mentioned in Tables 1 was obtained with the objective of making the detection or prediction of epileptic events. The data was always collected in a hospital or clinical environment.

2.3.3.2 Preprocessing

Preprocessing is the first step when speaking of processing a biosignal, and as mentioned above in Chapter 2 this step must be made in a controlled environment to prevent excessive noise. However, despite all the precautions, there is always external interference. This interference is referred to as artifacts, which can be of biological origins, such as a residual electrocardiogram or small voltage fluctuations measured by the electrodes due to patient perspiration, and of technical origins, such as electromagnetic interference from a building's electrical network.
To remove these artifacts it must be applied filtering and segmentation techniques, such as the Butterworth filter, as can be seen in [1], where the filter is used to obtain the frequency response, with as little noise as possible. Segmentation of the signal in moving windows, Finite impulse response (FIR) filters, which are filters whose impulse response is of finite duration and tends to zero, among others. From the SLR we may verify that all of the 81 articles use signal segmentation, from which 27 use a 5 second window. In relation to the

filters, the most used ones are the bandpass filters, Butterworth, and the Notch filters.

2.3.3.3 Feature Extraction

The feature extraction step is the second one made. This step is very important for the classification since without it the machine learning algorithm won't be able to make a successful classification.
Feature extraction is a technique that involves the selection of characteristics with the objective of obtaining a more efficient classification of the signal, and non-redundant and informative results [48].
Based on the information provided in Table 1, it is evident that the Statistical Domain encompasses the most frequently utilized features. Among these, Kurtosis and Skewness were employed in 15 and 14 articles respectively, while Mean appeared in 13 articles and Variance in 11. Apart from the Statistical Domain, the Hjorth Parameter, specifically complexity and mobility, emerged as the next most prevalent feature, employed in 10 articles. Additionally, several articles also incorporated features such as Entropy, number of zero crossings, and Spectral Power.

2.3.3.4 Classification and Class

To be able to employ the Classification method, the dataset must be divided into three, part of the dataset will be used for the training of the algorithm, another part for the validation, and at last, the other for testing [5].
Classification is a data mining approach that has been used to predict the membership of groups for data instances.
From Table 1, we can conclude that the three most frequently used methods are the Support Vector Machines (SVM), with 30 articles, Convolutional Neural Network (CNN), with 18 articles, Long short-term memory (LSTM), in 10, K-Nearest Neighbor (K-NN), Artificial neural networks (ANN) and Random Forest (RF), with 6, 5 and 4 articles respectively.
The K-NN technique consists in finding the nearest neighbor in relation to a certain K value, which will define the number of nearest neighbors needed to be able to describe a class of a sample data point [20].
SVM is considered to be a technique that relies on a hyperplane in a dimensional space to execute the data vector classification. The support vectors are the data that can be found closer to the decision surface [20].
The RF classifier is a technique that aggregates a set of unrelated decision tree results collected from a data forest, and as output presents the classification.
CNN is an algorithm that recognizes patterns in data and uses these patterns to make clusters of similar data and classify them.
ANN algorithm draws inspiration from the brain's structure and functions, replicating the layout of biological neural networks. It is a specific class of machine learning algorithms primarily utilized for pattern recognition and establishing relationships within

data. ANNs are comprised of interconnected nodes referred to as artificial neurons or neurons, which are organized in layers.
LSTM is a variant of an Artificial Neural Network, in which LSTM has a chain structure that contains four neural networks and different memory blocks called cells. The information is retained by the cells and memory operations are done by the gates.
As may be verified in Table 1, most articles use a binary classification of the signal, with 56 of them using the Preictal/ Interictal classes.
As for the validation usually, the methods used are the Leave-one-out Cross-Validation and the 10-fold Cross-validation, as we may see from the Tables.

2.4 Conclusive Notes

From the state of the art presented throughout this chapter, we may conclude that the method used for epileptic seizure prediction possesses certain limitations. One such limitation is the number of channels, that is, the use of fewer channels may be an asset in the ambit of a free-living context. For instance, a more practical configuration of channels is to use only peripheral channels.
From the SLR, we may verify that some of the authors make a channel reduction ([48, 49, 51, 53, 63, 70, 75, 89, 97]), however, none of these authors discuss said channel reduction, or takes into account the use of only peripheral channels.
Another aspect that may be improved is the use of fewer features, this is done through the use of feature selection techniques. From the research made for the SLR, it was possible to verify that in most of the articles that do apply this technique, the authors do not develop which of the features contributes more toward classification.
In the SLR it is possible to verify that by comparing some of the best performances, such as [89, 90], and [97]. It is possible to affirm that the results obtained by [90] and [97], present more balanced results than [89]. The results from [90] and [97] were made for a 10 min prediction while the results for [89] were for a 20 min prediction so it is possible to affirm that the best classification was for 10 minutes prediction.
In the course of this dissertation, the aim is to solve some of these limitations mentioned above.

Chapter 3

Epileptic seizure prediction approach

In this chapter, we describe and discuss the design process and choices for our implementation strategy of the proposed approach.

3.1 Data

For this approach, it will be used all of the available patients in the dataset CHB-MIT. This dataset consists of 23 pediatric patients, 17 females, and 5 males, with ages between 1.5 to 22 years of age, and one other patient, of whom we have no information on age or gender. However, there are 24 cases of studies, with the patient chb21 being obtained 1.5 years after the case chb01, from the same female subject [98].
The available recordings were made with a sample rate of 256 Hz and 16 bits resolution, with 23 electrodes positioned in each patient following the 10-20 international system. A total of 198 seizure events are available in the dataset [98].

3.1.1 Channels

For this dissertation, it will be used only 8 channels of the 23 available. The chosen channels are the ones that coincide with the peripheral position of devices that already exist and measure EEG in everyday life, such as:

- Macrotellect BrainLink Lite v2.0 EEG headset, this device presents 3 electrodes, one function as a reference, in the back of the ear and two on the forehead;
- AIR, Hero, and Diadem, these devices use 8 (pre-frontal and occipital),9 (fronto-central, central, and centro-parietal), and 12 (pre-frontal, frontal, parietal, and occipital) electrodes respectively.

These channels are the Fp1-F7, F7-T7, T7-P7, P7-O1, Fp2-F8, F8-T8, T8-P8, and P8-O2, and can be seen in Figure 1. Where:

- Fp- Frontopolar;
- F- Frontal;
- T- Temporal;
- P- Parietal;
- O- Occipital.

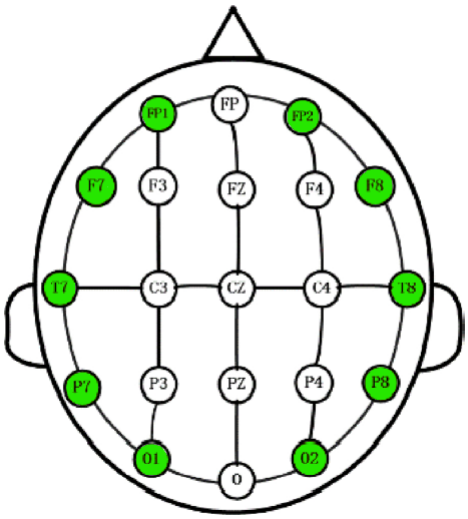


Figure 1: Chosen channels, adapted from [9].

3.1.2 Participants and files

In this approach, it was used all of the 24 cases available in this dataset, the data regarding the patients and which files were used can be seen in Table 1.

Table 1: Patientes data.

Patients	Gender	Age	File Preictal (10 min)	File Preictal (20 min)	File Interictal
1	F	11	3,4,15,16,18,26	3,4,15,18,26	1,2,14,13,17,25
2	M	11	16+,19	16+,19	1,18
3	F	14	2,4	4	5,6
4	M	22	5,8,28_I,	5,8,28_I	3,9,29
5	F	7	13,16	16	12,14
6	F	1.5	1,9,10,18	1,9,10,18	2,3,5,6
7	F	14.5	12,13,19	12,13,19	1,2,3
8	M	3.5	2,5,11,13,21	2,5,11,13,21	3,4,10,12,14
9	F	10	6,8,19	6,8,19	2,3,4
10	M	3	12,20,27,30,31,38,89	12,20,27,30,31,38,89	1,2,3,4,5,6,7
11	F	12	92,99	92,99	2,3
12	F	2	6,8,9,11,33,36,38,42	6,8,9,33,38	19,20,21,24,32,34,35,37
13	F	3	19,21,58,59,60,62	19,58,59	5,6,7,8,9,10
14	F	9	3,4,6,11,17,18,27	3,4,6,11,17,27	1,2,7,12,13,14,16
15	M	16	10,15,17,20,22,28,31,40,46,49,52,62	15,17,31,46	2,3,4,5,7,8,9,11,12,13,14,16
16	F	7	10,11,14,16,18	10,14,16	1,2,3,4,19
17	F	12	3,4,63	3,4,63	5,6,8
18	F	18	29,31,32,36	29,31,32,36	2,3,4,5
19	F	19	29,30	29,30	26,27
20	F	6	13,14,16,68	13,14,16,68	1,2,3,4
21	F	13	19,20,21,22	19,20,21,22	1,2,3,4
22	F	9	20,25,38	20,25,38	1,2,3
23	F	6	6,9	6,9	20,10
24	-	-	4,6,9,11,13,14,15,17,21	6,9,11,13,14,15,17,21	2,5,8,10,12,16,18,19,20

The files chosen to make the extraction were the ones that allowed to make the extraction for a minimum of 10 minutes. For each of the files where extracted 120 instances of each of the intervals (Preictal 0-10 min, Preictal 10-20 min, and Interictal).

3.2 Preprocessing

The proposed approach will resort to using the yasa package in python [99]. It will be made the non-overlapping signal segmentation in 5s moving windows as [9], this method, as we can see in the article, yields good results and is used in many articles.
Besides signal segmentation, an additional step will involve the application of a second order Butterworth filter ranging from 0.5 to 50 Hz. This filtering process aims to achieve a frequency response with minimal interference and eliminate specific frequencies[1].
If we analyze the Systematic Review, we can see that the chosen preprocessing methods apply the techniques that are more used throughout the literature.

3.3 Feature Extraction

Feature extraction will be made in python through the use of the antropy package [100]. With the objective of being able to obtain the best classification, and to be able to make the extraction of a 2D vector or matrix the proposed feature extraction techniques are the statistical features number of zero crossing, this feature was chosen due to multiple uses throughout the literature, and the good results obtained such as in [2]. Alongside this time domain features, other features within the space and frequency domain were selected. Such as the Petrosian fractal dimension, Katz fractal dimension, and specific Hjorth parameters, namely mobility and complexity, the Spectral Entropy feature was also chosen. These four features were specifically selected based on their demonstrated strong performance in [48].
In [15], we can see the use of the Hjorth mobility and complexity to make a seizure prediction. The Hjorth mobility, as defined in the article, quantifies the variance of slopes in a normalized time series, while complexity measures the variance of slope changes with an ideal sinusoidal reference.
A fractal dimension is an approach to the analysis of irregular or complex shapes in long-duration data, according to [101] fractal dimension features are widely used for seizure detection problems.
Katz Fractal dimension was proposed in 1988 by Katz, in this approach, the fractal dimension of the waveform is estimated and calculated through the sum of the Euclidean distance of two successive points in the wave [101].
Petrosian fractal dimension was proposed in 1995 by Petrosian, this algorithm is able to transform the original signal into a binary sequence [101].
The number of zero crossings is the number of times that the signal passes from positive to negative values and vice versa, this type of analysis has been made in previous studies of epilepsy, and Alzheimer's disease [102].
At last, Spectral Entropy is an entropy estimator that uses power spectrum amplitude components from the signal as the probabilities in entropy calculations. It quantifies the spectral complexity of the time series [103].

3.4 Classification

After performing a comparative study, in which it was studied the best balance between sensitivity and specificity, we selected Bagging Tree for the classifications with the following parameters: n estimators = 30, max features=48, random state = 7.

Bagging Tree classifier is short for bootstrap aggregating classifier, this classifier is a popular ensemble learning technique.

The Ensemble technique consists of a method that combines a set of different classifications with the aim of making predictions. Ensemble is used for improving the performance of the classifier thus improving the prediction[104].

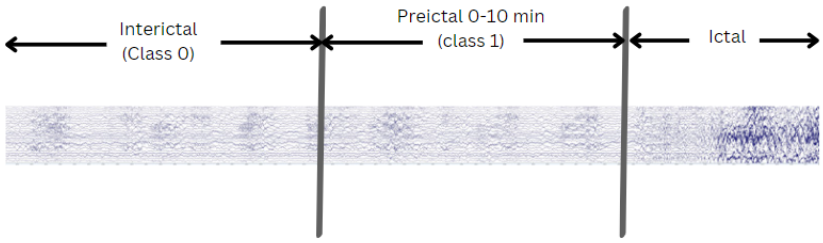
Bagging Tree consists of creating subsets of data and using said subsets to create multiple decision trees. The average of the different decisions is used at the end to minimize the variance of the decision tree. These models tend to be more robust against overfitting when compared with individual decision trees. In conclusion, Bagging tree algorithms are powerful ensemble methods that harness the diversity and collective intelligence of multiple decision trees to improve prediction accuracy and generalization capabilities[104].

In this study were used two categories of EEG signals for feature extraction:

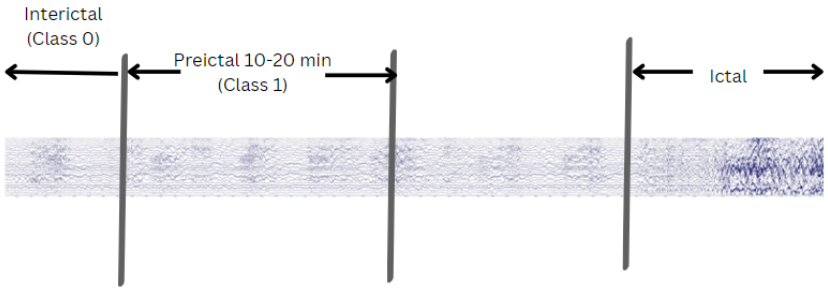
- Interictal (Class 0);
- Preictal (Class 1).

From the files that contain seizures, we only extract the features for the preictal class, regarding 10 and 20 minutes before the seizure event for all 24 patients. From the files that do not contain seizures, we extract the features for the interictal class. The objective of this distribution is to be able to study three different binary classification problems (Figure 2):

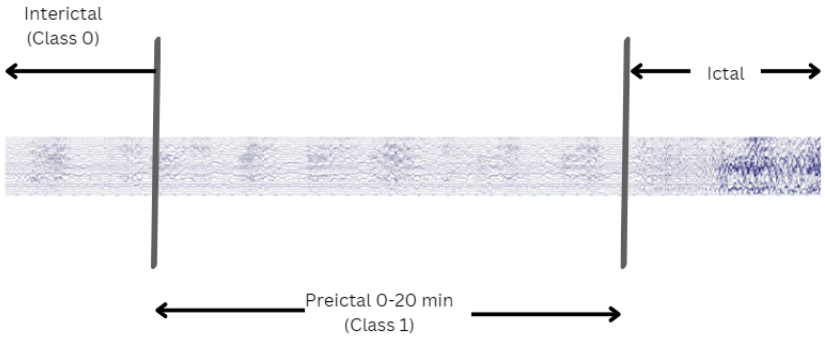
- 1) with interictal (class 0) vs. pre-ictal 10 minutes before the seizure (class 1);
- 2) with interictal (class 0) vs. pre-ictal defined between 10 and 20 minutes (class 1);
- 3) using interictal (class 0) vs. pre-ictal 20 minutes before the seizure (class 1).



(a) Binary problem 1, for 10 minutes



(b) Binary problem 2, between 10 and 20 minutes



(c) Binary problem 3, for 20 minutes

Figure 2: Representation of binary classification problems from file chb01_03

In this dissertation, the binary classification problem will be addressed to be able to distinguish between interictal and preictal.

From the data, it was extracted a total of 37842 instances of data, of which 12960 were from preictal of 10 min, 10442 from preictal of 20 min, and 12960 from interictal. Given the importance of having balanced data, there is a need for undersampling (eliminating data).

Undersampling is a technique to solve class imbalance problems, these problems occur when the number of instances from a class is higher than the number of instances in the other class. This difference in the number of samples of each class can lead to biased predictions and poor performance for the model. In undersampling, the class with the most samples is reduced by removing or randomly eliminating samples from that class.

The eliminated instances were sessions from different patients, intending to always have

data from each patient, and can be seen in Table 2.

Table 2: Deleted instances.

Dataset	Patients	Files
0-10 minutes	-	-
10-20 minutes	12	24,32,35,37
	13	5,9,10
	14	7,12,14
	15	3,7,1,13,16
	18	3
	20	4
	24	16,19,20
0-20 minutes	1	3,6
	2	16+
	4	28_I
	5	16
	6	10,18
	8	11,21
	10	12,27,38,89
	12	6,9,11,36,38,42
	13	19,21,58,59,60,62
	14	6,1118,27
	15	10,15,20,22,28,31,40,46,49,52,62
	16	11,16,18
	17	63
	18	31,36
	20	13,16
	21	19
	24	4,9,14

In terms of validation techniques, we used the Hold-out validation where the dataset is split into two datasets. In our first experiment, we used 75% of the data for training the algorithm and the remaining 25% is ”held out” so that it can be used as an independent dataset to evaluate how well the model generalizes to unseen data.
As this validation method is done randomly and may not really show how the classification is made for each patient, we decided to do a second experiment using leave-one-out validation by leaving all data from a patient out and training the model with the remaining patients.

3.5 Conclusive notes

The design of the proposed approach is made based on the conclusions of chapter 2. This chapter presented our approach design: the channels selected, the features for the extraction, the pre-ictal definition for the classification and the validation methods selected for evaluate our approach. The next chapter presents the results of the approach evaluation and the discussion of these results:

- 1) Interictal vs Preictal classification addressing different scenarios. For a pooled-population approach using a preictal window of 10 minutes, between 10 and 20 minutes, and 20 minutes. A patient-specific approach for the same preictal windows and a pooled-population approach using leaving-one patient out validation;
- 2) Channel and feature contribution using the maximum relevance and minimum redundancy (mRMR) algorithm.

- 3) Conclusive notes discussing how our results fit the research questions defined in Chapter 1.

Chapter 4

Results and Discussion

The chapter presents and discusses the evaluation results of the approach implemented. The results are presented in three subsections:

- Interictal vs Preictal classification using EEG peripheral channels;
- Channel and feature contribution;
- Conclusive notes.

4.1 Interictal vs Preictal classification using EEG peripheral channels

After the segmentation and filtering the EEG signal for each patient, it was extracted the six chosen features, from the eight channels selected, mentioned in Chapter 3 from every ictal file that contained at least 10 minutes of preictal data. In addition to these features, an equal amount of data was also extracted from files that do not contain seizures. A total of 48 features were extracted.
With the objective of answering the proposed question in Chapter 1 (Whether it is possible to predict events using only peripheral EEG channels?) a interictal vs preictal classification was made. Eight different channel configuration problems are studied as follows:

- 1-channel presenting 8 single channels;
- 2-channel, with 28 different configurations;
- 3-channel, with 56 different configurations;
- 4-channel, with 71 different configurations;
- 5-channel, with 56 different configurations;
- 6-channel, with 28 different configurations;
- 7-channel, with 8 different configurations;
- 8-channel using all channels.

For each of the 3 datasets: 1) 10 minutes, 2) between 10 and 20 minutes and 3) 20 minutes, the number of each class (0 and 1) was matched.
To test the performance of the proposed approach, it was made the classification resorting to the binary classification problem.

In the following 3 sections, we may analyze the best results for the proposed approaches using 75/25 hold-out validation. The results presented in Tables 1, 2, 3, are the best results, the remaining are available in Appendix A.1, A.2, A.3.

4.1.1 Preictal 10 minutes (0-10 minutes)

For the binary classification problem for a preictal time window of 0-10 min, using class 0 (Interictal) and class 1 (Preictal 10 minutes) 12960 instances of interictal and 12960 instances from the preictal. The obtained results from the dataset can be seen in Table 1 divided according to the location of the Channels.

Table 1: Performance results for a preictal 10 minutes.

Location	Nº Channels	Configuration	Accuracy	Recall(0)	Recall(1)
Left	1	F7-F7	61	64	59
	2	F7-T7/P7-O1	70	72	68
	3	FP1-F7/T7-P7/P7-O1	74	75	72
	4	FP1-F7/F7-T7/T7-P7/P7-O1	75	76	74
Right	1	F8-T8	61	63	59
	2	F8-T8/P8-O2	69	71	67
	3	FP2-F8/F8-T8/P8-O2	71	73	69
	3	FP2-F8/T8-P8/P8-O2	75	77	74
	3	F8-T8/T8-P8/P8-O2	72	74	70
	4	FP2-F8/F8-T8/T8-P8/P8-O2	73	74	72
Both	2	F7-T7/P8-O2	70	72	67
	3	F7-T7/P7-O1/FP2-F8	72	73	72
	4	T7-P7/P7-O1/FP2-F8/P8-O2	77	78	75
	5	FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2	80	80	80
	6	FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	78	79	78
	6	FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	78	79	78
	7	FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	79	80	78
	7	FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	79	80	79
	8	all	80	81	78

From the results shown in Table 1, we see that an accuracy above 70% was obtained for the channel configurations containing over 3 channels in both side. The best result (80% accuracy) was achieved using all channels.

4.1.2 Preictal between 10 and 20 minutes

For the binary classification problem using class 0 (interictal) and Class 1 (Preictal between 10 and 20 minutes) 10440 instances of interictal and 10440 instances from the preictal. The obtained results from the dataset can be seen in Table 2 divided according to the location of the Channels.

Table 2: Performance results for a preictal between 10 and 20 minutes.

Location	Nº Channels	Configuration	Accuracy	Recall(0)	Recall(2)
Left	1	F7-T7	61	63	59
	2	F7-F7/P7-O1	70	72	67
	3	FP1-F7/T7-P7/P7-O1	73	75	72
	4	FP1-F7/F7-T7/T7-P7/P7-O1	75	77	73
Right	1	F8-T8	62	62	61
	2	F8-T8/P8-O2	71	72	70
	3	FP2-F8/F8-T8/P8-O2	75	77	74
	3	FP2-F8/T8-P8/P8-O2	72	74	71
	3	F8-T8/T8-P8/P8-O2	72	74	70
	4	FP2-F8/F8-T8/T8-P8/P8-O2	74	76	72
Both	2	F7-T7/P8-O2	70	71	68
	3	F7-T7/P7-O1/FP2-F8	74	76	71
	4	T7-P7/P7-O1/FP2-F8/P8-O2	77	79	74
	5	FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2	77	80	75
	6	FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	78	81	75
	6	FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	78	81	75
	7	FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	79	81	76
	7	FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	80	82	77
	8	all	80	82	78

The results presented in Table 2 are very similar to results achieved for a preictal of 10 minutes. One configuration using only 2 channels on the right side achieved an accuracy above 70%.

4.1.3 Preictal 20 minutes (0-20 minutes)

For the binary classification problem using class 0 (interictal) and Class 1 (Preictal 20 minutes) 12960 instances of interictal and 12960 instances from the preictal. The obtained results from the dataset can be seen in Table 3 divided according to the location of the Channels.

Table 3: Performance results.

Location	Nº Channels	Configuration	Accuracy	Recall(0)	Recall(1)
Left	1	F7-T7	64	65	62
	2	F7-T7/P7-O1	71	72	71
	3	FP1-F7/T7-P7/P7-O1	76	77	75
	4	FP1-F7/F7-T7/T7-P7/P7-O1	78	79	77
Right	1	F8-T8	64	65	62
	2	F8-T8/P8-O2	72	73	70
	3	FP2-F8/F8-T8/P8-O2	75	77	74
	3	FP2-F8/T8-P8/P8-O2	75	77	74
	3	F8-T8/T8-P8/P8-O2	75	77	74
	4	FP2-F8/F8-T8/T8-P8/P8-O2	77	79	75
Both	2	F7-T7/P8-O2	72	73	71
	3	F7-T7/P7-O1/FP2-F8	75	75	76
	4	T7-P7/P7-O1/FP2-F8/P8-O2	79	80	78
	5	FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2	80	80	80
	6	FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	81	82	80
	6	FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	81	82	80
	7	FP1-FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	82	83	80
	7	FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	82	83	80
	8	all	81	82	81

From the results shown in Table 3, we see that an accuracy above 80% was obtained for the channel configurations containing over 5 channels in both side.
From the presented outcomes, we may conclude that the **best time window is the third**

approach (using 20 minutes of preictal) using a channel configuration containing at least 5 channels placed on both sides. When comparing the first and second approaches we verify that the best results are for the time window between 10 and 20 minutes. This conclusion is unexpected since according to the state of the art the best performing algorithms were for the 10 minutes prediction. However, it is possible that the algorithm identified a general pattern for most of the patients for this time window, so the results for this time window are better than for the preictal of 10 minutes.

4.1.4 Patient-specific approach

The results presented in Table 4 show the average individual performance achieved applying a patient-specific approach (results in Appendix A.4, A.5, A.6).

Table 4: Average individual performance in % .

Dataset	Avg. Acc	Avg. Recall (0)	Avg. Recall (1)
0-10 min	86.39	86.73	86.13
10-20 min	86.55	85.54	86.58
0-20 min	87.56	85.72	86.22

From the average results, we may verify that **the accuracy and recall have higher values than the pooled-population approach**. This is expected since the algorithm will more easily identify changes in the signal when a seizure is approaching, given that the algorithm has already studied similar situations.

Like in **the results obtained for the general data the best outcome is for 0-20 minutes of preictal.** However, contrary to the results obtained from the general data, when comparing the time window between 10 and 20 minutes, **the outcome for each patient was split, that is there were good results for each of the time windows**. This means that the preictal patterns are recognized for 0-10 and 10-20 minutes.

4.1.5 Pooled-population approach using leaving-one patient-out validation

We implemented this experiment in order to show how a pooled-population approach performs leaving one patient out to validate the models using a preictal window of 10 minutes and 20 minutes. The Tables 5, and 6 present the results obtained.

Table 5: Leave One patient Out Validation for 10 minutes of preictal.

Patiente	Accuracy	Recall (0)	Recall (1)
1	56	24	87
2	55	47	62
3	51	53	50
4	47	47	48
5	50	49	51
6	67	75	60
7	51	45	56
8	64	58	69
9	43	47	38
10	53	79	28
11	53	40	66
12	53	33	72
13	47	54	39
14	52	70	34
15	56	68	44
16	48	33	64
17	63	54	72
18	55	44	66
19	57	63	51
20	60	40	81
21	46	46	45
22	60	47	74
23	43	51	35
24	49	17	81

Table 6: Leave One patient Out Validation for 20 minutes of preictal.

Patiente	Accuracy	Recall (0)	Recall (1)
1	52	37	54
2	43	28	57
3	60	64	54
4	61	44	74
5	59	65	48
6	72	78	67
7	45	35	50
8	57	48	65
9	50	76	38
10	45	72	13
11	55	15	74
12	49	31	85
13	67	67	0
14	52	82	17
15	60	60	60
16	45	27	68
17	67	76	61
18	36	19	52
19	51	65	44
20	56	46	69
21	44	39	48
22	63	49	70
23	60	57	61
24	50	34	63

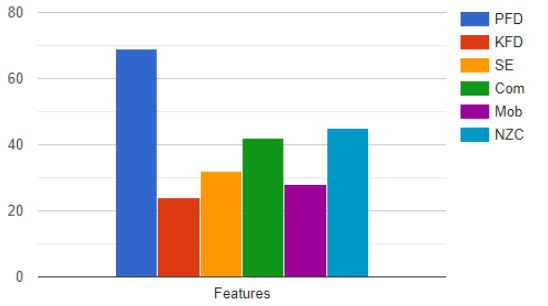
From the results achieved in this experiment, it may be concluded that **the findings gathered in the other experiments are not yet feasible results for the application of this algorithm in the real world**. This approach shows that **was not possible to generalize well without using data from the own patient**.

4.2 Channel and feature contribution

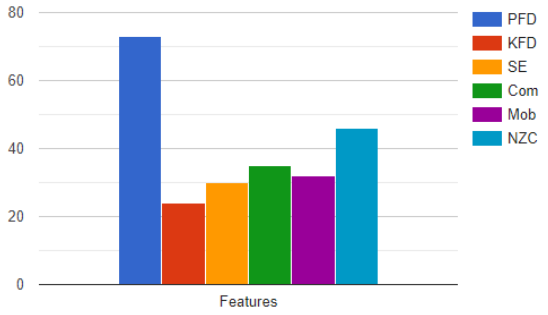
Another possible justification for the results seen in Tables 5 and 6 may be associated with the inter-variability of patients. For example, we do not have information about the epileptogenic focus for each patient and also, there are the influence of age on the EEG waveform and the influence of the acquisition scenario, e.g. the presence of sleep spindles.

So, in order to fill this lack of information, we choose to apply a feature selection technique, the maximum relevance and minimum redundancy (mRMR) algorithm, with the intention of realizing which channels and features contribute more for the classifications. The mRMR algorithm calculates a relevance score and a redundancy score for each feature in the dataset. The relevance score measures how well a feature is correlated with the target, while the redundancy score measures how similar a feature is to the other features already selected [76].

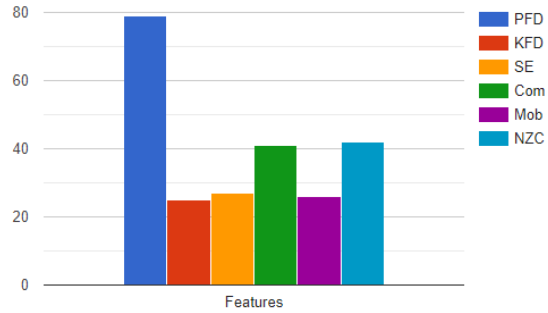
Figure 1 shows the most relevant features for 10 minutes, between 10 and 20 minutes, and 20 minutes. This analysis is made for the 10 most important features of each patient. From the analysis of Figure 1, we may notice a clear discrepancy between the Petrosian Fractal Dimension (PFD) and the other features, this means that this feature greatly influences the classification. In addition to the PFD, it is also noticeable the higher values from the Hjorth Complexity and the number of zero crossings. A possible dimensionality reduction is the use of only the three most relevant features, this would make the algorithm less redundant and more efficient. Another possible analysis that may be made through the results is the most important channels and features for each patient (presented in Appendix A.7, A.8, A.9). From this results, we may make some considerations in relation to the type of channel and feature more adequate for each patient thus making it possible to create a personalized algorithm for each patient. For example, for patient chb01 the feature selection method results show that Fp1-F7, F7-T7, T7-P7, T8-P8, and P8-O2 were between the channels with the best 10 features for both preictal 10 and 20 minutes. **These results suggest it would be possible, for this patient, to reduce the number of channels to five. By crossing these results with those obtained when we carried out the patient-specific approach, we noted that for one similar 5 channels configuration the model (in Figures 1 and 3) achieved an accuracy of 90% with a preictal of 10 minutes and 93%with 20 minutes of preictal.**



(d) 0-10 minutes



(e) 10-20 minutes



(f) 0-20 minutes

Figure 1: Feature importance.

4.3 Conclusive notes

From the obtained results it may be concluded that it is possible to make a classification using only peripheral channels, in fact, based on section 4.2 it is possible to consider using less than the 8 proposed channels thus using less computational power for the classification.
It is also possible to conclude that the optimal preictal window varies depending on the individual patients. For some individuals, the most suitable timeframe may be 10 minutes, while for others it could span from 0 to 20 minutes. Nonetheless, when considering a more general approach, adopting the 20-minute window would be preferable.

Chapter 5

Conclusions and Future Work

This chapter presents the main conclusions drawn from the research work described in this dissertation and also discusses some research topics that may be addressed as a continuation or a complement of this work.

5.1 Conclusion

This dissertation proposes an approach for epilepsy prediction using machine learning techniques and EEG. The literature shows an extensively studied approach for epileptic seizure prediction using data from EEG, but these approaches are not appropriate for patients in a free-living scenario. The definition of an approach that comprises the use of peripheral channels significantly contributes to the creation of suitable solutions for epileptic prevention to assist patients and caregivers in managing epilepsy. To support this dissertation, four main objectives were achieved:

- Analyze the existing open challenges in the current State-of-the-art for epileptic seizure prediction;
- Design and investigate the feasibility of using EEG peripheral channels for the epileptic seizure prediction approach;
- Identify the channels and features that contribute most to prediction;
- Evaluate and compare the performance using different pre-ictal periods.

Following, the research contributions regarding these objectives are summarized.

The **first objective** was presented in section 2.2, consists of a systematic literature review addressing the existing epileptic seizure prediction approaches. This review analyzes 81 studies in which the approaches have been addressed massively using all channels according to 10-20 System. From the SLR it was possible to verify that few authors make a channel reduction and this subject was not discussed in depth.

The **second objective** was divided into two parts. In chapter 3 we present the design and implementation strategy of the proposed approach for epileptic seizure prediction. We proposed an approach to make the classification using only 8 peripheral channels. Through the results presented in chapter 4, this first approach shows that it is possible to make a classification resorting to using only the peripheral channels. However, we found that the models do not generalize well without resorting to the patient's own data.

The **third objective** was presented in chapter 4 applying the mRMR feature selection algorithm. The results present the features and channels that contribute more towards the classification, concluding that for different patients, there are specific channels that produce better results. It was also possible to conclude that there are three features that contribute more to the classification.

The **fouth objective** was presented in chapter 4 concluding that the best preictal window for the classification performed using this pool of features was 20 minutes for the pooled-population approach and for the majority of Patient-specific models. With the achievement of these four objectives, we answered the questions stated in the chapter 1.

5.2 Future Work

Even though the proposed questions for this dissertation were answered, many others were raised.

- Whether by making a statistical analysis with the objective of being able to study the influence of age and gender influence the results?
- What kind of results will be obtained by the application of the feature selection method;
- Is it possible to conjugate this method with other Biosignals such as the ECG?
- It would also be interesting to apply a Patient specific validation, that is when applying the LOO algorithm instead of leaving a patient out, leave only a file of the patient, and use the rest of the data from the patient for training;
- The possibility of being able to identify the specific epileptogenic zone would also contribute to the achievement of better results;
- The application of a band filter, to classify EEG waveforms, would also possibly contribute to better results due to the possibility of differentiating between different activities such as sleeping and seizures.

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Appendix A

Appendix

A.1 General Results for 0-10 min

Table 1: General results for 1 Channel

1 Channel			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7	59	61	58
F7-T7	61	64	59
T7-P7	63	66	60
P7-O1	61	64	59
FP2-F8	60	62	57
F8-T8	61	63	60
T8-P8	61	63	59
P8-O2	60	63	57

Table 2: General results for 2 Channel

2 Channel			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7	68	68	67
FP1-F7/T7-P7	69	70	67
FP1-F7/P7-O1	69	71	68
FP1-F7/FP2-F8	65	65	64
FP1-F7/F8-T8	67	67	66
FP1-F7/T8-P8	69	70	68
FP1-F7/P8-O2	69	71	66
F7-T7/T7-P7	69	70	67
F7-T7/P7-O1	70	72	68
F7-T7/FP2-F8	68	69	66
F7-T7/F8-T8	68	69	66
F7-T7/T8-P8	69	71	68
F7-T7/P8-O2	70	72	67
T7-P7/P7-O1	69	72	66
T7-P7/FP2-F8	69	71	68
T7-P7/F8-T8	69	70	68
T7-P7/T8-P8	68	69	67
T7-P7/P8-O2	71	72	70
P7-O1/FP2-F8	70	72	68
P7-O1/F8-T8	70	72	68
P7-O1/T8-P8	69	72	66
P7-O1/P8-O2	67	70	65
FP2-F8/F8-T8	67	68	66
FP2-F8/T8-P8	68	69	67
FP2-F8/P8-O2	67	69	65
F8-T8/T8-P8	68	69	67
F8-T8/P8-O2	69	71	67
T8-P8/P8-O2	68	71	66

Table 3: General results for 3 Channel

3 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7	72	73	72
FP1-F7/F7-T7/P7-O1	73	74	72
FP1-F7/F7-T7/FP2-F8	71	72	70
FP1-F7/F7-T7/F8-T8	71	72	71
FP1-F7/F7-T7/T8-P8	73	73	72
FP1-F7/F7-T7/P8-O2	72	74	70
FP1-F7/T7-P7/P7-O1	74	75	72
FP1-F7/T7-P7/FP2-F8	72	73	71
FP1-F7/T7-P7/F8-T8	73	73	73
FP1-F7/T7-P7/T8-P8	74	74	73
FP1-F7/T7-P7/P8-O2	75	76	73
FP1-F7/P7-O1/FP2-F8	72	74	71
FP1-F7/P7-O1/F8-T8	73	74	72
FP1-F7/P7-O1/T8-P8	74	76	72
FP1-F7/P7-O1/P8-O2	72	75	70
FP1-F7/FP2-F8/F8-T8	70	70	69
FP1-F7/FP2-F8/T8-P8	70	72	69
FP1-F7/FP2-F8/P8-O2	71	73	68
FP1-F7/F8-T8/T8-P8	71	72	70
FP1-F7/F8-T8/P8-O2	72	73	71
FP1-F7/T8-P8/P8-O2	73	75	70
F7-T7/T7-P7/P7-O1	74	75	72
F7-T7/T7-P7/FP2-F8	72	72	72
F7-T7/T7-P7/F8-T8	73	73	72
F7-T7/T7-P7/T8-P8	73	74	71
F7-T7/T7-P7/P8-O2	74	75	72
F7-T7/P7-O1/FP2-F8	72	73	72
F7-T7/P7-O1/F8-T8	74	76	72
F7-T7/P7-O1/T8-P8	74	77	72
F7-T7/P7-O1/P8-O2	74	75	72
F7-T7/FP2-F8/F8-T8	72	73	70
F7-T7/FP2-F8/T8-P8	73	74	71
F7-T7/FP2-F8/P8-O2	72	74	71
F7-T7/F8-T8/T8-P8	72	73	71
F7-T7/F8-T8/P8-O2	73	75	71
F7-T7/T8-P8/P8-O2	73	75	71
T7-P7/P7-O1/FP2-F8	74	76	72
T7-P7/P7-O1/F8-T8	73	74	71
T7-P7/P7-O1/T8-P8	73	76	70
T7-P7/P7-O1/P8-O2	74	75	72
T7-P7/FP2-F8/F8-T8	72	74	71
T7-P7/FP2-F8/T8-P8	73	74	71
T7-P7/FP2-F8/P8-O2	74	75	73
T7-P7/F8-T8/T8-P8	72	74	71
T7-P7/F8-T8/P8-O2	74	76	73
T7-P7/T8-P8/P8-O2	73	75	71
P7-O1/FP2-F8/F8-T8	72	73	71
P7-O1/FP2-F8/T8-P8	73	76	71
P7-O1/FP2-F8/P8-O2	73	76	70
P7-O1/F8-T8/T8-P8	74	76	72
P7-O1/F8-T8/P8-O2	73	75	72
P7-O1/T8-P8/P8-O2	73	75	70
FP2-F8/F8-T8/T8-P8	71	71	70
FP2-F8/F8-T8/P8-O2	71	73	69
FP2-F8/T8-P8/P8-O2	72	74	70
F8-T8/T8-P8/P8-O2	72	74	71

Table 4: General results for 4 Channel

4 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1	75	76	74
FP1-F7/F7-T7/T7-P7FP2-F8	74	75	74
FP1-F7/F7-T7/T7-P7/F8-T8	74	74	74
FP1-F7/F7-T7/T7-P7/T8-P8	75	76	75
FP1-F7/F7-T7/T7-P7P8-O2	75	75	74
FP1-F7/F7-T7/P7-O1/FP2-F8	74	75	73
FP1-F7/F7-T7/P7-O1/F8-T8	75	76	75
FP1-F7/F7-T7/P7-O1/T8-P8	76	77	76
FP1-F7/F7-T7/P7-O1/P8-O2	75	77	74
FP1-F7/F7-T7/FP2-F8/F8-T8	73	74	72
FP1-F7/F7-T7/FP2-F8/T8-P8	74	75	74
FP1-F7/F7-T7/FP2-F8/P8-O2	74	76	72
FP1-F7/F7-T7/F8-T8/T8-P8	74	75	73
FP1-F7/F7-T7/F8-T8/P8-O2	74	76	73
FP1-F7/F7-T7/T8-P8/P8-O2	75	76	74
FP1-F7/T7-P7/P7-O1/FP2-F8	74	76	73
FP1-F7/T7-P7/P7-O1/F8-T8	76	78	74
FP1-F7/T7-P7/P7-O1/T8-P8	76	78	74
FP1-F7/T7-P7/P7-O1/P8-O2	76	77	75
FP1-F7/T7-P7/FP2-F8/F8-T8	74	74	74
FP1-F7/T7-P7/FP2-F8/T8-P8	75	76	74
FP1-F7/T7-P7/FP2-F8/P8-O2	75	77	74
FP1-F7/T7-P7/F8-T8/T8-P8	75	75	75
FP1-F7/T7-P7/F8-T8/P8-O2	75	76	74
FP1-F7/T7-P7/T8-P8/P8-O2	76	77	74
FP1-F7/P7-O1/FP2-F8/F8-T8	75	76	73
FP1-F7/P7-O1/FP2-F8/T8-P8	75	77	74
FP1-F7/P7-O1/FP2-F8/P8-O2	74	76	72
FP1-F7/P7-O1/F8-T8/T8-P8	76	78	75
FP1-F7/P7-O1/F8-T8/P8-O2	75	76	73
FP1-F7/P7-O1/T8-P8/P8-O2	76	78	73
FP1-F7/FP2-F8/F8-T8/T8-P8	72	72	72
FP1-F7/FP2-F8/F8-T8/P8-O2	73	74	72
FP1-F7/FP2-F8/T8-P8/P8-O2	74	75	73
FP1-F7/F8-T8/T8-P8/P8-O2	74	75	73
F7-T7/T7-P7/P7-O1/FP2-F8	75	76	74
F7-T7/T7-P7/P7-O1/F8-T8	75	76	74
F7-T7/T7-P7/P7-O1/T8-P8	76	78	74
F7-T7/T7-P7/P7-O1/P8-O2	76	77	74
F7-T7/T7-P7/FP2-F8/F8-T8	74	75	73
F7-T7/T7-P7/FP2-F8/T8-P8	75	76	74
F7-T7/T7-P7/FP2-F8/P8-O2	75	76	74
F7-T7/T7-P7/F8-T8/T8-P8	75	76	74
F7-T7/T7-P7/F8-T8/P8-O2	76	77	75
F7-T7/T7-P7/T8-P8/P8-O2	76	77	74
F7-T7/P7-O1/FP2-F8/F8-T8	75	76	75
F7-T7/P7-O1/FP2-F8/T8-P8	76	76	75
F7-T7/P7-O1/FP2-F8/P8-O2	76	77	74
F7-T7/P7-O1/F8-T8/T8-P8	75	78	73
F7-T7/P7-O1/F8-T8/P8-O2	76	78	74
F7-T7/P7-O1/T8-P8/P8-O2	76	78	74
F7-T7/FP2-F8/F8-T8/T8-P8	74	76	73
F7-T7/FP2-F8/F8-T8/P8-O2	74	76	72
F7-T7/FP2-F8/T8-P8/P8-O2	75	77	73
F7-T7/F8-T8/T8-P8/P8-O2	75	77	73
T7-P7/P7-O1/FP2-F8/F8-T8	76	77	75
T7-P7/P7-O1/FP2-F8/T8-P8	77	78	76
T7-P7/P7-O1/FP2-F8/P8-O2	77	78	75
T7-P7/P7-O1/F8-T8/T8-P8	76	78	73
T7-P7/P7-O1/F8-T8/P8-O2	76	78	75
T7-P7/P7-O1/T8-P8/P8-O2	75	77	73
T7-P7/FP2-F8/F8-T8/T8-P8	74	75	73
T7-P7/FP2-F8/F8-T8/P8-O2	75	76	74
T7-P7/FP2-F8/T8-P8/P8-O2	75	76	73
T7-P7/F8-T8/T8-P8/P8-O2	75	76	74
P7-O1/FP2-F8/F8-T8/T8-P8	74	76	73
P7-O1/FP2-F8/F8-T8/P8-O2	75	77	74
P7-O1/FP2-F8/T8-P8/P8-O2	75	77	73
P7-O1/F8-T8/T8-P8/P8-O2	75	77	73
FP2-F8/F8-T8/T8-P8/P8-O2	73	74	72

Table 5: General results for 5 Channel

5 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8	76	77	75
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8	77	78	76
FP1-F7/F7-T7/T7-P7/P7-O1/T8-P8	78	79	76
FP1-F7/F7-T7/T7-P7/P7-O1/P8-O2	77	77	76
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8	75	76	75
FP1-F7/F7-T7/T7-P7FP2-F8/T8-P8	76	76	76
FP1-F7/F7-T7/T7-P7/FP2-F8/P8-O2	76	77	75
FP1-F7/F7-T7/T7-P7/F8-T8/T8-P8	76	77	75
FP1-F7/F7-T7/T7-P7/F8-T8/P8-O2	77	77	76
FP1-F7/F7-T7/T7-P7/T8-P8/P8-O2	77	77	76
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8	77	77	76
FP1-F7/F7-T7/P7-O1/FP2-F8/T8-P8	77	77	77
FP1-F7/F7-T7/P7-O1/FP2-F8/P8-O2	77	78	75
FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8	77	79	76
FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2	77	78	76
FP1-F7/F7-T7/P7-O1/T8-P8/P8-O2	78	79	77
FP1-F7/F7-T7/FP2-F8/F8-T8/T8-P8	75	75	74
FP1-F7/F7-T7/FP2-F8/F8-T8/P8-O2	75	77	74
FP1-F7/F7-T7/FP2-F8/T8-P8/P8-O2	77	78	76
FP1-F7/F7-T7/F8-T8/T8-P8/P8-O2	76	78	74
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8	77	77	76
FP1-F7/T7-P7/P7-O1/FP2-F8/T8-P8	77	78	76
FP1-F7/T7-P7/P7-O1/FP2-F8/P8-O2	77	78	76
FP1-F7/T7-P7/P7-O1/F8-T8/T8-P8	78	79	76
FP1-F7/T7-P7/P7-O1/F8-T8/P8-O2	78	78	77
FP1-F7/T7-P7/P7-O1/T8-P8/P8-O2	77	80	75
FP1-F7/T7-P7/FP2-F8/F8-T8/T8-P8	76	77	75
FP1-F7/T7-P7/FP2-F8/F8-T8/P8-O2	77	78	75
FP1-F7/T7-P7/FP2-F8/T8-P8/P8-O2	76	77	75
FP1-F7/T7-P7/F8-T8/T8-P8/P8-O2	77	78	76
FP1-F7/P7-O1/FP2-F8/F8-T8/T8-P8	76	78	74
FP1-F7/P7-O1/FP2-F8/F8-T8/P8-O2	76	77	75
FP1-F7/P7-O1/FP2-F8/T8-P8/P8-O2	77	78	75
FP1-F7/P7-O1/F8-T8/T8-P8/P8-O2	77	79	75
FP1-F7/FP2-F8/F8-T8/T8-P8/P8-O2	75	76	76
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8	77	77	76
F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8	78	79	77
F7-T7/T7-P7/P7-O1/FP2-F8/P8-O2	78	79	77
F7-T7/T7-P7/P7-O1/F8-T8/T8-P8	77	79	75
F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	77	79	75
F7-T7/T7-P7/P7-O1/T8-P8/P8-O2	77	79	75
F7-T7/T7-P7/FP2-F8/F8-T8/T8-P8	76	77	76
F7-T7/T7-P7/FP2-F8/F8-T8/P8-O2	77	78	75
F7-T7/T7-P7/FP2-F8/T8-P8/P8-O2	77	78	77
F7-T7/T7-P7/F8-T8/T8-P8/P8-O2	76	77	75
F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8	76	78	75
F7-T7/P7-O1/FP2-F8/F8-T8/P8-O2	77	79	76
F7-T7/P7-O1/FP2-F8/T8-P8/P8-O2	76	78	75
F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	77	78	75
F7-T7/FP2-F8/F8-T8/T8-P8/P8-O2	76	78	74
T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	78	79	76
T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	77	78	76
T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	77	79	75
T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	77	79	76
T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	76	77	75
P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	76	79	74

Table 6: General results for 6 Channel

6 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8	78	78	77
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8	78	80	77
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/P8-O2	78	79	77
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8	79	80	77
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	78	79	78
FP1-F7/F7-T7/T7-P7/P7-O1/T8-P8/P8-O2	79	80	78
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/T8-P8	77	78	77
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/P8-O2	78	79	77
P1-F7/F7-T7/T7-P7FP2-F8/T8-P8/P8-O2	78	79	78
P1-F7/F7-T7/T7-P7/F8-T8/T8-P8/P8-O2	77	78	76
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8	77	79	76
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/P8-O2	78	79	78
FP1-F7/F7-T7/P7-O1/FP2-F8/T8-P8/P8-O2	78	80	77
FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	78	79	78
FP1-F7/F7-T7/FP2-F8/F8-T8/T8-P8/P8-O2	76	77	75
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	78	79	77
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	78	79	78
FP1-F7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	78	80	77
FP1-F7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	78	80	77
FP1-F7/T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	78	79	77
FP1-F7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	77	79	75
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	78	80	76
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	78	79	77
F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	78	79	77
F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	78	79	77
F7-T7/T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	78	79	77
F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	78	79	77
T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	78	78	77

Table 7: General results for 7 Channel

7 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	79	79	78
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	79	80	78
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	79	80	78
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	79	80	79
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/T8-P8/P8-O2	78	79	78
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	79	80	77
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	80	81	78
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	79	80	78

Table 8: General results for 8 Channel

8 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	80	81	78

A.2 General Results for 10-20 min

Table 9: General results for 1 Channel

1 Channel			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7	59	61	57
F7-T7	61	63	59
T7-P7	60	62	61
P7-O1	63	65	61
FP2-F8	59	61	57
F8-T8	62	63	61
T8-P8	62	62	61
P8-O2	61	63	59

Table 10: General results for 2 Channel

2 Channels			
	Accuracy	**Recall (0)**	**Recall (2)**
FP1-F7/F7-T7	67	68	66
FP1-F7/T7-P7	68	69	66
FP1-F7/P7-O1	70	72	67
FP1-F7/FP2-F8	65	65	63
FP1-F7/F8-T8	67	70	64
FP1-F7/T8-P8	68	70	66
FP1-F7/P8-O2	69	71	67
F7-T7/T7-P7	68	70	66
F7-T7/P7-O1	70	73	67
F7-T7/FP2-F8	67	69	65
F7-T7/F8-T8	67	69	65
F7-T7/T8-P8	68	70	66
F7-T7/P8-O2	70	70	68
T7-P7/P7-O1	69	70	68
T7-P7/FP2-F8	67	69	65
T7-P7/F8-T8	68	70	66
T7-P7/T8-P8	68	69	66
T7-P7/P8-O2	69	70	68
P7-O1/FP2-F8	71	73	69
P7-O1/F8-T8	70	73	67
P7-O1/T8-P8	69	70	69
P7-O1/P8-O2	69	73	66
FP2-F8/F8-T8	67	69	65
FP2-F8/T8-P8	68	71	66
FP2-F8/P8-O2	68	69	67
F8-T8/T8-P8	66	67	65
F8-T8/P8-O2	71	72	70
T8-P8/P8-O2	68	69	68

Table 11: General results for 3 Channel

3 Channels			
	Accuracy	**Recall (0)**	**Recall (2)**
FP1-F7/F7-T7/T7-P7	71	72	70
FP1-F7/F7-T7/P7-O1	74	77	71
FP1-F7/F7-T7/FP2-F8	70	72	68
FP1-F7/F7-T7/F8-T8	71	73	68
FP1-F7/F7-T7/T8-P8	71	72	69
FP1-F7/F7-T7/P8-O2	73	74	73
FP1-F7/T7-P7/P7-O1	73	75	72
FP1-F7/T7-P7/FP2-F8	71	73	69
FP1-F7/T7-P7/F8-T8	72	74	70
FP1-F7/T7-P7/T8-P8	71	73	69
FP1-F7/T7-P7/P8-O2	74	75	72
FP1-F7/P7-O1/FP2-F8	72	74	70
FP1-F7/P7-O1/F8-T8	73	77	69
FP1-F7/P7-O1/T8-P8	74	76	72
FP1-F7/P7-O1/P8-O2	73	76	70
FP1-F7/FP2-F8/F8-T8	70	73	67
FP1-F7/FP2-F8/T8-P8	71	73	69
FP1-F7/FP2-F8/P8-O2	72	73	71
FP1-F7/F8-T8/T8-P8	70	73	68
FP1-F7/F8-T8/P8-O2	74	76	71
FP1-F7/T8-P8/P8-O2	73	76	70
F7-T7/T7-P7/P7-O1	74	76	71
F7-T7/T7-P7/FP2-F8	71	73	69
F7-T7/T7-P7/F8-T8	71	73	69
F7-T7/T7-P7/T8-P8	72	73	72
F7-T7/T7-P7/P8-O2	73	74	72
F7-T7/P7-O1/FP2-F8	74	76	71
F7-T7/P7-O1/F8-T8	74	77	70
F7-T7/P7-O1/T8-P8	75	76	73
F7-T7/P7-O1/P8-O2	74	76	71
F7-T7/FP2-F8/F8-T8	71	73	69
F7-T7/FP2-F8/T8-P8	72	74	70
F7-T7/FP2-F8/P8-O2	73	74	71
F7-T7/F8-T8/T8-P8	70	72	68
F7-T7/F8-T8/P8-O2	73	75	71
F7-T7/T8-P8/P8-O2	73	75	72
T7-P7/P7-O1/FP2-F8	74	75	72
T7-P7/P7-O1/F8-T8	73	76	70
T7-P7/P7-O1/T8-P8	73	74	71
T7-P7/P7-O1/P8-O2	73	75	72
T7-P7/FP2-F8/F8-T8	72	74	69
T7-P7/FP2-F8/T8-P8	71	73	70
T7-P7/FP2-F8/P8-O2	73	74	73
T7-P7/F8-T8/T8-P8	71	73	70
T7-P7/F8-T8/P8-O2	73	75	71
T7-P7/T8-P8/P8-O2	73	73	73
P7-O1/FP2-F8/F8-T8	74	76	72
P7-O1/FP2-F8/T8-P8	73	75	71
P7-O1/FP2-F8/P8-O2	74	76	71
P7-O1/F8-T8/T8-P8	72	75	69
P7-O1/F8-T8/P8-O2	74	77	71
P7-O1/T8-P8/P8-O2	73	74	71
FP2-F8/F8-T8/T8-P8	71	73	69
FP2-F8/F8-T8/P8-O2	73	74	73
FP2-F8/T8-P8/P8-O2	72	74	71
F8-T8/T8-P8/P8-O2	72	74	70

Table 12: General results for 4 Channel

4 Channels			
	Accuracy	**Recall (0)**	**Recall (2)**
FP1-F7/F7-T7/T7-P7/P7-O1	75	77	73
FP1-F7/F7-T7/T7-P7FP2-F8	73	75	72
FP1-F7/F7-T7/T7-P7/F8-T8	74	76	72
FP1-F7/F7-T7/T7-P7/T8-P8	73	75	72
FP1-F7/F7-T7/T7-P7P8-O2	74	75	74
FP1-F7/F7-T7/P7-O1/FP2-F8	75	77	73
FP1-F7/F7-T7/P7-O1/F8-T8	75	78	72
FP1-F7/F7-T7/P7-O1/T8-P8	76	78	74
FP1-F7/F7-T7/P7-O1/P8-O2	76	79	74
FP1-F7/F7-T7/FP2-F8/F8-T8	72	75	70
FP1-F7/F7-T7/FP2-F8/T8-P8	73	74	71
FP1-F7/F7-T7/FP2-F8/P8-O2	74	76	73
FP1-F7/F7-T7/F8-T8/T8-P8	73	75	71
FP1-F7/F7-T7/F8-T8/P8-O2	75	77	74
FP1-F7/F7-T7/T8-P8/P8-O2	75	77	73
FP1-F7/T7-P7/P7-O1/FP2-F8	75	78	73
FP1-F7/T7-P7/P7-O1/F8-T8	76	80	73
FP1-F7/T7-P7/P7-O1/T8-P8	76	78	73
FP1-F7/T7-P7/P7-O1/P8-O2	76	78	73
FP1-F7/T7-P7/FP2-F8/F8-T8	74	76	72
FP1-F7/T7-P7/FP2-F8/T8-P8	74	76	71
FP1-F7/T7-P7/FP2-F8/P8-O2	75	76	75
FP1-F7/T7-P7/F8-T8/T8-P8	75	77	72
FP1-F7/T7-P7/F8-T8/P8-O2	76	78	74
FP1-F7/T7-P7/T8-P8/P8-O2	75	77	74
FP1-F7/P7-O1/FP2-F8/F8-T8	75	78	71
FP1-F7/P7-O1/FP2-F8/T8-P8	75	77	73
FP1-F7/P7-O1/FP2-F8/P8-O2	75	77	73
FP1-F7/P7-O1/F8-T8/T8-P8	74	76	72
FP1-F7/P7-O1/F8-T8/P8-O2	76	79	72
FP1-F7/P7-O1/T8-P8/P8-O2	76	79	73
FP1-F7/FP2-F8/F8-T8/T8-P8	72	74	70
FP1-F7/FP2-F8/F8-T8/P8-O2	75	76	75
FP1-F7/FP2-F8/T8-P8/P8-O2	75	77	73
FP1-F7/F8-T8/T8-P8/P8-O2	75	77	72
F7-T7/T7-P7/P7-O1/FP2-F8	75	77	73
F7-T7/T7-P7/P7-O1/F8-T8	76	78	74
F7-T7/T7-P7/P7-O1/T8-P8	76	78	75
F7-T7/T7-P7/P7-O1/P8-O2	75	78	72
F7-T7/T7-P7/FP2-F8/F8-T8	74	77	72
F7-T7/T7-P7/FP2-F8/T8-P8	74	76	73
F7-T7/T7-P7/FP2-F8/P8-O2	76	77	74
F7-T7/T7-P7/F8-T8/T8-P8	74	76	71
F7-T7/T7-P7/F8-T8/P8-O2	75	77	73
F7-T7/T7-P7/T8-P8/P8-O2	76	77	74
F7-T7/P7-O1/FP2-F8/F8-T8	75	78	72
F7-T7/P7-O1/FP2-F8/T8-P8	76	78	75
F7-T7/P7-O1/FP2-F8/P8-O2	76	78	74
F7-T7/P7-O1/F8-T8/T8-P8	75	76	74
F7-T7/P7-O1/F8-T8/P8-O2	76	79	72
F7-T7/P7-O1/T8-P8/P8-O2	76	79	73
F7-T7/FP2-F8/F8-T8/T8-P8	74	76	71
F7-T7/FP2-F8/F8-T8/P8-O2	75	78	73
F7-T7/FP2-F8/T8-P8/P8-O2	75	77	73
F7-T7/F8-T8/T8-P8/P8-O2	74	76	73
T7-P7/P7-O1/FP2-F8/F8-T8	76	78	74
T7-P7/P7-O1/FP2-F8/T8-P8	76	78	74
T7-P7/P7-O1/FP2-F8/P8-O2	77	79	74
T7-P7/P7-O1/F8-T8/T8-P8	75	77	73
T7-P7/P7-O1/F8-T8/P8-O2	76	79	72
T7-P7/P7-O1/T8-P8/P8-O2	75	78	72
T7-P7/FP2-F8/F8-T8/T8-P8	73	75	70
T7-P7/FP2-F8/F8-T8/P8-O2	75	77	73
T7-P7/FP2-F8/T8-P8/P8-O2	75	77	73
T7-P7/F8-T8/T8-P8/P8-O2	74	76	73
P7-O1/FP2-F8/F8-T8/T8-P8	75	78	72
P7-O1/FP2-F8/F8-T8/P8-O2	76	78	73
P7-O1/FP2-F8/T8-P8/P8-O2	76	79	73
P7-O1/F8-T8/T8-P8/P8-O2	76	79	72
FP2-F8/F8-T8/T8-P8/P8-O2	74	76	72

Table 13: General results for 5 Channel

5 Channel			
	Accuracy	**Recall (0)**	**Recall (2)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8	77	78	75
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8	77	80	73
FP1-F7/F7-T7/T7-P7/P7-O1/T8-P8	77	79	75
FP1-F7/F7-T7/T7-P7/P7-O1/P8-O2	77	80	75
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8	75	78	72
FP1-F7/F7-T7/T7-P7FP2-F8/T8-P8	74	76	72
FP1-F7/F7-T7/T7-P7FP2-F8/P8-O2	76	78	74
FP1-F7/F7-T7/T7-P7/F8-T8/T8-P8	75	77	73
FP1-F7/F7-T7/T7-P7/F8-T8/P8-O2	77	78	76
FP1-F7/F7-T7/T7-P7/T8-P8/P8-O2	76	78	74
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8	77	79	74
FP1-F7/F7-T7/P7-O1/FP2-F8/T8-P8	77	78	76
FP1-F7/F7-T7/P7-O1/FP2-F8/P8-O2	77	79	74
FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8	76	78	74
FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2	77	80	75
FP1-F7/F7-T7/P7-O1/T8-P8/P8-O2	78	80	75
FP1-F7/F7-T7/FP2-F8/F8-T8/T8-P8	74	76	72
FP1-F7/F7-T7/FP2-F8/F8-T8/P8-O2	76	78	74
FP1-F7/F7-T7/FP2-F8/T8-P8/P8-O2	76	78	74
FP1-F7/F7-T7/F8-T8/T8-P8/P8-O2	76	78	75
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8	77	80	74
FP1-F7/T7-P7/P7-O1/FP2-F8/T8-P8	76	79	74
FP1-F7/T7-P7/P7-O1/FP2-F8/P8-O2	78	80	75
FP1-F7/T7-P7/P7-O1/F8-T8/T8-P8	77	80	75
FP1-F7/T7-P7/P7-O1/F8-T8/P8-O2	78	81	75
FP1-F7/T7-P7/P7-O1/T8-P8/P8-O2	78	80	75
FP1-F7/T7-P7/FP2-F8/F8-T8/T8-P8	75	78	72
FP1-F7/T7-P7/FP2-F8/F8-T8/P8-O2	77	78	75
FP1-F7/T7-P7/FP2-F8/T8-P8/P8-O2	77	78	75
FP1-F7/T7-P7/F8-T8/T8-P8/P8-O2	77	80	75
FP1-F7/P7-O1/FP2-F8/F8-T8/T8-P8	76	79	74
FP1-F7/P7-O1/FP2-F8/F8-T8/P8-O2	77	80	75
FP1-F7/P7-O1/FP2-F8/T8-P8/P8-O2	77	80	74
FP1-F7/P7-O1/F8-T8/T8-P8/P8-O2	77	80	74
FP1-F7/FP2-F8/F8-T8/T8-P8/P8-O2	76	78	74
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8	78	79	76
F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8	77	78	75
F7-T7/T7-P7/P7-O1/FP2-F8/P8-O2	78	79	76
F7-T7/T7-P7/P7-O1/F8-T8/T8-P8	77	78	75
F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	77	80	75
F7-T7/T7-P7/P7-O1/T8-P8/P8-O2	77	80	75
F7-T7/T7-P7/FP2-F8/F8-T8/T8-P8	75	77	72
F7-T7/T7-P7/FP2-F8/F8-T8/P8-O2	76	79	74
F7-T7/T7-P7/FP2-F8/T8-P8/P8-O2	77	77	76
F7-T7/T7-P7/F8-T8/T8-P8/P8-O2	76	78	74
F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8	77	80	75
F7-T7/P7-O1/FP2-F8/F8-T8/P8-O2	77	79	75
F7-T7/P7-O1/FP2-F8/T8-P8/P8-O2	77	80	74
F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	77	80	73
F7-T7/FP2-F8/F8-T8/T8-P8/P8-O2	76	78	74
T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	77	80	75
T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	78	80	75
T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	77	80	75
T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	76	80	73
T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	76	78	74
P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	77	80	74

Table 14: General results for 6 Channel

6 Channels			
	Accuracy	**Recall (0)**	**Recall (2)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8	78	80	75
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8	77	79	75
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/P8-O2	78	80	76
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8	77	79	75
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	78	81	75
FP1-F7/F7-T7/T7-P7/P7-O1/T8-P8/P8-O2	79	81	76
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/T8-P8	75	78	72
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/P8-O2	77	79	76
P1-F7/F7-T7/T7-P7FP2-F8/T8-P8/P8-O2	76	77	76
P1-F7/F7-T7/T7-P7/F8-T8/T8-P8/P8-O2	77	79	76
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8	77	80	75
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/P8-O2	78	80	77
FP1-F7/F7-T7/P7-O1/FP2-F8/T8-P8/P8-O2	79	81	77
FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	78	81	75
FP1-F7/F7-T7/FP2-F8/F8-T8/T8-P8/P8-O2	77	79	75
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	78	81	75
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	79	80	77
FP1-F7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	78	80	77
FP1-F7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	79	82	76
FP1-F7/T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	78	80	75
FP1-F7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	79	81	76
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	77	79	76
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	79	81	77
F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	79	81	76
F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	78	87	75
F7-T7/T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	77	79	76
F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	78	81	74
T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	78	81	76

Table 15: General results for 7 Channel

7 Channels			
	Accuracy	**Recall (0)**	**Recall (2)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	78	80	76
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	79	81	76
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	79	81	77
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	80	82	77
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/T8-P8/P8-O2	78	79	77
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	79	82	77
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	79	81	76
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	80	82	77

Table 16: General results for 8 Channel

8 Channels			
	Accuracy	**Recall (0)**	**Recall (2)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2 80 81 78	80	82	78

A.3 General Results for 0-20 min

Table 17: General results for 1 Channel

1 Channel			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7	60	62	57
F7-T7	64	65	62
T7-P7	62	64	61
P7-O1	62	65	60
FP2-F8	61	64	58
F8-T8	62	65	60
T8-P8	64	65	62
P8-O2	61	67	56

Table 18: General results for 2 Channel

2 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7	69	70	67
FP1-F7/T7-P7	71	72	70
FP1-F7/P7-O1	71	72	70
FP1-F7/FP2-F8	67	69	65
FP1-F7/F8-T8	69	70	69
FP1-F7/T8-P8	70	71	70
FP1-F7/P8-O2	71	72	71
F7-T7/T7-P7	70	72	69
F7-T7/P7-O1	71	72	71
F7-T7/FP2-F8	69	69	69
F7-T7/F8-T8	70	71	68
F7-T7/T8-P8	71	72	70
F7-T7/P8-O2	72	75	69
T7-P7/P7-O1	71	72	69
T7-P7/FP2-F8	71	72	69
T7-P7/F8-T8	70	72	69
T7-P7/T8-P8	70	71	69
T7-P7/P8-O2	72	73	71
P7-O1/FP2-F8	71	71	71
P7-O1/F8-T8	71	72	71
P7-O1/T8-P8	71	73	70
P7-O1/P8-O2	68	72	65
FP2-F8/F8-T8	69	70	68
FP2-F8/T8-P8	71	72	70
FP2-F8/P8-O2	70	72	69
F8-T8/T8-P8	69	71	68
F8-T8/P8-O2	72	73	70
T8-P8/P8-O2	71	74	68

Table 19: General results for 3 Channel

3 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7	74	75	74
FP1-F7/F7-T7/P7-O1	75	76	74
FP1-F7/F7-T7/FP2-F8	72	73	71
FP1-F7/F7-T7/F8-T8	73	73	72
FP1-F7/F7-T7/T8-P8	74	75	73
FP1-F7/F7-T7/P8-O2	76	77	74
FP1-F7/T7-P7/P7-O1	76	77	75
FP1-F7/T7-P7/FP2-F8	73	74	72
FP1-F7/T7-P7/F8-T8	74	75	73
FP1-F7/T7-P7/T8-P8	75	76	73
FP1-F7/T7-P7/P8-O2	77	79	76
FP1-F7/P7-O1/FP2-F8	74	75	73
FP1-F7/P7-O1/F8-T8	75	75	74
FP1-F7/P7-O1/T8-P8	76	77	75
FP1-F7/P7-O1/P8-O2	75	76	74
FP1-F7/FP2-F8/F8-T8	72	73	70
FP1-F7/FP2-F8/T8-P8	73	74	72
FP1-F7/FP2-F8/P8-O2	74	75	72
FP1-F7/F8-T8/T8-P8	73	74	72
FP1-F7/F8-T8/P8-O2	75	76	74
FP1-F7/T8-P8/P8-O2	76	78	74
F7-T7/T7-P7/P7-O1	75	75	75
F7-T7/T7-P7/FP2-F8	74	73	74
F7-T7/T7-P7/F8-T8	73	75	72
F7-T7/T7-P7/T8-P8	75	76	74
F7-T7/T7-P7/P8-O2	75	76	74
F7-T7/P7-O1/FP2-F8	75	75	76
F7-T7/P7-O1/F8-T8	76	77	74
F7-T7/P7-O1/T8-P8	76	76	75
F7-T7/P7-O1/P8-O2	75	75	75
F7-T7/FP2-F8/F8-T8	73	73	72
F7-T7/FP2-F8/T8-P8	75	74	75
F7-T7/FP2-F8/P8-O2	74	75	73
F7-T7/F8-T8/T8-P8	74	75	73
F7-T7/F8-T8/P8-O2	76	78	74
F7-T7/T8-P8/P8-O2	76	77	74
T7-P7/P7-O1/FP2-F8	76	77	75
T7-P7/P7-O1/F8-T8	76	76	75
T7-P7/P7-O1/T8-P8	75	76	74
T7-P7/P7-O1/P8-O2	74	75	73
T7-P7/FP2-F8/F8-T8	74	75	73
T7-P7/FP2-F8/T8-P8	75	76	73
T7-P7/FP2-F8/P8-O2	76	77	74
T7-P7/F8-T8/T8-P8	73	74	73
T7-P7/F8-T8/P8-O2	75	77	74
T7-P7/T8-P8/P8-O2	75	76	74
P7-O1/FP2-F8/F8-T8	75	75	75
P7-O1/FP2-F8/T8-P8	75	76	73
P7-O1/FP2-F8/P8-O2	74	76	73
P7-O1/F8-T8/T8-P8	74	75	73
P7-O1/F8-T8/P8-O2	75	76	75
P7-O1/T8-P8/P8-O2	74	77	72
FP2-F8/F8-T8/T8-P8	74	75	73
FP2-F8/F8-T8/P8-O2	75	77	74
FP2-F8/T8-P8/P8-O2	75	77	74
F8-T8/T8-P8/P8-O2	75	77	74

Table 20: General results for 4 Channel

4 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1	78	79	77
FP1-F7/F7-T7/T7-P7FP2-F8	75	75	75
FP1-F7/F7-T7/T7-P7/F8-T8	76	77	75
FP1-F7/F7-T7/T7-P7/T8-P8	76	77	75
FP1-F7/F7-T7/T7-P7P8-O2	77	79	76
FP1-F7/F7-T7/P7-O1/FP2-F8	76	77	76
FP1-F7/F7-T7/P7-O1/F8-T8	78	78	77
FP1-F7/F7-T7/P7-O1/T8-P8	78	78	77
FP1-F7/F7-T7/P7-O1/P8-O2	78	79	77
FP1-F7/F7-T7/FP2-F8/F8-T8	75	75	75
FP1-F7/F7-T7/FP2-F8/T8-P8	76	77	76
FP1-F7/F7-T7/FP2-F8/P8-O2	76	77	76
FP1-F7/F7-T7/F8-T8/T8-P8	77	77	76
FP1-F7/F7-T7/F8-T8/P8-O2	78	80	76
FP1-F7/F7-T7/T8-P8/P8-O2	78	81	76
FP1-F7/T7-P7/P7-O1/FP2-F8	76	77	76
FP1-F7/T7-P7/P7-O1/F8-T8	78	78	77
FP1-F7/T7-P7/P7-O1/T8-P8	78	78	77
FP1-F7/T7-P7/P7-O1/P8-O2	78	79	77
FP1-F7/T7-P7/FP2-F8/F8-T8	75	75	75
FP1-F7/T7-P7/FP2-F8/T8-P8	76	77	76
FP1-F7/T7-P7/FP2-F8/P8-O2	76	77	76
FP1-F7/T7-P7/F8-T8/T8-P8	77	77	76
FP1-F7/T7-P7/F8-T8/P8-O2	78	80	76
FP1-F7/T7-P7/T8-P8/P8-O2	78	81	76
FP1-F7/P7-O1/FP2-F8/F8-T8	77	77	76
FP1-F7/P7-O1/FP2-F8/T8-P8	78	78	77
FP1-F7/P7-O1/FP2-F8/P8-O2	76	78	74
FP1-F7/P7-O1/F8-T8/T8-P8	77	79	75
FP1-F7/P7-O1/F8-T8/P8-O2	78	79	77
FP1-F7/P7-O1/T8-P8/P8-O2	78	80	76
FP1-F7/FP2-F8/F8-T8/T8-P8	75	76	75
FP1-F7/FP2-F8/F8-T8/P8-O2	77	78	76
FP1-F7/FP2-F8/T8-P8/P8-O2	77	78	76
FP1-F7/F8-T8/T8-P8/P8-O2	77	80	75
F7-T7/T7-P7/P7-O1/FP2-F8	77	77	78
F7-T7/T7-P7/P7-O1/F8-T8	77	78	76
F7-T7/T7-P7/P7-O1/T8-P8	78	79	77
F7-T7/T7-P7/P7-O1/P8-O2	78	78	77
F7-T7/T7-P7/FP2-F8/F8-T8	76	77	75
F7-T7/T7-P7/FP2-F8/T8-P8	77	77	76
F7-T7/T7-P7/FP2-F8/P8-O2	77	78	76
F7-T7/T7-P7/F8-T8/T8-P8	76	77	75
F7-T7/T7-P7/F8-T8/P8-O2	77	79	76
F7-T7/T7-P7/T8-P8/P8-O2	77	79	75
F7-T7/P7-O1/FP2-F8/F8-T8	78	78	78
F7-T7/P7-O1/FP2-F8/T8-P8	79	79	79
F7-T7/P7-O1/FP2-F8/P8-O2	78	79	77
F7-T7/P7-O1/F8-T8/T8-P8	77	78	77
F7-T7/P7-O1/F8-T8/P8-O2	78	80	77
F7-T7/P7-O1/T8-P8/P8-O2	78	79	77
F7-T7/FP2-F8/F8-T8/T8-P8	77	77	76
F7-T7/FP2-F8/F8-T8/P8-O2	78	79	77
F7-T7/FP2-F8/T8-P8/P8-O2	78	79	77
F7-T7/F8-T8/T8-P8/P8-O2	78	79	76
T7-P7/P7-O1/FP2-F8/F8-T8	78	77	78
T7-P7/P7-O1/FP2-F8/T8-P8	78	80	76
T7-P7/P7-O1/FP2-F8/P8-O2	79	80	78
T7-P7/P7-O1/F8-T8/T8-P8	77	78	76
T7-P7/P7-O1/F8-T8/P8-O2	78	78	77
T7-P7/P7-O1/T8-P8/P8-O2	77	79	75
T7-P7/FP2-F8/F8-T8/T8-P8	76	77	76
T7-P7/FP2-F8/F8-T8/P8-O2	78	79	76
T7-P7/FP2-F8/T8-P8/P8-O2	78	80	77
T7-P7/F8-T8/T8-P8/P8-O2	77	79	76
P7-O1/FP2-F8/F8-T8/T8-P8	77	79	75
P7-O1/FP2-F8/F8-T8/P8-O2	78	78	77
P7-O1/FP2-F8/T8-P8/P8-O2	77	80	75
P7-O1/F8-T8/T8-P8/P8-O2	77	79	75
FP2-F8/F8-T8/T8-P8/P8-O2	77	79	75

Table 21: General results for 5 Channel

5 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
P1-F7/F7-T7/T7-P7/P7-O1/FP2-F8	77	77	77
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8	79	80	78
FP1-F7/F7-T7/T7-P7/P7-O1/T8-P8	79	79	79
FP1-F7/F7-T7/T7-P7/P7-O1/P8-O2	80	80	79
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8	77	78	77
FP1-F7/F7-T7/T7-P7FP2-F8/T8-P8	78	79	77
FP1-F7/F7-T7/T7-P7/FP2-F8/P8-O2	78	79	77
FP1-F7/F7-T7/T7-P7/F8-T8/T8-P8	78	79	77
FP1-F7/F7-T7/T7-P7/F8-T8/P8-O2	79	81	78
FP1-F7/F7-T7/T7-P7/T8-P8/P8-O2	79	80	78
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8	79	79	79
FP1-F7/F7-T7/P7-O1/FP2-F8/T8-P8	79	80	78
FP1-F7/F7-T7/P7-O1/FP2-F8/P8-O2	79	80	78
FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8	79	81	77
FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2	80	80	80
FP1-F7/F7-T7/P7-O1/T8-P8/P8-O2	80	82	79
FP1-F7/F7-T7/FP2-F8/F8-T8/T8-P8	78	78	77
FP1-F7/F7-T7/FP2-F8/F8-T8/P8-O2	79	81	77
FP1-F7/F7-T7/FP2-F8/T8-P8/P8-O2	79	80	78
FP1-F7/F7-T7/F8-T8/T8-P8/P8-O2	79	81	77
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8	78	79	78
FP1-F7/T7-P7/P7-O1/FP2-F8/T8-P8	79	80	78
FP1-F7/T7-P7/P7-O1/FP2-F8/P8-O2	79	81	78
FP1-F7/T7-P7/P7-O1/F8-T8/T8-P8	79	81	77
FP1-F7/T7-P7/P7-O1/F8-T8/P8-O2	79	81	78
FP1-F7/T7-P7/P7-O1/T8-P8/P8-O2	79	82	77
FP1-F7/T7-P7/FP2-F8/F8-T8/T8-P8	78	78	78
FP1-F7/T7-P7/FP2-F8/F8-T8/P8-O2	79	80	78
FP1-F7/T7-P7/FP2-F8/T8-P8/P8-O2	79	81	78
FP1-F7/T7-P7/F8-T8/T8-P8/P8-O2	79	81	78
FP1-F7/P7-O1/FP2-F8/F8-T8/T8-P8	78	79	78
FP1-F7/P7-O1/FP2-F8/F8-T8/P8-O2	79	80	78
FP1-F7/P7-O1/FP2-F8/T8-P8/P8-O2	78	81	76
FP1-F7/P7-O1/F8-T8/T8-P8/P8-O2	79	81	77
FP1-F7/FP2-F8/F8-T8/T8-P8/P8-O2	79	80	77
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8	79	80	79
F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8	79	80	78
F7-T7/T7-P7/P7-O1/FP2-F8/P8-O2	79	80	78
F7-T7/T7-P7/P7-O1/F8-T8/T8-P8	78	79	77
F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	79	80	78
F7-T7/T7-P7/P7-O1/T8-P8/P8-O2	80	80	79
F7-T7/T7-P7/FP2-F8/F8-T8/T8-P8	78	78	77
F7-T7/T7-P7/FP2-F8/F8-T8/P8-O2	79	81	78
F7-T7/T7-P7/FP2-F8/T8-P8/P8-O2	79	79	79
F7-T7/T7-P7/F8-T8/T8-P8/P8-O2	79	81	78
F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8	79	80	79
F7-T7/P7-O1/FP2-F8/F8-T8/P8-O2	79	80	79
F7-T7/P7-O1/FP2-F8/T8-P8/P8-O2	80	81	79
F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	79	80	78
F7-T7/FP2-F8/F8-T8/T8-P8/P8-O2	79	80	78
T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	79	81	77
T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	80	81	79
T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	79	81	78
T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	79	80	77
T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	79	81	78
P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	78	80	76

Table 22: General results for 6 Channel

6 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8	80	81	80
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8	80	80	79
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/P8-O2	80	81	79
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8	79	81	78
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/P8-O2	81	82	80
FP1-F7/F7-T7/T7-P7/P7-O1/T8-P8/P8-O2	80	82	79
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/T8-P8	79	79	78
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/P8-O2	80	81	79
P1-F7/F7-T7/T7-P7FP2-F8/T8-P8/P8-O2	79	81	78
P1-F7/F7-T7/T7-P7/F8-T8/T8-P8/P8-O2	80	82	79
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8	80	81	79
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/P8-O2	80	82	79
FP1-F7/F7-T7/P7-O1/FP2-F8/T8-P8/P8-O2	79	80	79
FP1-F7/F7-T7/P7-O1/F8-T8/T8-P8/P8-O2	81	82	80
FP1-F7/F7-T7/FP2-F8/F8-T8/T8-P8/P8-O2	80	81	78
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	80	82	79
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	80	82	79
FP1-F7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	80	83	78
FP1-F7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	80	82	79
FP1-F7/T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	80	82	79
FP1-F7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	80	87	79
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	79	80	79
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	80	82	79
F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	80	82	79
F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	80	82	79
F7-T7/T7-P7/FP2-F8/F8-T8/T8-P8/P8-O2	79	81	78
F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	81	82	79
T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	80	81	79

Table 23: General results for 7 Channel

7 Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
P1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8	81	81	80
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/P8-O2	82	83	80
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/T8-P8/P8-O2	81	82	79
FP1-F7/F7-T7/T7-P7/P7-O1/F8-T8/T8-P8/P8-O2	82	83	80
FP1-F7/F7-T7/T7-P7FP2-F8/F8-T8/T8-P8/P8-O2	81	83	79
FP1-F7/F7-T7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	81	81	80
FP1-F7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	81	82	80
F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	81	81	80

Table 24: General results for 8 Channel

Channels			
	Accuracy	**Recall (0)**	**Recall (1)**
FP1-F7/F7-T7/T7-P7/P7-O1/FP2-F8/F8-T8/T8-P8/P8-O2	81	82	81

A.4 Individual Results for 0-10 min

Table 25: Individual results for the best Channel

Paciente	Nºchanels	Configuration	Acc	Recall (0)	Recall (1)
1	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	86	86	87
		T7-P7/P7-O1/FP2-F8/P8-O2	89	90	88
		FP2-F8/F8-T8/T8-P8/P8-O2	87	86	88
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	90	90	89
	8	**all**	88	90	86
2	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	88	86	89
		T7-P7/P7-O1/FP2-F8/P8-O2	84	83	86
		FP2-F8/F8-T8/T8-P8/P8-O2	81	81	81
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	84	83	86
	8	**all**	82	79	84
3	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	97	97	96
		T7-P7/P7-O1/FP2-F8/P8-O2	95	95	95
		FP2-F8/F8-T8/T8-P8/P8-O2	97	95	98
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	96	97	95
	8	**all**	97	98	96
4	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	96	95	96
		T7-P7/P7-O1/FP2-F8/P8-O2	93	95	90
		FP2-F8/F8-T8/T8-P8/P8-O2	97	99	94
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	94	96	93
	8	**all**	96	96	96
5	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	83	83	84
		T7-P7/P7-O1/FP2-F8/P8-O2	88	94	91
		FP2-F8/F8-T8/T8-P8/P8-O2	75	71	79
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	88	90	84
	8	**all**	89	89	89
6	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	85	87	83
		T7-P7/P7-O1/FP2-F8/P8-O2	83	84	82
		FP2-F8/F8-T8/T8-P8/P8-O2	82	83	81
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	85	88	82
	8	**all**	85	86	84
7	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	94	93	95
		T7-P7/P7-O1/FP2-F8/P8-O2	91	89	94
		FP2-F8/F8-T8/T8-P8/P8-O2	93	90	96
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	93	92	94
	8	**all**	94	92	96
8	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	83	80	87
		T7-P7/P7-O1/FP2-F8/P8-O2	85	84	85
		FP2-F8/F8-T8/T8-P8/P8-O2	79	73	84
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	84	84	84
	8	**all**	86	85	88
9	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	98	97	99
		T7-P7/P7-O1/FP2-F8/P8-O2	94	94	94
		FP2-F8/F8-T8/T8-P8/P8-O2	95	95	95
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	97	96	99
	8	**all**	97	96	98
10	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	78	79	77
		T7-P7/P7-O1/FP2-F8/P8-O2	80	81	79
		FP2-F8/F8-T8/T8-P8/P8-O2	80	84	76
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	81	86	77
	8	**all**	83	85	82
11	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	91	94	88
		T7-P7/P7-O1/FP2-F8/P8-O2	91	92	89
		FP2-F8/F8-T8/T8-P8/P8-O2	88	89	88
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	92	94	89
	8	**all**	91	92	89
12	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	85	81	88
		T7-P7/P7-O1/FP2-F8/P8-O2	84	78	90
		FP2-F8/F8-T8/T8-P8/P8-O2	86	84	89
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	84	81	87
	8	**all**	86	83	90

Table 26: Individual results for the best Channel

Paciente	Nºchanels	Configuration	Acc	Recall (0)	Recall (1)
13	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	97	98	97
		T7-P7/P7-O1/FP2-F8/P8-O2	97	98	96
		FP2-F8/F8-T8/T8-P8/P8-O2	97	98	96
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	98	99	98
	8	**all**	98	99	98
14	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	64	68	59
		T7-P7/P7-O1/FP2-F8/P8-O2	68	69	67
		FP2-F8/F8-T8/T8-P8/P8-O2	66	74	59
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	67	72	62
	8	**all**	68	76	61
15	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	87	92	81
		T7-P7/P7-O1/FP2-F8/P8-O2	86	89	84
		FP2-F8/F8-T8/T8-P8/P8-O2	78	80	76
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	83	85	82
	8	**all**	89	93	86
16	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	78	81	75
		T7-P7/P7-O1/FP2-F8/P8-O2	81	84	77
		FP2-F8/F8-T8/T8-P8/P8-O2	82	88	77
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	83	86	79
	8	**all**	82	85	79
17	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	92	91	94
		T7-P7/P7-O1/FP2-F8/P8-O2	91	86	95
		FP2-F8/F8-T8/T8-P8/P8-O2	90	89	92
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	92	89	95
	8	**all**	90	89	92
18	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	87	91	83
		T7-P7/P7-O1/FP2-F8/P8-O2	84	90	77
		FP2-F8/F8-T8/T8-P8/P8-O2	88	87	88
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	87	87	87
	8	**all**	87	91	83
19	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	96	95	96
		T7-P7/P7-O1/FP2-F8/P8-O2	92	90	93
		FP2-F8/F8-T8/T8-P8/P8-O2	90	87	93
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	95	95	95
	8	**all**	95	95	95
20	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	99	99	99
		T7-P7/P7-O1/FP2-F8/P8-O2	100	100	100
		FP2-F8/F8-T8/T8-P8/P8-O2	100	100	100
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	100	100	100
	8	**all**	100	100	100
21	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	68	69	67
		T7-P7/P7-O1/FP2-F8/P8-O2	68	68	70
		FP2-F8/F8-T8/T8-P8/P8-O2	70	66	74
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	67	70	64
	8	**all**	70	71	68
22	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	89	83	96
		T7-P7/P7-O1/FP2-F8/P8-O2	91	89	93
		FP2-F8/F8-T8/T8-P8/P8-O2	92	90	94
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	88	84	93
	8	**all**	92	91	93
23	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	81	79	82
		T7-P7/P7-O1/FP2-F8/P8-O2	79	81	77
		FP2-F8/F8-T8/T8-P8/P8-O2	78	79	75
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	82	83	81
	8	**all**	81	83	79
24	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	73	74	72
		T7-P7/P7-O1/FP2-F8/P8-O2	70	70	70
		FP2-F8/F8-T8/T8-P8/P8-O2	73	73	73
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	72	71	74
	8	**all**	76	74	77

A.5 Individual Results for 10-20 min

Table 27: Individual results for the best Channel

Paciente	Nºchanels	Configuration	Acc	Recall (0)	Recall (1)
1	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	89	91	87
		T7-P7/P7-O1/FP2-F8/P8-O2	90	92	88
		FP2-F8/F8-T8/T8-P8/P8-O2	89	92	85
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	92	93	91
	8	**all**	92	95	88
2	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	82	83	81
		T7-P7/P7-O1/FP2-F8/P8-O2	78	79	75
		FP2-F8/F8-T8/T8-P8/P8-O2	84	89	79
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	84	89	79
	8	**all**	86	89	82
3	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	98	98	97
		T7-P7/P7-O1/FP2-F8/P8-O2	97	97	97
		FP2-F8/F8-T8/T8-P8/P8-O2	99	98	100
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	99	98	100
	8	**all**	98	98	97
4	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	96	94	99
		T7-P7/P7-O1/FP2-F8/P8-O2	94	95	94
		FP2-F8/F8-T8/T8-P8/P8-O2	96	98	94
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	94	97	90
	8	**all**	97	97	98
5	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	89	90	88
		T7-P7/P7-O1/FP2-F8/P8-O2	96	95	97
		FP2-F8/F8-T8/T8-P8/P8-O2	84	97	62
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	96	98	91
	8	**all**	96	97	94
6	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	82	87	76
		T7-P7/P7-O1/FP2-F8/P8-O2	78	81	75
		FP2-F8/F8-T8/T8-P8/P8-O2	76	81	71
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	79	83	75
	8	**all**	82	85	79
7	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	89	86	93
		T7-P7/P7-O1/FP2-F8/P8-O2	93	91	95
		FP2-F8/F8-T8/T8-P8/P8-O2	93	92	95
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	91	86	95
	8	**all**	91	86	95
8	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	87	88	86
		T7-P7/P7-O1/FP2-F8/P8-O2	86	82	90
		FP2-F8/F8-T8/T8-P8/P8-O2	81	77	86
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	86	86	86
	8	**all**	89	87	91
9	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	95	96	94
		T7-P7/P7-O1/FP2-F8/P8-O2	93	94	93
		FP2-F8/F8-T8/T8-P8/P8-O2	97	97	96
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	98	97	100
	8	**all**	98	98	98
10	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	77	75	78
		T7-P7/P7-O1/FP2-F8/P8-O2	75	77	74
		FP2-F8/F8-T8/T8-P8/P8-O2	79	83	75
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	79	79	78
	8	**all**	81	84	78
11	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	88	86	91
		T7-P7/P7-O1/FP2-F8/P8-O2	86	81	91
		FP2-F8/F8-T8/T8-P8/P8-O2	77	79	74
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	90	87	93
	8	**all**	88	87	89
12	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	91	92	91
		T7-P7/P7-O1/FP2-F8/P8-O2	90	89	91
		FP2-F8/F8-T8/T8-P8/P8-O2	92	89	94
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	91	90	91
	8	**all**	93	93	91

Table 28: Individual results for the best Channel

Paciente	Nºchanels	Configuration	Acc	Recall (0)	Recall (1)
13	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	97	96	98
		T7-P7/P7-O1/FP2-F8/P8-O2	97	96	98
		FP2-F8/F8-T8/T8-P8/P8-O2	97	95	100
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	98	98	98
	8	**all**	98	98	99
14	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	62	43	76
		T7-P7/P7-O1/FP2-F8/P8-O2	66	51	77
		FP2-F8/F8-T8/T8-P8/P8-O2	62	36	81
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	65	42	82
	8	**all**	66	46	80
15	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	87	94	77
		T7-P7/P7-O1/FP2-F8/P8-O2	89	96	78
		FP2-F8/F8-T8/T8-P8/P8-O2	86	95	73
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	89	97	78
	8	**all**	88	95	77
16	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	76	86	60
		T7-P7/P7-O1/FP2-F8/P8-O2	78	84	67
		FP2-F8/F8-T8/T8-P8/P8-O2	82	89	71
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	75	86	57
	8	**all**	81	89	68
17	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	89	91	88
		T7-P7/P7-O1/FP2-F8/P8-O2	90	93	87
		FP2-F8/F8-T8/T8-P8/P8-O2	91	90	92
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	93	93	94
	8	**all**	95	95	95
18	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	80	74	85
		T7-P7/P7-O1/FP2-F8/P8-O2	80	74	86
		FP2-F8/F8-T8/T8-P8/P8-O2	84	78	89
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	84	83	84
	8	**all**	85	80	89
19	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	96	92	100
		T7-P7/P7-O1/FP2-F8/P8-O2	91	95	86
		FP2-F8/F8-T8/T8-P8/P8-O2	87	87	86
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	96	94	98
	8	**all**	95	92	98
20	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	100	100	100
		T7-P7/P7-O1/FP2-F8/P8-O2	99	98	99
		FP2-F8/F8-T8/T8-P8/P8-O2	99	98	99
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	99	98	100
	8	**all**	99	98	99
21	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	76	73	78
		T7-P7/P7-O1/FP2-F8/P8-O2	79	74	82
		FP2-F8/F8-T8/T8-P8/P8-O2	70	69	71
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	80	72	85
	8	**all**	78	72	83
22	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	88	86	89
		T7-P7/P7-O1/FP2-F8/P8-O2	90	90	90
		FP2-F8/F8-T8/T8-P8/P8-O2	89	84	94
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	89	88	92
	8	**all**	91	92	89
23	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	82	86	77
		T7-P7/P7-O1/FP2-F8/P8-O2	79	76	82
		FP2-F8/F8-T8/T8-P8/P8-O2	73	65	81
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	79	76	82
	8	**all**	81	76	86
24	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	70	61	78
		T7-P7/P7-O1/FP2-F8/P8-O2	70	60	78
		FP2-F8/F8-T8/T8-P8/P8-O2	70	56	81
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	70	60	79
	8	**all**	75	64	83

A.6 Individual Results for 0-20 minl

Table 29: Individual results for the best Channel

Paciente	Nºchanels	Configuration	Acc	Recall (0)	Recall (1)
1	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	90	88	92
		T7-P7/P7-O1/FP2-F8/P8-O2	92	89	95
		FP2-F8/F8-T8/T8-P8/P8-O2	91	90	92
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	93	91	94
	8	**all**	91	88	93
2	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	75	73	77
		T7-P7/P7-O1/FP2-F8/P8-O2	76	70	82
		FP2-F8/F8-T8/T8-P8/P8-O2	70	71	68
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	74	78	70
	8	**all**	82	79	84
3	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	95	93	96
		T7-P7/P7-O1/FP2-F8/P8-O2	93	95	91
		FP2-F8/F8-T8/T8-P8/P8-O2	93	95	91
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	95	95	96
	8	**all**	96	95	97
4	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	93	95	92
		T7-P7/P7-O1/FP2-F8/P8-O2	93	93	94
		FP2-F8/F8-T8/T8-P8/P8-O2	93	91	95
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	95	95	95
	8	**all**	95	97	94
5	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	91	93	87
		T7-P7/P7-O1/FP2-F8/P8-O2	92	95	87
		FP2-F8/F8-T8/T8-P8/P8-O2	76	90	48
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	90	97	77
	8	**all**	88	93	77
6	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	90	86	92
		T7-P7/P7-O1/FP2-F8/P8-O2	89	81	95
		FP2-F8/F8-T8/T8-P8/P8-O2	90	80	98
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	90	85	93
	8	**all**	90	84	95
7	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	94	87	98
		T7-P7/P7-O1/FP2-F8/P8-O2	95	86	99
		FP2-F8/F8-T8/T8-P8/P8-O2	93	81	99
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	95	87	99
	8	**all**	95	87	99
8	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	88	86	89
		T7-P7/P7-O1/FP2-F8/P8-O2	87	86	87
		FP2-F8/F8-T8/T8-P8/P8-O2	85	75	92
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	89	90	89
	8	**all**	89	88	90
9	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	98	95	95
		T7-P7/P7-O1/FP2-F8/P8-O2	95	92	97
		FP2-F8/F8-T8/T8-P8/P8-O2	97	96	98
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	98	95	99
	8	**all**	98	97	99
10	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	83	85	79
		T7-P7/P7-O1/FP2-F8/P8-O2	79	80	78
		FP2-F8/F8-T8/T8-P8/P8-O2	83	86	78
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	80	81	79
	8	**all**	86	89	82
11	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	88	84	90
		T7-P7/P7-O1/FP2-F8/P8-O2	84	84	85
		FP2-F8/F8-T8/T8-P8/P8-O2	86	77	90
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	87	80	90
	8	**all**	86	79	89
12	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	91	95	84
		T7-P7/P7-O1/FP2-F8/P8-O2	91	94	86
		FP2-F8/F8-T8/T8-P8/P8-O2	89	93	80
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	92	95	86
	8	**all**	96	98	92

Table 30: Individual results for the best Channel

Paciente	Nºchanels	Configuration	Acc	Recall (0)	Recall (1)
13	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**			
		T7-P7/P7-O1/FP2-F8/P8-O2			
		FP2-F8/F8-T8/T8-P8/P8-O2			
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**			
	8	**all**			
14	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	64	75	52
		T7-P7/P7-O1/FP2-F8/P8-O2	68	72	63
		FP2-F8/F8-T8/T8-P8/P8-O2	73	79	66
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	73	79	65
	8	**all**	75	78	90
15	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	92	99	52
		T7-P7/P7-O1/FP2-F8/P8-O2	90	97	46
		FP2-F8/F8-T8/T8-P8/P8-O2	92	98	57
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	94	99	65
	8	**all**	94	100	57
16	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	77	83	69
		T7-P7/P7-O1/FP2-F8/P8-O2	78	83	72
		FP2-F8/F8-T8/T8-P8/P8-O2	80	87	72
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	79	84	72
	8	**all**	76	82	69
17	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	93	90	95
		T7-P7/P7-O1/FP2-F8/P8-O2	92	86	96
		FP2-F8/F8-T8/T8-P8/P8-O2	91	89	93
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	91	88	94
	8	**all**	94	91	95
18	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	87	92	84
		T7-P7/P7-O1/FP2-F8/P8-O2	88	92	85
		FP2-F8/F8-T8/T8-P8/P8-O2	88	89	87
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	91	95	88
	8	**all**	89	93	86
19	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	98	100	98
		T7-P7/P7-O1/FP2-F8/P8-O2	93	84	98
		FP2-F8/F8-T8/T8-P8/P8-O2	89	77	94
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	99	98	99
	8	**all**	99	98	99
20	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	98	96	99
		T7-P7/P7-O1/FP2-F8/P8-O2	98	96	99
		FP2-F8/F8-T8/T8-P8/P8-O2	99	98	100
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	99	98	100
	8	**all**	99	97	100
21	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	72	64	77
		T7-P7/P7-O1/FP2-F8/P8-O2	76	70	80
		FP2-F8/F8-T8/T8-P8/P8-O2	76	64	84
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	75	64	82
	8	**all**	78	70	84
22	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	90	76	98
		T7-P7/P7-O1/FP2-F8/P8-O2	90	80	96
		FP2-F8/F8-T8/T8-P8/P8-O2	89	80	94
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	89	78	94
	8	**all**	91	81	96
23	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	84	77	87
		T7-P7/P7-O1/FP2-F8/P8-O2	83	73	87
		FP2-F8/F8-T8/T8-P8/P8-O2	88	56	89
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	89	82	92
	8	**all**	91	82	94
24	**4**	**FP1-F7/F7-T7/T7-P7/P7-O1**	73	69	77
		T7-P7/P7-O1/FP2-F8/P8-O2	73	71	74
		FP2-F8/F8-T8/T8-P8/P8-O2	72	67	77
	5	**FP1-F7/F7-T7/P7-O1/F8-T8/P8-O2**	76	68	83
	8	**all**	77	71	81

A.7 Results for Features Selection 0-10 min

Table 31: Features Selection results 0-10 min

Patients	Channels	Features
1	FP1-F7	NZC
	T7-P7	Com
	P8-O2	Com
	T7-P7	Mob
	FP1-F7	PFD
	T7-P7	NZC
	T7-P7	SE
	T7-P7	KFD
	T8-P8	Com
	F7-T7	NZC
2	F8-T8	Mob
	P7-O1	SE
	F8-T8	Com
	F8-T8	NZC
	F8-T8	SE
	T7-P7	Mob
	P7-O1	Mob
	T7-P7	Com
	F8-T8	KFD
	T8-P8	Mob
3	T8-P8	SE
	FP1-F7	Com
	P7-O1	Com
	T8-P8	Com
	FP1-F7	SE
	T8-P8	NZC
	T7-P7	Com
	F8-P8	Com
	FP1-F7	NZC
	P8-O2	Com
4	T7-P7	PFD
	P7-O1	PFD
	T8-P8	Mob
	T7-P7	SE
	T8-P8	PFD
	T7-P7	Mob
	T8-P8	SE
	T7-P7	NZC
	T8-P8	NZC
	P7-O1	SE
5	F7-T7	PFD
	P8-O2	Com
	F7-T7	Com
	T7-P7	PFD
	P7-O1	SE
	P7-O1	Com
	P8-O2	SE
	P7-O1	Mob
	FP1-F7	KFD
	P7-O1	KFD

Table 32: Features Selection results 0-10 min

Patients	Channels	Features
6	T7-P7	PFD
	FP1-F7	Com
	F7-T7	PFD
	T8-P8	PFD
	F8-T8	PFD
	T7-P7	SE
	P7-O1	PFD
	T8-P8	KFD
	T8-P8	SE
	T8-P8	Mob
7	P7-O1	PFD
	FP2-F8	Com
	T7-P7	PFD
	T8-P8	PFD
	P8-O2	PFD
	P8-O2	Mob
	P8-O2	NZC
	P8-O2	SE
	F7-T7	PFD
	F8-T8	PFD
8	T8-P8	NZC
	F7-T7	PFD
	T7-P7	PFD
	T8-P8	Mob
	T8-P8	SE
	F8-T8	PFD
	T8-P8	Com
	P7-O1	PFD
	F8-T8	NZC
	P8-O2	NZC
9	F7-T7	PFD
	F8-T8	PFD
	T7-P7	PFD
	T8-P8	PFD
	P7-O1	PFD
	FP1-F7	PFD
	P8-O2	PFD
	FP2-F8	PFD
	T8-P8	Mob
	T8-P8	NZC
10	FP1-F7	SE
	T7-P7	PFD
	F7-T7	SE
	FP1-F7	NZC
	T8-P8	PFD
	FP2-F8	NZC
	FP1-F7	PFD
	F8-T8	PFD
	FP1-F7	Mob
	F8-P8	KFD

Table 33: Features Selection results 0-10 min

Patients	Channels	Features
11	FP2-F8	NZC
	T7-P7	SE
	FP1-F7	NZC
	P7-O1	PFD
	FP2-F8	Com
	FP1-F7	KFD
	FP2-F7	KFD
	P7-O1	NZC
	FP2-F8	PFD
	FP1-F7	Mob
12	T7-P7	NZC
	FP1-F7	KFD
	T7-P7	PFD
	T8-P8	NZC
	T7-P7	Mob
	T8-P8	Mob
	P7-O1	NZC
	F8-T8	NZC
	T8-P8	KFD
	T7-P7	KFD
13	FP1-F7	PFD
	P8-O2	PFD
	P7-O1	PFD
	P7-O1	KFD
	FP1-F7	KFD
	P8-O2	KFD
	FP1-F7	Mob
	F8-T8	Com
	FP1-F7	SE
	P7-O1	NZC
14	FP2-F8	PFD
	T8-P8	PFD
	T7-P7	Com
	F8-T8	PFD
	FP2-F8	NZC
	F8-T8	NZC
	P7-O1	Com
	Fp1-F7	PFD
	P8-O2	PFD
	F8-T8	KFD
15	F7-T7	PFD
	FP2-F8	Mob
	T8-P8	Com
	FP2-F8	Com
	T7-P7	Com
	F8-T8	PFD
	FP1-F7	Com
	FP2-F8	PFD
	T7-P7	PFD
	T8-P8	Mob

Table 34: Features Selection results 0-10 min

Patients	Channels	Features
16	P8-O2	Com
	FP2-F8	Mob
	P8-O2	KFD
	P8-O2	SE
	P8-O2	NZC
	FP2-F8	Com
	P8-O2	Mob
	FP1-F7	Mob
	F8-T8	PFD
	P7-O1	Com
17	FP2-F8	PFD
	F8-T8	NZC
	T8-P8	PFD
	FP1-F7	PFD
	FP1-F7	NZC
	F8-T8	PFD
	T8-P8	NZC
	FP2-F8	NZC
	T8-P8	Mob
	T8-P8	SE
18	F7-T7	Com
	F8-T8	PFD
	P7-O1	NZC
	FP1-F7	Com
	F7-T7	KFD
	F7-T7	SE
	FP1-F7	KFD
	P8-O2	NZC
	FP1-F7	SE
	F7-T7	Mob
19	FP1-F7	PfD
	F8-T8	SE
	F7-T7	SE
	F8-T8	Com
	T8-P8	PFD
	T8-P8	Com
	T7-P7	Com
	P7-O1	PFD
	T7-P7	SE
	P8-O2	PFD
20	T8-P8	SE
	T7-P7	SE
	T8-P8	Mob
	T8-P8	PFD
	T8-P8	NZC
	P8-O2	SE
	F8-T8	SE
	T8-P8	Com
	P7-O1	SE
	T7-P7	PFD

Table 35: Features Selection results 0-10 min

Patients	Channels	Features
21	P8-O2	Mob
	FP1-F7	PFD
	T7-P7	KFD
	P8-O2	NZC
	F7-T7	NZC
	P8-O2	Com
	T7-P7	NZC
	P8-O2	SE
	F7-T7	KFD
	T7-P7	Mob
22	P8-O2	Com
	T8-P8	Com
	P7-O1	Com
	P8-O2	NZC
	F7-T7	PFD
	T7-P7	PFD
	P8-O2	Mob
	T8-P8	NZC
	F8-T8	PFD
	P7-O1	NZC
23	F8-T8	PFD
	FP2-F8	NZC
	P7-O1	Com
	F8-T8	NZC
	T7-P7	NZC
	F8-T8	KFD
	P8-O2	KFD
	F7-T7	NZC
	F8-T8	Com
	P8-O2	PFD
24	P7-O1	PFD
	FP1-F7	KFD
	P7-O1	Com
	P8-O2	PFD
	P8-O2	NZC
	FP2-F8	KFD
	P8-O2	Com
	P7-O1	SE
	P7-O1	NZC
	T8-P8	PFD

A.8 Results for Features Selection 10-20 min

Table 36: Features Selection results 10-20 min

Patients	Channels	Features
1	P7-O1	SE
	P7-O1	PFD
	P7-O1	NZC
	P7-O1	Mob
	P7-O1	KFD
	P7-O1	Com
	T7-P7	SE
	T7-P7	PFD
	T7-P7	NZC
	T7-P7	Mob
2	F8-T8	PFD
	F8-T8	NZC
	F8-T8	Mob
	FP1-F7	PFD
	P7-O1	NZC
	T7-P7	NZC
	T7-P7	PFD
	F7-T7	PFD
	P7-O1	Mob
	FP2-F8	PFD
3	FP1-F7	NZC
	FP2-F8	NZC
	T8-P8	NZC
	F8-T8	NZC
	T7-P7	NZC
	T8-P8	Mob
	F7-T7	NZC
	T7-P7	Mob
	T8-P8	KFD
	F8-T8	Mob
4	T8-P8	PFD
	P8-O2	PFD
	T7-P7	PFD
	T8-P8	Mob
	T7-P7	Mob
	T8-P8	SE
	T8-P8	KFD
	T7-P7	NZC
	T8-P8	NZC
	T8-P8	Com
5	F7-T7	PFD
	P8-O2	Com
	T7-P7	PFD
	P7-O1	Com
	T7-P7	NZC
	F7-T7	KFD
	T7-P72	KFD
	F7-T7	NZC
	T7-P7	Mob
	P7-O1	SE

Table 37: Features Selection results 10-20 min

Patients	Channels	Features
6	T7-P7	PFD
	T8-P8	PFD
	F7-T7	PFD
	F8-T8	PFD
	T7-P7	SE
	P7-O1	PFD
	T7-P7	Mob
	T8-P8	KFD
	T7-P7	NZC
	T8-P8	Mob
7	P7-O1	PFD
	P8-O2	Mob
	T7-P7	PFD
	P8-O2	NZC
	P8-O2	SE
	P8-O2	PFD
	T8-P8	PFD
	P8-O2	Com
	P7-O1	Mob
	P7-O1	NZC
8	T7-P7	PFD
	F7-T7	PFD
	F8-T8	PFD
	T8-P8	NZC
	T8-P8	Com
	P7-O1	PFD
	T8-P8	Mob
	T8-P8	PFD
	T8-P8	SE
	P8-O2	PFD
9	F7-T7	PFD
	T8-P8	Com
	F8-T8	PFD
	T7-P7	PFD
	T8-P8	PFD
	P7-O1	PFD
	FP1-F7	PFD
	P8-O2	PFD
	FP2-F8	PFD
	T7-P7	NZC
10	P8-O2	PFD
	F7-T7	Com
	FP1-F7	SE
	T8-P8	PFD
	P7-O1	PFD
	F7-T7	SE
	F8-T8	SE
	T7-P7	PFD
	F8-T8	Com
	FP1-F7	NZC

Table 38: Features Selection results 10-20 min

Patients	Channels	Features
11	FP1-F7	KFD
	P7-O1	PFD
	FP1-F7	NZC
	FP2-F8	KFD
	P7-O1	NZC
	FP2-F8	NZC
	FP1-F7	PFD
	FP2-F8	Com
	FP2-F8	PFD
	P7-O1	KFD
12	T8-P8	NZC
	FP1-F7	KFD
	P8-O2	NZC
	F8-T8	NZC
	P8-O2	SE
	T8-P8	KFD
	P7-O1	NZC
	P8-O2	Com
	T8-P8	Mob
	P8-O2	PFD
13	F7-T7	Com
	FP2-F8	KFD
	F7-T7	KFD
	T8-P8	Com
	FP2-F8	Com
	F7-T7	SE
	F8-T8	Com
	T7-P7	KFD
	FP2-F8	SE
	T7-P7	Com
14	FP1-F7	PFD
	FP1-F7	Com
	P8-O2	PFD
	FP2-F8	Mob
	FP2-F8	SE
	FP2-F8	Com
	T7-P7	Mob
	FP2-F8	KFD
	FP2-F8	NZC
	FP1-F7	Mob
15	F7-T7	Com
	P7-O1	Mob
	F8-T8	Com
	F7-T7	SE
	F8-T8	SE
	F7-T7	NZC
	T8-P8	Com
	F8-T8	NZC
	F7-T7	Mob
	FP1-F7	NZC

Table 39: Features Selection results 10-20 min

Patients	Channels	Features
16	F8-T8	PFD
	FP1-F7	PFD
	F8-T8	NZC
	F7-T7	PFD
	T8-P8	PFD
	T8-P8	Mob
	F8-T8	NZC
	T8-P8	SE
	FP2-F8	PFD
	P8-O2	Com
17	T7-P7	PFD
	FP2-F8	PFD
	P8-O2	Com
	P7-O1	PFD
	P8-O2	SE
	P8-O2	Mob
	P8-O2	KFD
	P8-O2	NZC
	FP1-F7	NZC
	P7-O1	Mob
18	T7-P7	PFD
	FP1-F7	Mob
	F8-T8	Mob
	T7-P7	Com
	P8-O2	Com
	FP2-F8	Mob
	FP1-F7	PFD
	T8-P8	SE
	FP2-F8	Com
	F8-T8	KFD
19	F8-T8	Mob
	T8-P8	PFD
	F8-T8	SE
	P8-O2	KFD
	F8-T8	KFD
	T8-P8	Mob
	F8-T8	NZC
	F7-T7	PFD
	F8-T8	Com
	FP2-F8	KFD
20	P8-O2	Com
	T8-P8	KFD
	P7-O1	Com
	FP2-F8	PFD
	T8-P8	SE
	T7-P7	Com
	F7-T7	NZC
	T8-P8	Com
	FP1-F7	PFD
	F8-T8	PFD

Table 40: Features Selection results 0-10 min

Patients	Channels	Features
21	P8-O2	PFD
	FP2-F8	NZC
	T7-P7	PFD
	FP1-F7	PFD
	F7-P7	PFD
	P8-O2	NZC
	P7-O1	PFD
	P8-O2	Mob
	P8-O2	KFD
	FP1-F7	NZC
22	F7-T7	PFD
	T7-P7	PFD
	P8-O2	SE
	P8-O2	NZC
	P7-O1	SE
	T7-P7	SE
	P7-O1	Com
	P8-O2	Mob
	T8-P8	SE
	P8-O2	KFD
23	T7-P7	SE
	T8-P8	PFD
	T8-P8	SE
	T7-P7	Com
	T7-P7	PFD
	T8-P8	Mob
	P8-O2	SE
	F8-P8	PFD
	P7-O1	SE
	T8-P8	Com
24	F7-T7	PFD
	FP1-F7	Com
	T8-P8	NZC
	F8-T8	PFD
	F7-T7	NZC
	F8-T8	NZC
	T7-P7	SE
	T7-P7	NZC
	T8-P8	KFD
	FP1-F7	PFD

A.9 Results for Features Selection 0-20 min

Table 41: Features Selection results 0-20 min

Patients	Channels	Features
1	T7-P7	NZC
	P8-O2	Com
	T7-P7	Mob
	FP1-F7	NZC
	T7-P7	KFD
	FP1-F7	PFD
	T7-P7	Com
	T7-P7	SE
	F7-T7	NZC
	T8-P8	Com
2	F8-T8	Mob
	F8-T8	NZC
	F8-T8	PFD
	F8-T8	Com
	T7-P7	Mob
	P7-O1	Mob
	T7-P7	NZC
	F8-T8	SE
	F8-T8	KFD
	P7-O1	NZC
3	T8-P8	SE
	FP1-F7	Com
	P7-O1	Com
	T8-P8	NZC
	T8-P8	Com
	F8-T8	Com
	T7-P7	Com
	T7-P7	SE
	FP1-F7	NZC
	T8-P8	Mob
4	T7-P7	PFD
	P8-O2	PFD
	T8-P8	PFD
	T8-P8	SE
	T7-P7	Mob
	T8-P8	Mob
	T7-P7	SE
	T7-P7	NZC
	T8-P8	Com
	T7-P7	Com
5	F7-T7	PFD
	F7-T7	Com
	P7-O1	Com
	T7-P7	PFD
	P7-O1	SE
	F7-T7	KFD
	P8-O2	Com
	T7-P7	KFD
	FP1-F7	KFD
	FP1-F7	PFD

Table 42: Features Selection results 0-20 min

Patients	Channels	Features
6	T7-P7	PFD
	F7-T7	PFD
	T8-P8	PFD
	F8-T8	PFD
	T7-P7	SE
	P7-O1	PFD
	T8-P8	KFD
	T7-P7	NZC
	T8-P8	Mob
	T7-P7	Mob
7	P7-O1	PFD
	FP2-F8	Com
	T7-P7	PFD
	P8-O2	PFD
	T8-P8	PFD
	P8-O2	Mob
	P8-O2	SE
	F7-T7	PFD
	P8-O2	NZC
	F8-T8	PFD
8	T7-P7	PFD
	T8-P8	Com
	F8-T8	PFD
	P7-O1	PFD
	T8-P8	NZC
	T8-P8	PFD
	T8-P8	SE
	F7-T7	PFD
	T8-P8	Mob
	P8-O2	PFD
9	F7-T7	PFD
	F8-T8	PFD
	T7-P7	PFD
	T8-P8	PFD
	FP1-F7	PFD
	P7-O1	PFD
	P8-O2	PFD
	FP2-F8	PFD
	T8-P8	Mob
	T8-P8	NZC
10	F7-T7	SE
	T8-P8	PFD
	FP1-F7	SE
	T7-P7	PFD
	P8-O2	PFD
	P7-O1	PFD
	F7-T7	Com
	FP1-F7	NZC
	F8-T8	KFD
	FP2-F8	NZC

Table 43: Features Selection results 0-20 min

Patients	Channels	Features
11	FP2-F8	NZC
	P7-O1	KFD
	FP1-F7	NZC
	P7-O1	PFD
	FP1-F7	KFD
	FP2-F8	KFD
	P7-O1	NZC
	FP2-F(	Com
	FP1-F7	Mob
	FP1-F8	Mob
12	T8-P8	NZC
	FP1-F7	KFD
	T7-P7	PFD
	T7-P7	NZC
	T8-P8	Mon
	T8-P8	KFD
	F8-T8	NZC
	T7-P7	Mob
	P7-O1	NZC
	P8-O2	NZC
13	P8-O2	PFD
	FP1-F7	PFD
	P7-O1	PFD
	P8-O2	KFD
	P7-O1	KFD
	FP1-F7	Mob
	F8-T8	Com
	FP1-F7	KFD
	FP1-F7	Com
	P7-O1	NZC
14	F8-T8	PFD
	T7-P7	Com
	T8-P8	PFD
	FP2-F8	PFD
	T8-P8	KFD
	FP2-F8	NZC
	P7-O1	Com
	P8-O2	PFD
	F8-T8	NZC
	P8-O2	NZC
15	F7-T7	PFD
	FP1-F7	NZC
	T8-P8	Com
	F8-T8	PFD
	FP2-F8	Com
	T7-P7	Com
	T7-P7	PFD
	FP1-F7	Com
	FP2-F8	PFD
	T8-P8	Mob

Table 44: Features Selection results 0-20 min

Patients	Channels	Features
16	P8-O2	Com
	F8-T8	PFD
	FP1-F7	Mob
	P8-O2	KFD
	P8-O2	PFD
	P8-O2	SE
	P8-O2	NZC
	T8-P8	PFD
	P8-O2	Mob
	T7-P7	PFD
17	T8-P8	PFD
	FP2-F8	PFD
	T8-P8	SE
	F8-T8	PFD
	F8-T8	NZC
	T8-P8	NZC
	FP1-F7	PFD
	T8-P8	Mob
	T7-P7	PFD
	FP1-F7	NZC
18	F7-T7	Com
	T8-P8	PFD
	P7-O1	NZC
	FP1-F7	Com
	F7-T7	KFD
	F7-T7	SE
	FP1-F7	KFD
	F8-T8	PFD
	F8-T8	Com
	P7-O1	KFD
19	FP1-F7	PFD
	F8-T8	SE
	F8-T8	Com
	F7-T7	SE
	T8-P8	Com
	T8-P8	PFD
	P7-O1	PFD
	T7-P7	Com
	P8-O2	PFD
	FP2-F8	SE
20	T8-P8	SE
	T7-P7	SE
	T8-P8	Mob
	T8-P8	NZC
	T8-P8	PFD
	T7-P7	Mob
	P8-O2	Mob
	P7-O1	Mob
	P8-O2	SE
	F8-T8	Se

Table 45: Features Selection results 0-20 min

Patients	Channels	Features
21	P8-O2	Mob
	P8-O2	NZC
	F7-T7	NZC
	P8-O2	SE
	P8-O2	Com
	P8-O2	PFD
	P8-O2	KFD
	P7-O1	PFD
	F7-T7	KFD
	P7-O1	KFD
22	P8-O2	Com
	F7-T7	PFD
	T8-P8	Com
	F8-T8	PFD
	P7-O1	Com
	T7-P7	PFD
	T8-P8	NZC
	T8-P8	SE
	T7-P7	SE
	P8-O2	NZC
23	F8-T8	PFD
	P8-O2	KFD
	FP1-F7	PFD
	F8-T8	NZC
	T8-P8	PFD
	FP2-F8	Com
	T8-P8	SE
	F7-T7	PFD
	F8-T8	KFD
	T8-P8	NZC
24	P7-O1	Com
	FP2-F8	Com
	P8-O2	PFD
	P8-O2	NZC
	P7-O1	PFD
	P8-O2	Com
	P7-O1	SE
	FP1-F7	KFD
	P7-O1	NZC
	P7-O1	Mob