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**EPILEPSY SEIZURE DETECTION BASED ON ARTIFICIAL NEURAL NETWORKS
USING TIME-FREQUENCY SIGNAL PROCESSING**

Belo Horizonte

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CRISTINA NATALIA ESPINOSA MARTINEZ

**EPILEPSY SEIZURE DETECTION BASED ON ARTIFICIAL NEURAL NETWORKS
USING TIME-FREQUENCY SIGNAL PROCESSING**

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DETECÇÃO DE CRISES EPILÉPTICAS BASEADO EM REDES NEURAIS ARTIFICIAIS USANDO PROCESSAMENTO DO SINAL EM TEMPO-FREQUÊNCIA

CRISTINA NATALIA ESPINOSA MARTINEZ

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To my mom, who has ever been my inspiration, my guide, and my strength, without whom this would not be possible.

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RESUMO

A epilepsia é uma doença neural crônica que afeta 50 milhões de pessoas no mundo. Devido às crises epiléticas serem espontâneas, em alguns casos não podem ser controladas. Portanto, um método ou uma tecnologia para prever e identificar os episódios é altamente requerido. Neste estudo apresenta-se o desenvolvimento de dois métodos baseados em aprendizado de máquina. O primeiro método está baseado na Rede Neural Feedforward (FNN) com backpropagation (BP) que funciona com um canal de eletroencefalografia (EEG), onde as entradas da rede são adquiridas mediante Transformada Discreta de Wavelet (DWT) e Transformada Rápida de Fourier (FFT). No segundo método aplicou-se Redes Neurais Convulsionais (CNN) usando 21 canais de EEG, sendo analisado para três entradas diferentes como domínio do tempo, domínio da frequência usando FFT e domínio do tempo-frequência aplicando-se a Transformada de Fourier em Tempo Curto (STFT). Tanto o modelo FNN quanto o CNN fazem uma classificação binária, onde 1 representa atividade ictal e 0 simboliza um período livre de crises. Para testar ambos modelos foi usado oito EEG da base de dados Temple University Hospital Seizure Corpus (TUH-SC). Além disso, aplicou-se dois casos de treinamento para avaliar o rendimento dos modelos. Para o caso 1 criou-se um modelo treinado com o conjunto de treinamento de cada paciente. No caso 2, gerou-se um conjunto de treinamento que contém diferentes tipos de crises para treinar um modelo único. Os resultados mostraram que o treinamento 1, utilizando o modelo CNN com entrada no domínio de tempo-frequência reporta uma acurácia de 95.3%, recall de 81.6%, precisão de 92.5%, F-score de 85.7%, e um erro de 4.7%. No caso do treinamento 2, foi aplicado o modelo CNN com entrada no domínio do tempo-frequência, dado que este foi capaz de detectar atividade ictal em todos os pacientes testados, obtendo uma acurácia, recall, precisão, F-score, e erro de 78.1%, 76.9%, 66.2%, 65.4%, e 21.9%, respectivamente. Conforme os resultados obtidos e demonstrados, conclui-se que os métodos desenvolvidos atendem ao objetivo de detectar atividade ictal, sendo que o modelo CNN mostrou melhor solução proposta. Diante disso, o modelo CNN foi utilizado para desenvolver um protótipo de uma aplicação que facilita o monitoramento de um paciente com epilepsia.

Palavras chave— *Deteção de Epilepsia, Redes Neurais Convolucionais, Rede Neural Feedforward, Transformada de Fourier em Tempo Curto, Transformada Rápida de Fourier, Eletroencefalograma*

ABSTRACT

Epilepsy is a chronic neural disease that suffers around 50 million people in the world. Since epileptic seizures are spontaneous and, in some cases, cannot be controlled, the approach to detect or even anticipate them is highly required. This dissertation presents the development of two methods of epilepsy seizure detection based on Machine Learning. The first approach based on Feedforward Neural Network (FNN) works on a single electroencephalogram (EEG) channel and extracts the model's input parameters via Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT). The second approach based on Convolutional Neural Network (CNN) uses 21 EEG channels, besides the model was analyzed for three input types, in the time domain, the frequency domain via FFT, and the time-frequency domain via Short Time Fourier Transform (STFT). Both FNN and CNN models make a binary classification, where 1 represents ictal activity, and 0 symbolizes a seizure-free period. Then, the models are tested on eight EEGs from Temple University Hospital Seizure Corpus (TUH-SC) database. In addition, the models' performance is evaluated via two training cases. In case 1, one model per patient is created, whereas in case 2, one training set is built, which contains several sessions with different seizure types to train a single model. Hence, analyzing the training case 1, the CNN model with input in the time-frequency domain via STFT reports the best results, achieving an accuracy of 95.3%, recall of 81.6%, the precision of 92.5%, F-score of 85.7%, and error of 4.7%. Training case 2 is applied to the CNN model with input in the time-frequency domain, given that this method was able to detect ictal activity in all patients. Obtaining an accuracy, recall, precision, F-score, and error of 78.1%, 76.9%, 66.2%, 65.4%, and 21.9% respectively. In conclusion, both detection methods meet the objective of detecting ictal activity. However, the CNN model developed achieves better results when an individual model is created. Therefore, the CNN model was used to develop a prototype of an application that makes it easy to monitor an epilepsy patient.

Keywords— *Epilepsy detection, Convolutional Neural Network, Feedforward Neural Network, Short Time Fourier Transform, Fast Fourier Transform, Electroencephalogram*

List of Abbreviations

ABSZ Absence Seizure

ANN Artificial Neural Network

BP Backpropagation

CHB-MIT Boston Children's Hospital–MIT

CNN Convolutional Neural Network

CNSZ Clonic Seizure

CPSZ Complex Partial Seizure

CWT Continuous Wavelet Transform

DFT Discrete Fourier Transform

DWT Discrete Wavelet Transform

EDF European Data Files

EEG Electroencephalogram

EKG Electrocardiogram

EMG Electromyogram

FFT Fast Fourier Transform

FNN Feedforward Neural Network

FNSZ Focal Seizure

FN False Negative

FP False Positive

GNSZ Generalized Seizure

HFOs High-Frequency Oscillations

HIC High-Income Countries

iEEG Intracranial Electroencephalogram

ILAE International League Against Epilepsy

IoMT Internet of Medical Things

KNN K-Nearest Neighbor

LMIC Low and Middle-Income Countries

MLPNN Multi-Layer Perceptron Neural Network

NMI Natus Medical Incorporated

PDF Probability Density Function

PSD Power Spectrum Density

ReLU Rectified Linear Unit

SGD Stochastic Gradient Descent

SPSZ Simple Partial Seizure

SSWs Spikes and Sharp Waves

STFT Short Time Fourier Transform

SVM Support Vector Machine

TCP Temporal Central Parasagittal

TCSZ Tonic-Clonic Seizure

TNSZ Tonic Seizure

TN True Negative

TP True Positive

TUH-SC Temple University Hospital Seizure Corpus

WHO World Health Organization

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1 INTRODUCTION

Epilepsy is a common neurological disorder produced by transient and unexpected electrical disturbances in the brain (GAUTAM; SRIYA; CHAUHAN, 2015). World Health Organization (WHO) and International League Against Epilepsy (ILAE) define epilepsy as a brain disease, characterized by at least two unprovoked seizures occurring higher 24 hours apart with a recurrence risk (FISHER et al., 2014). Seizures can range from brief to prolonged and severe episodes, and occurrence frequency can vary from less than one per year to some per day. Sometimes seizures cause trauma or serious injury. Conscience loss and involuntary bowel movements have also been reported (WORLD HEALTH ORGANIZATION, 2019).

WHO estimates that epilepsy affects around 50 million people in the world, and about 80% of patients living in low and middle-income countries (LMIC), causing they do not receive adequate treatment. Besides, the premature death risk is three times higher for people who suffer from this disease. Annually, 2.4 million epilepsy cases are diagnosed. On the other hand, in high-income countries (HIC) are registered 30 to 50 cases per 100,000 inhabitants each year, while in LMIC the number can double, probably due to the incidence of injuries related to traffic accidents, lesions derived from childbirth, the inefficient public health system, and others. Although being a common disease, patients with epilepsy are still stigmatized by society (WORLD HEALTH ORGANIZATION, 2019).

According to seizure onset location, epilepsy can be classified as follows the **generalized epilepsy** usually present spike-wave activity on the Electroencephalogram (EEG), this kind of epilepsy may show absence, tonic, atonic, myoclonic, and tonic-clonic seizures, besides, involves both brain hemispheres. On the other hand, the **focal epilepsy** activity is center into one of the brain hemispheres, could be extended to the whole brain. Also, it exists disturbances like Dravet syndrome and Lennox-Gastaut syndrome where both generalize and focal epilepsies are presented, know as **combined epilepsy**. Finally, an **unknown epilepsy** occurs when it is not possible to identify the epilepsy onset location (SCHEFFER et al., 2017). Occasionally, it can not control seizures with antiseizure medicine, perhaps because the diagnosis and/or treatment are wrong. However, if after two good trials with the appropriate drug and dose, the seizure persists, it means that the person has drug-resistant epilepsy, so other treatments are considered, such as surgery, vagus nerve stimulation, and others. Yet, 70% of the people effectively diagnosed and treated could live seizure-free. Besides, 60% of the epilepsy cases would resolve if the patient continues out of seizure for the last ten years and without antiseizure medicine for the

last five years ([FISHER et al., 2014](#); [WORLD HEALTH ORGANIZATION, 2019](#); [EPILEPSY FOUNDATION, 2014](#)). However, there is not a way to prevent or detect epilepsy seizures before occurring yet.

1.1 MOTIVATION

The development of an automated epilepsy seizure detection system involves many challenges since epilepsy is a catastrophic disease, causing psychoemotional, family, and economic impacts on the people who suffer it. Including the worst scene where it is not possible to control seizures with medicament. State of the art (section 2.1) details several published methods and devices focused on medical diagnosis aid, epilepsy patient monitoring, epilepsy onset detection, real-time or anticipated epilepsy detection. However, most developed prototypes of wearable devices identify tonic-clonic seizures, recognizing prominent movements in person, but these systems are still prone to errors. In contrast, it is evident that the methods which achieve better performance are the ones that used EEG records, seeing that provide valuable information to detect ictal activity, this will explain deeply in section 2.2. Therefore, based on the reviewed methods and techniques, it can propose an automated system to predict the onset, duration, and end of the ictal activity, regardless of seizure type. Besides, to use the algorithm in the epilepsy diagnosis or adapt it to a portable device; in this way to make it possible to improve the quality of the patient's life or even save lives.

1.2 OBJECTIVES

The main objective of this master dissertation is to develop an automatic system able to predict ictal activity regardless of the seizure type which the patient presents, applying signal processing techniques to EEG databases.

To achieve the main objective, the following specific objectives are proposed:

1. Chose the best option to process the EEG signal via the study of epilepsy detection methods based on EEG databases analysis.
2. Detect the ictal activity on EEG records using classification methods that apply machine learning techniques, like artificial neural networks.
3. Implement an algorithm to distinguish an ictal state from the background continues on EEG and evaluate obtained performance.

4. Employ the implemented method to develop an epilepsy seizure detection application.

1.3 OVERVIEW

This chapter introduces the health problem that epilepsy represents and how an algorithm or device to detect epilepsy would depict a solution to monitor or alert aid to people who suffer from this disease and cannot control the seizure with drugs. Furthermore, the main and specific objectives were formulated for the dissertation. The document is organized as follows:

- Chapter 2 addresses the state of the art reviewed methods and the theoretical foundation to develop seizure detection methods.
- Chapter 3 presents the implementation of epilepsy seizure detection algorithms based on Artificial Neural Networks (ANN) and Deep Learning focused on Convolutional Neural Networks (CNN).
- Chapter 4 discusses the performance results obtained by both neural network models for ictal and free seizure period detection.
- Chapter 5 shows the development of a prototype application to detect ictal activity on EEG records using the CNN model described in Chapter 3.
- Chapter 6 summarizes the contribution results of this dissertation and possible future research lines.

1.4 LIST OF PUBLICATIONS

The following papers were published during the Master course:

References

- ESPINOSA, N.; HUEBNER, R. Methods of Epileptic Seizure Detection-Review. **7mo Congresso Brasileiro de Neurovisão, Setembro 2019. Belo Horizonte-MG, Brasil. 2019.**
- ESPINOSA, N.; AMORIM, A.; HUEBNER, R. Feedforward Neural Network with Backpropagation for Epilepsy Seizure Detection. **IEEE EMBS International Student Conference 2020 in Latin America, Nov 27-28, 2020. Quito - Ecuador. 2020.**

2 LITERATURE REVIEW

This chapter addresses the literature review to develop this project. Therefore, Section 2.1 presents some reviewed epilepsy detection methods. Section 2.2 presents the principles and characteristics of electroencephalogram (EEG), besides the brain wave interpretation. Section 2.3 describes the foundation of signal processing techniques applied to develop the methods implemented in the next chapter. Finally, Section 2.4 describes the concepts of Artificial Neural Networks.

2.1 STATE OF THE ART

Follow is shown some experimental seizure detection methods, which use EEG records on the scalp and intracranial. Most works use signal processing tools to remove artifacts and noise from EEG. In addition, some machine learning methods are used in seizure detection.

Since epileptic seizures are spontaneous, the approach to detect or even anticipate them is varied. In (ZANDI et al., 2010), the authors proposed an algorithm based on wavelet index to determine the frequency bands where the transition occurs, from non-seizure to seizure state, using the probability density function (PDF) of the EEG energy.

The work by (SCHAD et al., 2008) indicates the performance of two algorithms for seizure detection and another one for seizure prediction; both focus on local slopes in EEG signals and use multivariate techniques based on the Fire Neuron model, using 22 EEG channels. Seizure detection occurs when the spiking rate (SR) surpasses a fixed threshold. Whereas, if $F_{Sz}(t)$, the feature extracted of SR exceeds a detection fixed time point, the algorithm detects changes before a seizure. The methods are applied to EEG and iEEG databases obtaining the best performance for seizure detection on scalp EEG.

An algorithm for automated seizure onset detection is reported by (CHAN et al., 2008), applying Support Vector Machine (SVM) binary classifier, and regression analysis to estimate onset time seizure. To compute the spectral power is used a sliding window 2.05-second size, decomposing each window with 8th order Discrete Wavelet Transform (DWT), into five frequency bands, Theta, Alpha, Beta, Gamma (30-60 Hz), and High Gamma (60-100Hz). Besides, it estimates the power spectral density via Fast Fourier Transform (FFT). Finally, the SVM classifier is trained on ten positive iEEG records with seizure onset and twenty negatives iEEG records. This method works within a single representative iEEG channel. The study by (ZHANG; CHEN, 2017) applies the Local Mean Decomposition algorithm that divides the EEG signal into a se-

ries of product functions and classifies it with SVM optimized by the genetic algorithm. The authors in (ZAZZARO et al., 2019) offer an analysis of EEG data using Data Mining techniques, implementing a signal processing tool called Training Builder based on SVM.

The paper by (DORAI, 2010) presents an algorithm with the potential to predict a seizure one minute before it occurs, using linear and nonlinear techniques to process the iEEG signal, like Phase Shift Correlation, Lyapunov Exponents, DWT, FFT, Hilbert Transform Statistics, Power Spectra Analysis, and others. As well as the combination of four classifiers: Linear Discriminant Analysis and K-Nearest Neighbor (KNN) distinguish among several classes at once; then, SVM and Cross-Validation by Elimination make a binary comparison and take a decision between the preictal and ictal state, however, the main limitation is to define the preictal state. Authors in (SAYEED et al., 2018b) suggested an Internet of Medical Things (IoMT) platform for seizure detection in epilepsy patients monitoring in real-time, applying DWT and the KNN classifier. In this same way, the authors in (LASEFR; REDDY; ELLEITHY, 2018) performed a smartphone application for epilepsy detection decomposing the signal into subbands and classifying it via SVM, Artificial Neural Network (ANN), and KNN algorithms.

(GUO et al., 2010) developed an algorithm for epilepsy detection based on Multi-Layer Perceptron Neural Network (MLPNN), using segments of 23.6 seconds duration, cut, and selected from multichannel EEG records. Moreover, it was created three classification problems. The first distinguishes between healthy with open eyes and seizure EEG sets. The second classifies between non-seizure excluding healthy with eyes closed and seizure EEG sets, and the last one picks between non-seizure and seizure sets to evaluate the method's performance. EEG signal is decomposed with a 4th level DWT and the line length measure is extracted from each frequency sub-band to feed the MLPNN. Other approach based on Feedforward Neural Network (FNN) with Backpropagation (BP) is submitted by (AZAMIMI et al., 2012) and (AL-OMAR et al., 2013), extracting statistical features in time and frequency via DWT and FFT. Then, the EEG signal is classified into epilepsy and normal activity. Therefore, applying the same techniques, (AZAMIMI et al., 2012) analyzes the algorithm performance combining DWT and FFT and varying the FNN parameters like hidden neurons and epochs. Whereas (AL-OMAR et al., 2013) considered tests with features extracted in different combinations to feed the network. And (RASHID; AHMAD, 2017) acquires the input parameters via DWT for ANN training. Authors in (DAMAYANTI; PRATIWI; MISWANTO, 2017) applied a BP combination, firefly algorithm, and simulated annealing, using the last one to determine the optimal learning rate and

the number of hidden units in the BP process.

A graphical interface to detect High-Frequency Oscillations (HFOs) in EEG is examined by (CHAIBI et al., 2012), which comprise the 80-500 Hz range and are significant biomarkers of epileptic zones. Processing the signal via DWT and classifying it with the neural network Matching Pursuit. On the other hand, (BESIO et al., 2014) suggested using three-pole concentric ring electrodes since they automatically attenuate muscle artifacts and provide a better quality signal, so make it easier to detect high-frequency waves in EEG studies.

The authors in (KIM et al., 2013) presented a cascade architecture combining different algorithms to analyze the signal in the time and frequency domain, like the absolute average of the signal's amplitude, Multi-Window Count, and Spectral Entropy, improving the accuracy of detection in implantable devices. The study by (LIU; AIMIN; XU, 2017) uses the increased entropy method to extract EEG features and SVM to classify the signal. The work by (KRISHNAN; BALASUBRAMANIAN, 2017) offers a time analysis of minimized EEG by measuring the entropy in time-frequency and processing the EEG signal via the S-transform, then classifying the signal via Least Square Support Vector Machine. (SAYEED et al., 2018a) recommended an architecture for an implantable seizure detector using a hyper-synchronous signal detection circuit and a signal rejection algorithm, reducing the detection of false positives by 12%.

Over the last ten years, the focus has shifted to use Convolutional Neural Network (CNN) for seizure detection, as shown in the following studies. (SCHIRRMESTER et al., 2017) applied CNN on scalp EEG from the Temple University Hospital Seizure Corpus (TUH-SC) database to distinguish pathological from normal EEG. The authors in (ZHOU et al., 2018) use CNN in the intracranial Freiburg Hospital and scalp Boston Children's Hospital-MIT (CHB-MIT) databases to detect the ictal, preictal, and interictal periods from EEG. The study by (ACHARYA et al., 2018) uses deep learning for epilepsy diagnosis implementing a 13-layers deep convolutional neural network, applied to Freiburg and CHB-MIT and American Epilepsy Society Seizure Prediction Challenge (Kaggle) databases, which is an EEG dataset from dogs. The authors in (ALHUSSEIN; MUHAMMAD; HOSSAIN, 2019) employ a neural network already trained (AlexNet) for pathology detection on the TUH-SC database. The work by (HUGLE et al., 2018) performed a CNN called SeizureNet for early seizure detection using the Epilepsiae iEEG database to apply to an implantable device.

Other approaches without using EEG signals are indicated by (CONRADSEN et al., 2009; JALLON et al., 2009; JAGTAP; BHOSALE, 2018; KUSMAKAR et al., 2019; HELDBERG et

al., 2015), who are focused on muscular movement detection caused by tonic-clonic seizures. Authors developed device prototypes based on measuring Electrodermal Activity, EMG sensors, accelerometers, and angular velocity sensors; some of these devices are suggested for remote monitoring patients or seizure onset detection. On the other hand, the method of super magnetic nanoparticles is exposed by (PEDRAM et al., 2015) where using the magnetic field makes a contrasting study with Magnetic Resonance Image for localization and detection of epilepsy.

2.2 ELECTROENCEPHALOGRAM (EEG)

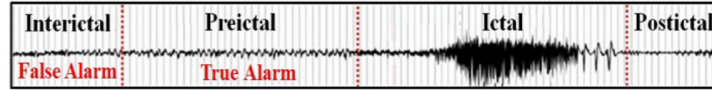
The first human Electroencephalogram (EEG) recording was done by Hans Berger in 1924, who was able to measure the irregular and small electric potential of 50 to 100 μV from the brain. Analyzing EEG waveforms in frequency, morphology, voltage, and topography, he observed that the brain's activity changes depending on the subject's status, for example, during a seizure, the EEG amplitude increases and the frequency decreases, besides the morphology is different than background EEG (BRONZINO, 2006; SAZGAR; YOUNG, 2019; TATUM et al., 2007).

EEG is one most used clinical studies that provide valuable information for epilepsy diagnosis since it is a noninvasive and low-cost study. It is based on postsynaptic potential recordings generated by cortical neurons using electrodes attached to the scalp to monitor brain activity in detail. These electrodes consist of Ag–AgCl conductor discs, 1 to 3 mm in diameter, with flexible leads plugged into the amplifiers and to keep the electrode in place is used a conductive electrode paste obtaining a low impedance between the electrode and skin, i.e., less than 10 $k\Omega$ (BRONZINO, 2006). However, its main limitation is a long time to analyze by professionals specialized in EEG (SCHIRRMESTER et al., 2017). Moreover, to complement the diagnosis often used other biological registers like the electrocardiogram (EKG), electrooculogram, electromyogram (EMG), neuroimage by tomography, temperature, etc. Additionally, to discard hydroelectric alterations and endocrine disease that can simulate an epileptic seizure is necessary done analytical studies, which give information about blood glucose levels, sodium, potassium, calcium, and others (TORRES, 2015). Regrettably, most epilepsy patients are located in rural areas of LMIC, making it impossible to access these tests (WORLD HEALTH ORGANIZATION, 2019).

On the other hand, interpreting EEG, physicians have identified the four states of brain activity illustrated in Figure 1. **Preictal state** defined as the period just before the seizure, **ictal state** is the period during seizure occurs, **postictal state** is the period after the seizure. Finally,

interictal state refers to the period between seizures, i.e., the period between the postictal and preictal state (DAOUD; BAYOUMI, 2019).

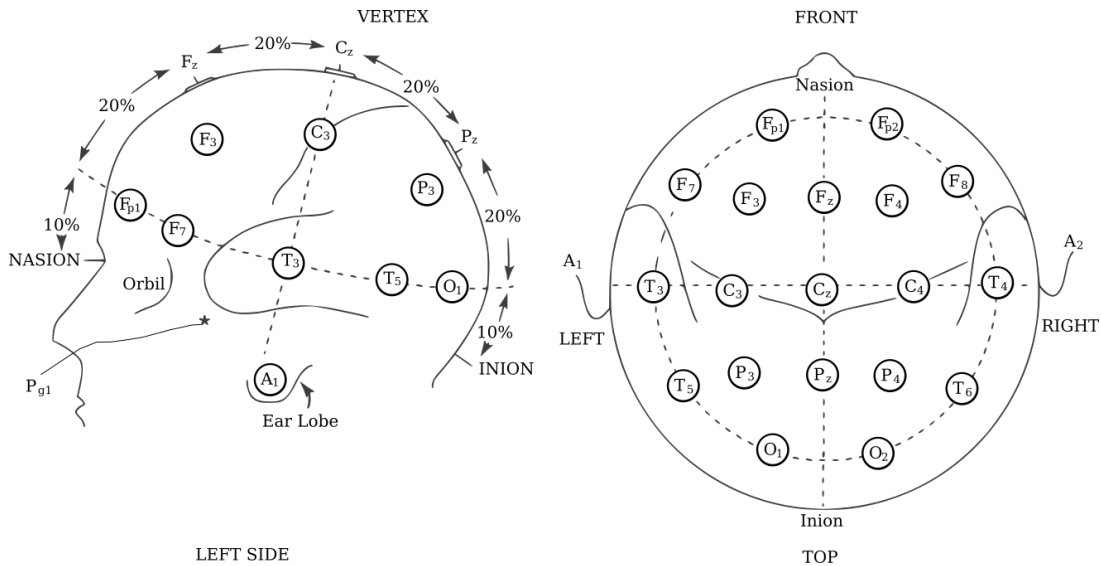
Figure 1: Brain states into EEG records



Source: (DAOUD; BAYOUMI, 2019)

Electrode placement on EEG has been standardized by the International Federation of Electroencephalography and Clinical Neurophysiology, which adopted the international 10-20 system shown in Figure 2, where the electrode distribution is done at intervals of 10% to 20%, using anatomical landmarks on the skull (BRONZINO, 2006).

Figure 2: Electrode placements 10-20 system

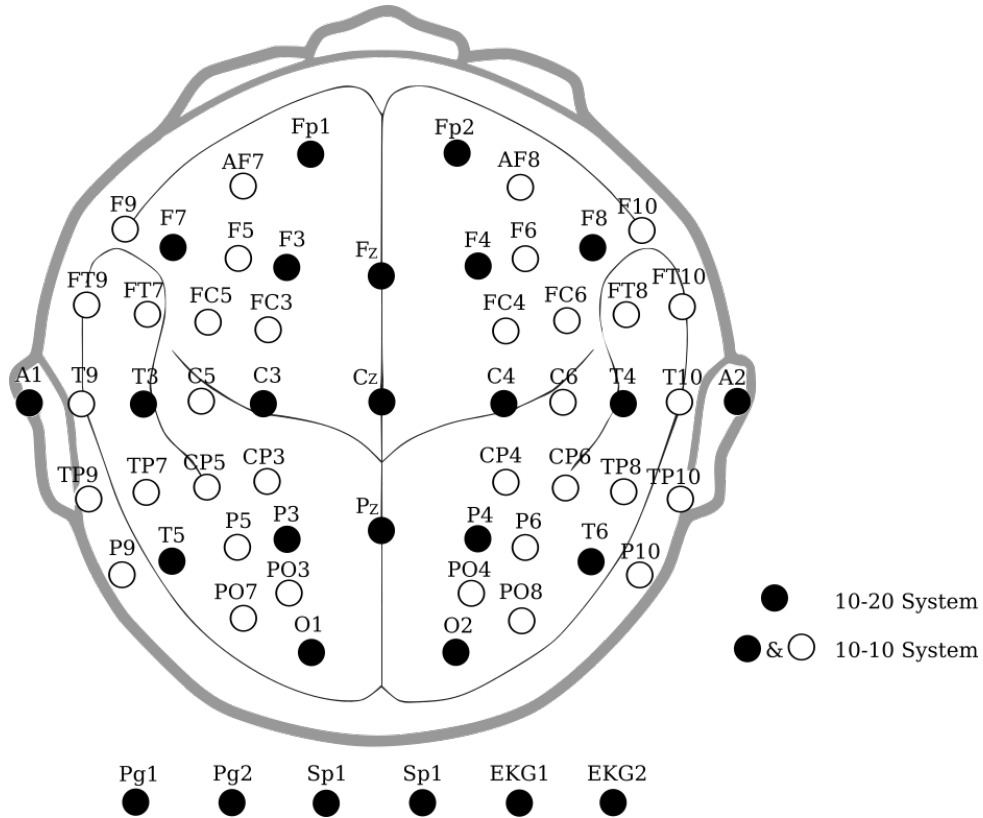


Source: Adapted from (SAZGAR; YOUNG, 2019)

The standard set of electrodes recommended for a clinical study are 21 and 1 ground electrode. Nevertheless, in some cases, it is necessary to use more electrodes with a closer space using the 10-10 system shown in Figure 3. Furthermore, the EEG includes additional electrodes like electrocardiogram (EKG), electromyogram (EMG), respiratory, and eye movement monitors, which aid in epilepsy diagnosis (SAZGAR; YOUNG, 2019; TATUM et al., 2007; BRONZINO, 2006). However, the EEG can be corrupted by so-called biological artifacts that consist of residuals picked up via amplifiers from additional electrodes previously described, besides the slow fluctuation of EEG electrodes induced by transpiration. Furthermore, the EEG measuring can be affected by technical artifacts, which have many reasons like the

electromagnetic or electrostatic effect of the power line obtaining 60 Hz noise, fluctuating voltages caused by electrode movement, defective or poorly cleaned electrode material (MOORE; ZOURIDAKIS, 2004).

Figure 3: Electrode placements systems; black electrodes represent 10-20 system, while the 10-10 system includes the black plus the white electrodes.

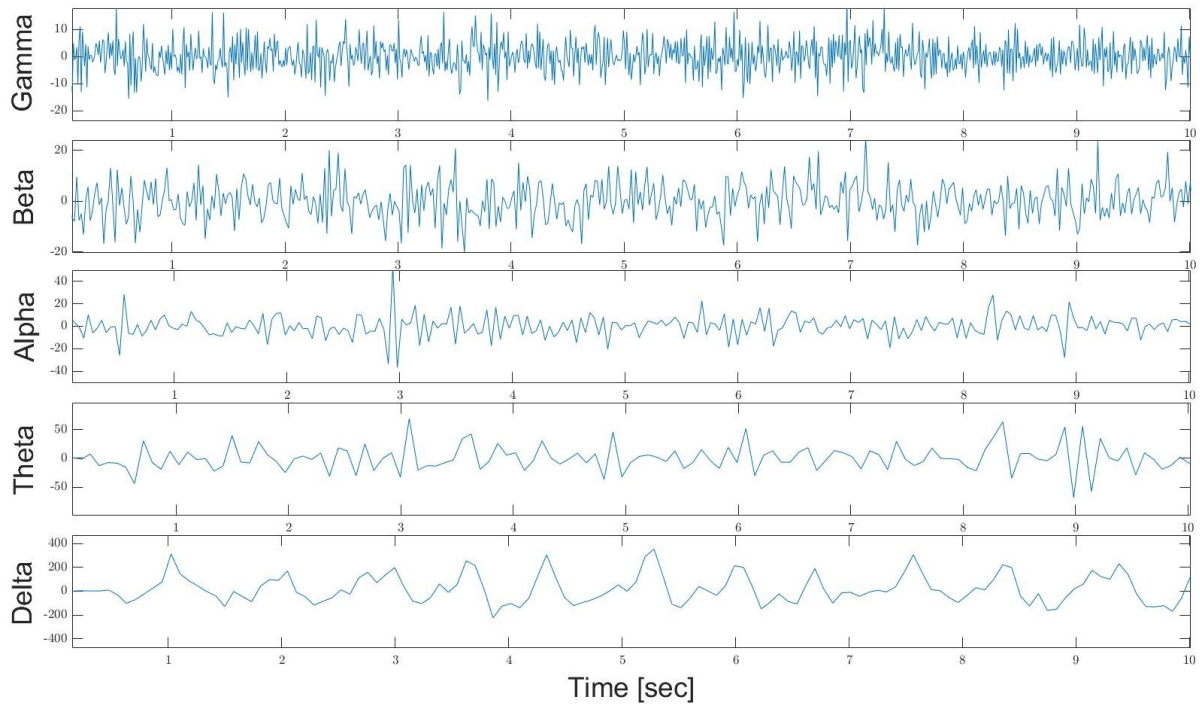


Source: Adapted from (TATUM et al., 2007)

In general, the EEG amplitude and frequency ranges are between 0.1 to 100 μV and 0.05 to 500 Hz, respectively. EEG rhythms are divided according to their frequencies into five frequency bands, such as shown in Figure 4, using a Greek letter to call each frequency interval. Delta is a slow rhythm with less than 4 Hz, often presenting a large amplitude typically encountered during deep sleep, which also indicates cerebral damage or brain disease. Theta rhythm (4 to 7 Hz) usually occurs during sleep or drowsiness. Alpha rhythm (8 to 13 Hz) is eminent in the occipital cortex and is related to relaxation states and awake with close eyes, since when open eyes, this activity is suppressed. Beta rhythm (14 to 30 Hz) is fast with low amplitude, frequently present in the frontal and central brain areas, and is associated with an activated cortex and can be observed during certain sleep stages. Gamma rhythm (30 to 100 Hz) implies an active or alert cortex in the processing of visual, auditory, and motor stimuli (SORNMO; LAGUNA, 2005).

The epileptic activity is characterized by spikes and sharp waves (SSWs), which are tran-

Figure 4: Brain Frequency Bands; Gamma (30-100 Hz), concentration state; Beta (14-30 Hz), anxiety dominant, active, external attention, relaxed; Alpha (8-13Hz) very relaxed, passive attention; Theta (4-7Hz), deeply relaxed, inward focused; Delta (0.5-4Hz), sleep state.



Source: Author

sient waves with irregular and unpredictable temporal patterns (paroxysmal activity). It presents a greater amplitude when compared with the continuous background EEG. Generally, SSWs have a steep initial upstroke, where a spike-wave has a duration in the range of 20-70 ms while a sharp wave is 70-200 ms long. Their morphology is monophasic, with repetition rates ranging from less than 3 to 6 Hz (SORNMO; LAGUNA, 2005).

2.3 SIGNAL PROCESSING

Follow are described the signal processing tools applied in this work, which allow analyse the biosignals in time and frequency domain.

2.3.1 Discrete Wavelet Transform (DWT)

Since EEG is a nonstationary signal, a DWT is an efficient tool for processing it (ZANDI et al., 2010) because it provides a more flexible representation of time-frequency and is possible to analyze the signal with variable window size. Very useful to work with biomedical signals, which often contain high-frequency information with short time duration and low-frequency

information with a long time duration (GUO et al., 2010).

The Continuous Wavelet Transform (CWT) defined by (1) computes the wavelet coefficient, which is the correlation between the signal $x(t)$ and the wavelet $\Psi_{a,b}(t)$. Higher correlation produces a large coefficient (CHUI, 1997)

$$CWT_{(a,b)} = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \Psi^* \left(\frac{t-b}{a} \right) dt, \quad (1)$$

where * superscript indicates the complex conjugate of the wavelet, but it can be omitted if the wavelet is real, e.g., Haar and Daubechies wavelets, which are orthogonal wavelet families. The parameter a is the scale of wavelets, and b is the translation.

DWT is used to reduce the redundancies existing in CWT. When the scale and translation take the following values (CHUI, 1997):

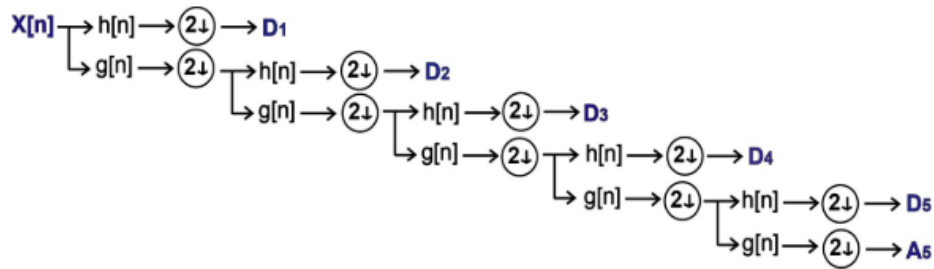
$$a = \frac{1}{2^j} \quad \text{and} \quad b = \frac{k}{2^j} \quad \text{with} \quad j, k \in \mathbb{Z},$$

Thus, DWT is determined by (2):

$$DWT_{(j,k)} = 2^{j/2} \int_{-\infty}^{\infty} x(t) \Psi^* \left(\frac{t - \frac{k}{2^j}}{\frac{1}{2^j}} \right) dt. \quad (2)$$

Therefore, the original signal is decomposed using the Mallat algorithm via DWT, which consists of to pass the original signal $x[n]$ thought a filter bank, high-pass filter ($h[n]$) and low pass filter ($g[n]$) (GUO et al., 2010), as illustrated in Figure 5. Downsampling the frequency by half according to the Nyquist criterion, the frequency range of each level is computed. This process repeats the number of chosen levels.

Figure 5: Five-level Wavelet Decomposition; five-level filter bank where the frequency range of each level downsampling by a factor of 2 ($2 \downarrow$) according to the Nyquist criterion.



Source: (RASHID; AHMAD, 2017)

2.3.2 Fast Fourier Transform (FFT)

Fast Fourier Transform (FFT) is an optimized algorithm of Discrete Fourier Transform (DFT) defined by (3)

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\Omega kn}, \quad \Omega = \frac{2\pi}{N}, \quad (3)$$

where $x(n)$ is the input signal, Ω is a sample frequency and N is the number of samples.

The principle function of FFT is to reduce the number of computationally demanding multiplication steps required for a given number of samples N , while DFT needs N^2 multiplications for N points, FFT requires only $N\log_2(N)$ multiplications ([DRONGELEN, 2018](#)).

2.3.3 Short Time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) allows to make a time-frequency analysis and is used to acquire the information of the local time and frequency content of the signal ([RAJOUB, 2020](#)). The STFT for a signal $x(t)$ is defined by:

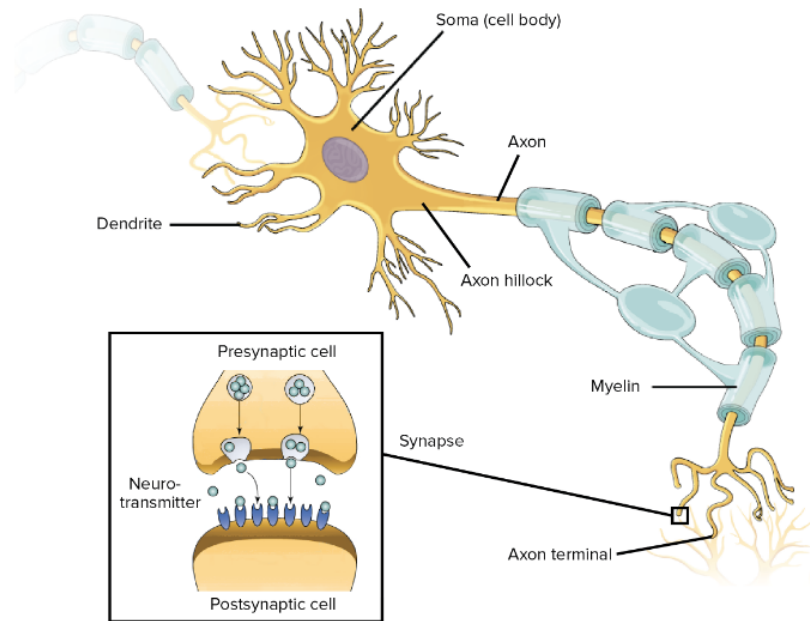
$$X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)w(t - \tau)e^{-j\omega t}dt, \quad (4)$$

where $w(t)$ is a non-null window for a short period of time, the Hann window is the most used. Note that the window moves τ times along the time, resulting in a representation of X is a function with two independent variables; therefore $X(\tau, \omega)$ is the Fourier Transform of $x(t)w(t - \tau)$.

2.4 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are nonlinear mapping systems inspired by the fundamental principles observed in the biological nervous system. A biological neuron perceives ambient modifications and is the center of information processing. Figure 6 shows the basic neuron structure, which consists of dendrites, which receive signals from other nearby neurons; then, in the soma or cell body, these signals are processed and produce a response distributed by the axon to other nearby neurons via the junction between them known as synapses ([HAYKIN, 1999](#); [BEAR](#); [CONNORS](#); [PARADISO, 2017](#)).

A neural network is a parallel distributed processor, consists of processing simple units, and is similar to the brain in two aspects. First, the network obtains knowledge from the ambient via a learning process, and second, the knowledge acquired is stored in on-called synapse

Figure 6: Biological neuron

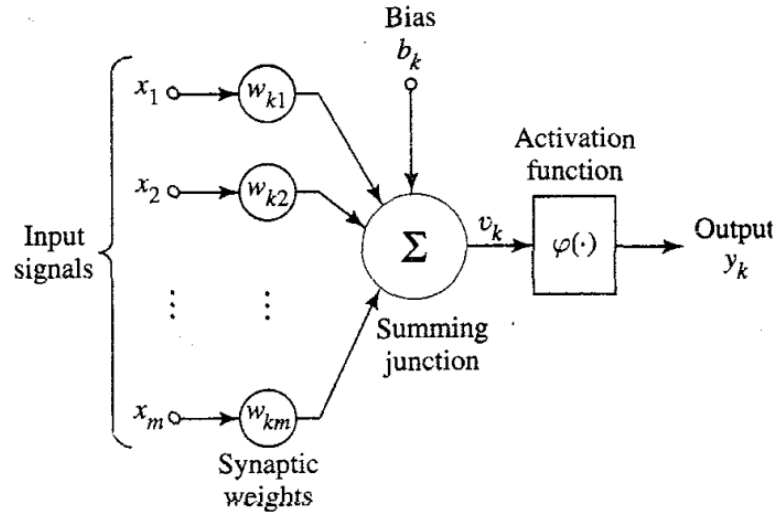
Source: ([KHAN ACADEMY, 2015](#))

weights (i.e., connections between neurons). The ability of ANN to learn and produce suitable outputs for inputs not present in the training process makes it possible to resolve complex problems generally intractable ([HAYKIN, 1999](#)).

2.4.1 Neurons or Processing Elements (PEs)

Computationally, we can consider each neuron as a node. Figure 7 shows the artificial neuron model, the base of ANN, defined by three main components: Synapse or link connection is modeled as weights, e.g., the signal x_j in the synapse input j connected to neuron k multiplies by weight w_{kj} . Contrary to brain synapses, the ANN synapse is represented as an interval that contains positives and negatives values. Then, an adder to sum all input signals pondered by their respective weights. Finally, an activation function that restricts the neuron output, i.e., limits the output amplitude of the neuron to a finite value. Typically, the normalized interval is $[0,1]$, alternatively $[-1,1]$. Besides, the model includes the bias b_k , applied externally, which increases or decreases the network input of the activation function, depending on whether its value is positive or negative ([HAYKIN, 1999](#)).

Figure 7: Model of a neuron



Source: (HAYKIN, 1999)

Mathematically, the neuron k is defined by:

$$u_k = \sum_{j=1}^m w_{kj} x_j, \quad (5)$$

$$y_k = \varphi(u_k + b_k), \quad (6)$$

where $x_1, x_2, \dots, x_m$ are input signals; $w_{k1}, w_{k2}, \dots, w_{km}$ are synaptic weights; u_k is the linear combination output; b_k is the bias; $\varphi(\cdot)$ is the activation function and y_k is the neuron output.

The activation potential v_k is described by $(u_k + b_k)$, thus it is possible to rewrite (5) and (6) as follows:

$$v_k = \sum_{j=0}^m w_{kj} x_j, \quad (7)$$

$$y_k = \varphi(v_k). \quad (8)$$

ANNs are composed of neuron sets grouped in layers, and their vector notation directly indicates how to do the parallel implementation of the ANN algorithms.

2.4.2 Activation Functions

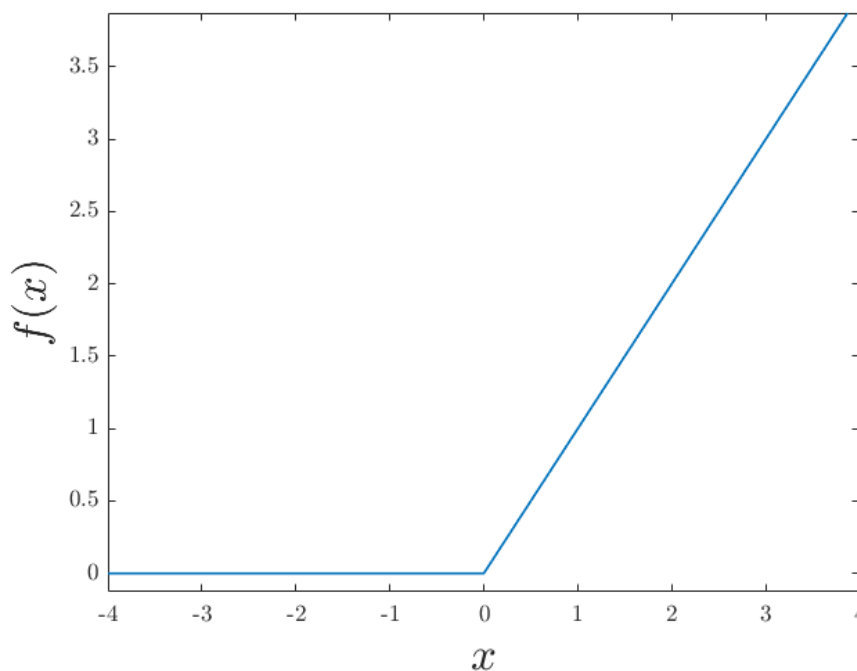
ANN models combine their inputs using weights that shape their synaptic connections, then, to the total neuron's input is applied an activation function, which determines the neuron's output (remember Figure 7) (BERZAL, 2018). The activation functions most used in neural networks are Linear, Step, Hyperbolic Tangent, Rectified Linear Unit (ReLU), Sigmoid, Softmax, among others. This work delves into the last three activation functions in terms of activation potential $\varphi(v)$.

Rectified linear unit (ReLU) Activation Function

ReLU function is a linear and nonsaturated function, i.e., it does not saturate at -1, 0, or 1 due to its range being from 0 to infinite, it is defined by (9) or its alternative form $\varphi(v) = \max(0, v)$. ReLU typically achieves a better performance than other activation functions in hidden layers (HEATON, 2015). Figure 8 shows the ReLU activation function, where we can see that the negative values are eliminated.

$$\varphi(v) = \begin{cases} v & \text{if } v > 0 \\ 0 & \text{if } v < 0 \end{cases} \quad (9)$$

Figure 8: ReLU Activation Function



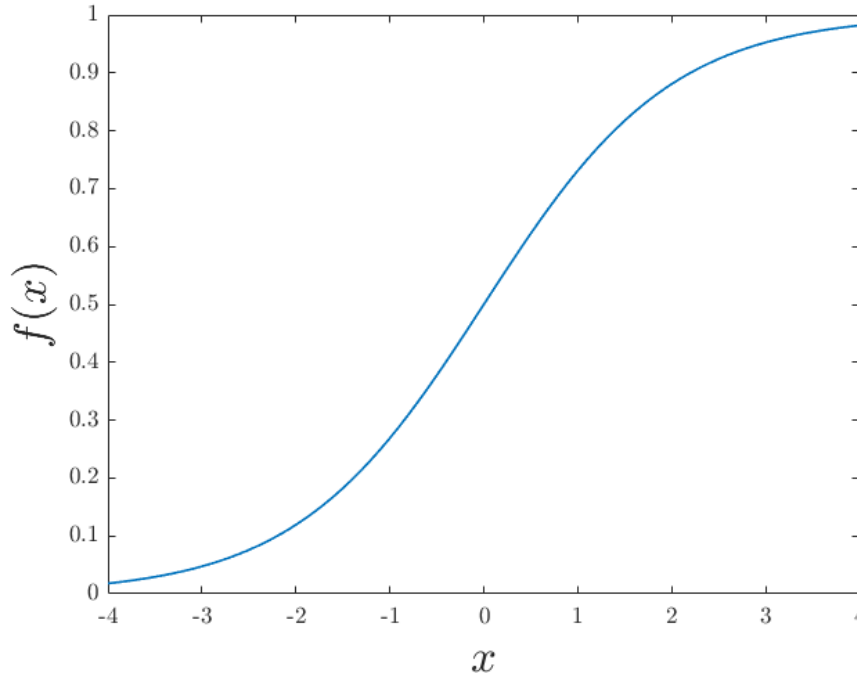
Source: Author

Sigmoid Activation Function

This function is increasing, continuous, and derivable, which is very useful for networks trained with the backpropagation algorithm (error propagation). Sigmoid function is characterized by its "S" shape, such as seen in Figure 9. Some Sigmoid function examples are: logistic function, hyperbolic tangent, and gudermannian function ([BERZAL, 2018](#)). In this work is used the logistic activation function defined by (10) is the most used for neural network construction, its range is between 0 and 1, which provides a binary classification, the use of this function ensures that the values stay within a small range ([HAYKIN, 1999](#)).

$$\varphi(v) = \frac{1}{1 + e^{-v}} \quad (10)$$

Figure 9: Sigmoid Activation Function



Source: Author

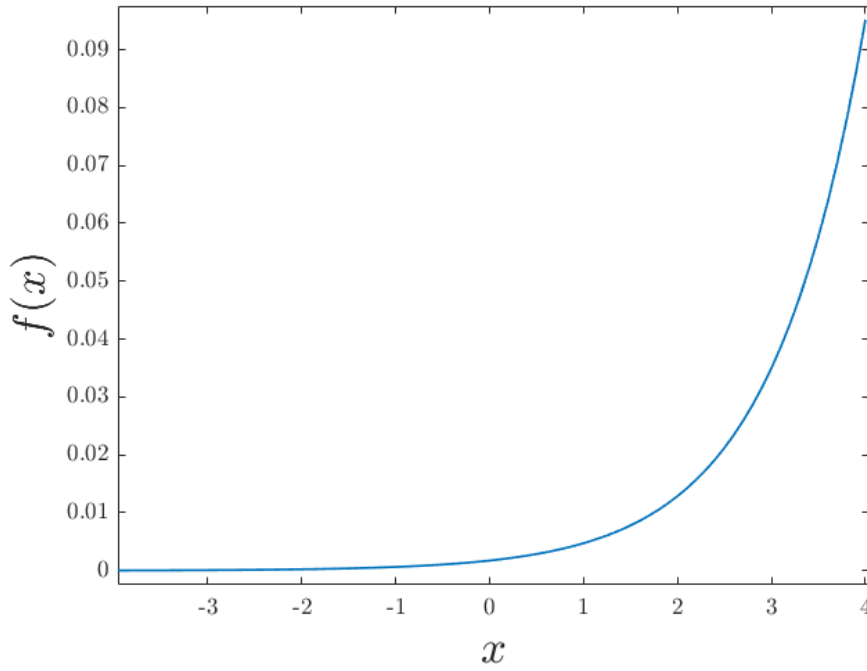
Softmax Activation Function

This function is usually used in the output layer, due to it is widely applied in multiclass problems to represent the probability that the input falls into each of the classes. Note that this function defined by (11) is calculated differently than the other two presented in this chapter ([HEATON, 2015](#)).

$$\varphi_i(\vec{z}) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}, \quad (11)$$

where $\vec{z}$ is the output array of neuron, $z_i \in \mathbb{R}$ are the elements of the array of the output neurons, $\sum_{j=1}^K e^{z_j}$ is the sum of exponential function of each element of the output array, and K is the number of classes in a multiclass classifier. Figure 10 represents the softmax activation function.

Figure 10: Softmax Activation Function



Source: Author

2.4.3 Neural Network Architectures

In general, in the architecture of an ANN, we can distinguish two kinds of layers. Visible layers usually are the first and last layer of the net or input and output layer, while all middle layers are named hidden layers. The **input layer** receives the input signals to the network; the **hidden layers** contain the computational nodes or neurons, and the **output layer** presents the neural network output.

Remember which connections of all networks can be excitatory or inhibitory, depending on the sign associated with them. The connection will be excitatory if the output is positive and inhibitory when the output is negative; the contrary occurs if the synaptic weights are negatives. Activation functions are helpful when the sign change influences the next neuron's behavior (BERZAL, 2018).

Following is explained the main network architectures:

Feedforward Networks

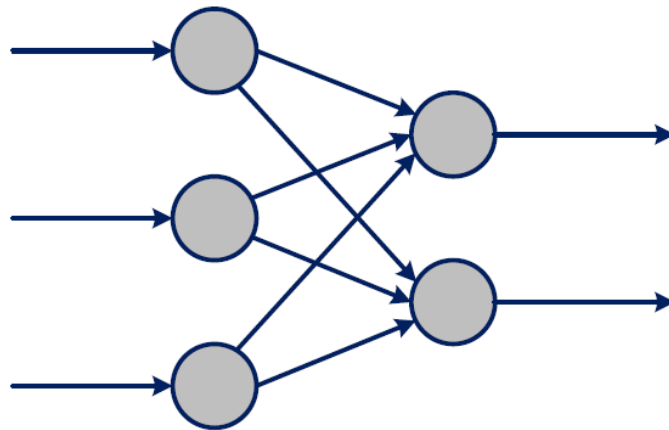
The regular topology of the feedforward networks consists of neurons in each layer, independent of each other, working in parallel, which aids in their implementation. Connecting each layer to the next one forward, i.e., they lack the feedback mechanism. Thus, these networks do not have memory (BERZAL, 2018). For this reason, the backpropagation method is used to train neural networks, which calculates the gradient (i.e., the error function derivatives) of each network weight, minimizing the total squared errors of the network output (HEATON, 2015; DAMAYANTI; PRATIWI; MISWANTO, 2017).

Hence, most signal classifying applications employ feedforward networks with the training method of backpropagation. Besides, there are several architecture options in the function of the hidden layers' number (BERZAL, 2018).

a) Simple Network

This network does not have any hidden layer, as seen in Figure 11 it has only an input and output layer, so the network receives the inputs then redistributed to the output layer (BERZAL, 2018).

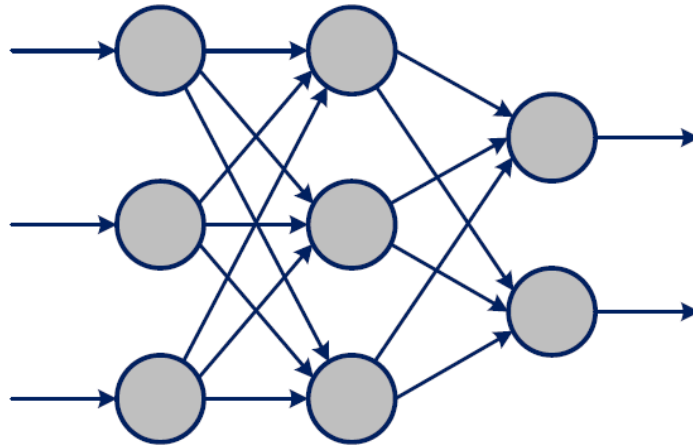
Figure 11: Simple Network



Source: (BERZAL, 2018)

b) Multilayer Network (one hidden layer)

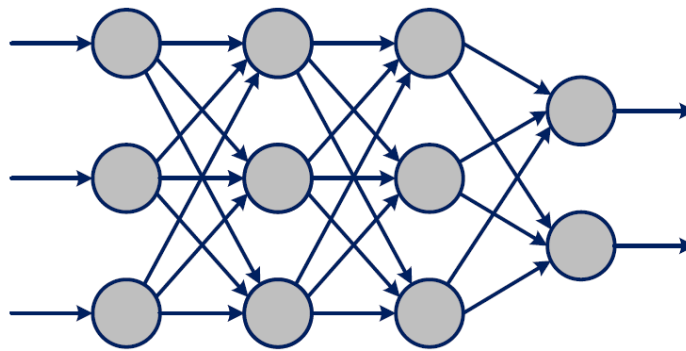
This kind of network presented in Figure 12 was popular from the 80s to the end of the 20th century. It consists of an input and output layer and a single hidden layer, so it is necessary to use the backpropagation algorithm (BERZAL, 2018).

Figure 12: Multilayer Network

Source: (BERZAL, 2018)

c) Deep Network (several hidden layers)

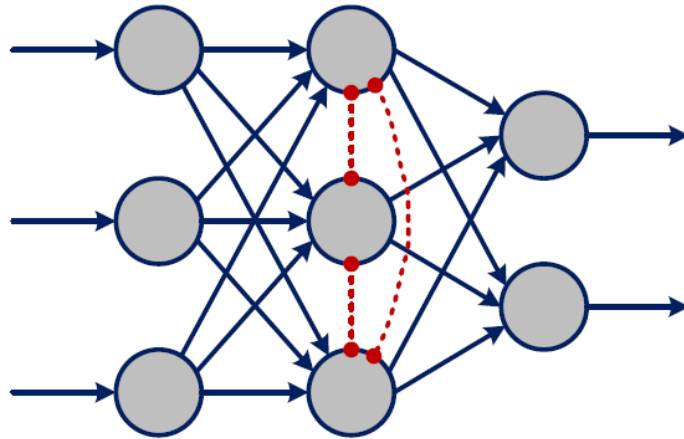
These networks apply deep learning techniques to design modular solutions to complex problems, including multiple hidden layers (BERZAL, 2018). Figure 13 shows a neural network with two hidden layers.

Figure 13: Deep Network

Source: (BERZAL, 2018)

Competitive Networks

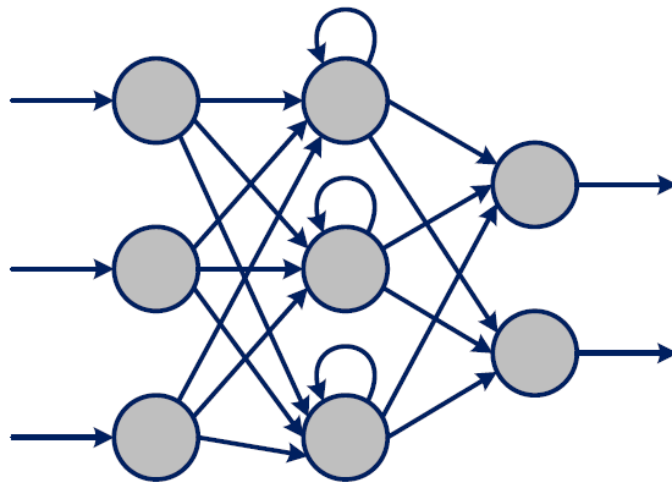
The competitive networks include inhibitory connections between neurons of the same layer. Therefore, when a neuron is activated, an inhibitory influence on the others is applied. Figure 14 shows the inhibitory connections in the network represented by the red dashed lines. This network is appropriate to model situations when the layer should respond depending on the context (BERZAL, 2018).

Figure 14: Competitive Network

Source: ([BERZAL, 2018](#))

Recurrent Networks

The recurrent neural networks (RNNs) are networks with memory since having generalized connections, i.e., admit the output connections from a layer as input of a previous layer, such as shown in Figure 15. The main difference between feedforward and recurrent networks is their activation. When we use a feedforward network, each pattern is independent of the previous. Thus, it would be like employing a new net each time. On the other hand, the recurrent network has the saturation risk and will stay stuck on a fixed value if we do not appropriately design the network due to its topology.

Figure 15: Recurrent Network

Source: ([BERZAL, 2018](#))

2.4.4 Convolutional Neural Network

The Convolutional Neural Network is widely used for image recognition, but recently, the challenge is to use it for EEG pattern recognition. CNNs employ the convolution math operation and their architecture consists of an input layer, which typically is an image set, followed by convolutional layers, a pooling layer, fully connected layers, and an output layer. In the convolutional layer are defined several filters (kernels) that are convolved with the input, using (12), to obtain the output known as feature maps (GOODFELLOW; BENGIO; COURVILLE, 2016).

$$y(t) = x * h, \quad (12)$$

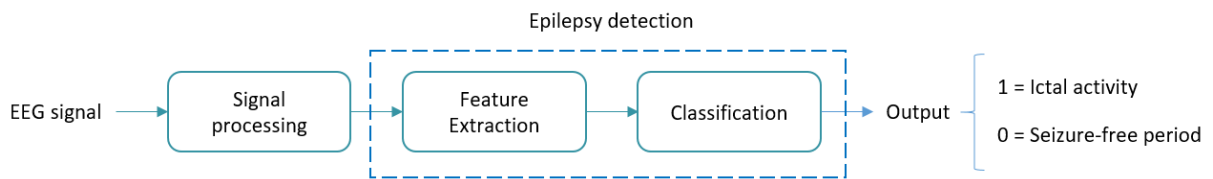
where $y(t)$ is the feature map, x is the input signal, and h is the filter.

Next, in the Pooling layer is downsampling the previous convolutional layer output. The most pooling operations used are max-pooling, which gets the maximum output within a rectangular region (GOODFELLOW; BENGIO; COURVILLE, 2016). Then, in the fully connected layers occur the classification learned by the network. Finally, the output layer returns the network output.

3 MATERIALS AND METHODS

This chapter presents the materials and the two methods developed for epileptic seizure detection. In this research, the seizure detection process was divided into two stages. Signal processing and epileptic seizure detection, as seen in Figure 16, in the epileptic seizure detection stage, the signal features are extracted, which aids to classify in epileptic seizure or seizure-free periods.

Figure 16: Epileptic seizure detection algorithm based on Machine Learning



Source: Author

ANNs are tools of machine learning, an Artificial Intelligence area. The ANNs provide the computers the ability to learn from data to solve specific problems. Allowing that the system anticipates future events through the knowledge acquired by a training process, with the data available. The training process can occur offline (i.e., before using the system) or online (i.e., at the moment to use the system). Therefore, in the first case, the system will remain stable along the time, where it is possible to predict the performance in a controlled environment. While in the second case, the system adapts to environment changes that can do it unpredictable. Hence, machine learning is highly suggested in pattern recognition, voice, and image identification problems. However, since the system learns from the data available; if the future data look like the training data, the system has a high chance to be successful, but if not, we have to trust that the heuristic bias, which every learning technique incorporates, will be adequate to solve the problem (BERZAL, 2018).

The learning techniques can be classified by the knowledge acquisition process into supervised and no supervised learning. Supervised learning consists of providing training examples and correct outputs, which the system can reproduce, where the essential is that the trained model can be generalized. Besides, supervised learning includes rote learning, parameter setting learning, and several classification models like decision trees, support vector machine, neural networks, among others. In contrast, no supervised learning, descriptions, hypotheses, or theory are built from an observation set, without the additional information of how classified it, so the

system decides how to cluster the training set ([BERZAL, 2018](#)).

This chapter is arranged as follows, Section 3.1 describes the hardware, software, and EEG database used in this research. Section 3.2 presents the first approach based on Feedforward Neural Network (FNN) with Backpropagation. Finally, Section 3.3 shows the second method based on Convolutional Neural Network (CNN) for ictal period detection.

3.1 MATERIALS

This section describes the applied materials to develop the epilepsy detection algorithms based on FNN and CNN. Consequently, to implement both epilepsy detection methods explained later, the used computer was CPU i7-7700HQ with 12 GB RAM and graphics card NVIDIA GTX1060 3 GB. Besides, the programming language Python version 3.8.8.

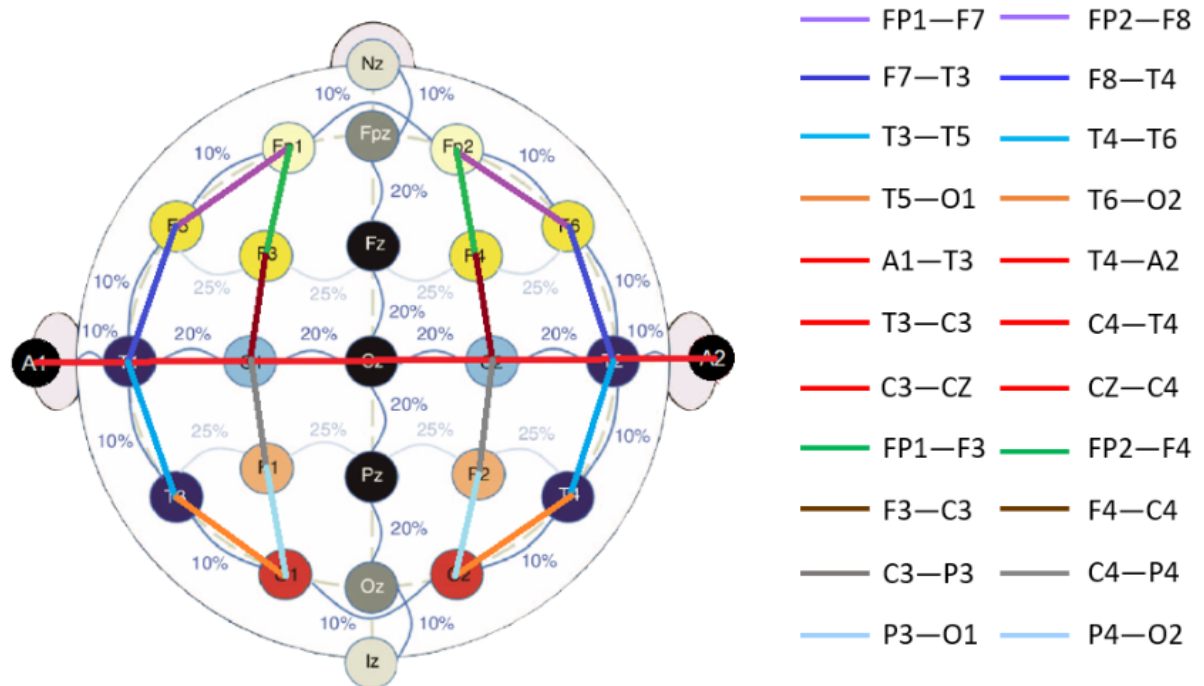
3.1.1 Temple University Hospital Seizure Corpus Database

The Temple University Hospital Seizure Corpus (TUH-SC), the database used in this work, consists of EEG records and reports written by the attending neurologist of each patient. The recordings are saved into European Data Files (EDF) and the neurologists' annotations into (txt) files. In the recordings' header are the main information of each patient and signal condition. This clinical database has been collected since 2002 to 2020 at Temple University Hospital, using various generations of EEG equipment Natus Medical Incorporated's (NMI) NicoletOne. The stored files are available for open-source access. The database aims to motivate the development of high-performance seizure detection algorithms using machine learning, providing 1423 total sessions from 642 patients, whose 451 are seizure sessions from 241 patients, presenting 3055 total seizures, i.e., about 30% of the data contain seizure events ([FERRELL et al., 2020](#); [SHAH et al., 2018](#)).

The EEG records have a resolution of 16 bits and a sampling frequency of 256 Hz. Then, to remove artifacts is applied an analogical filter of 128 Hz low pass. Additionally, for electrode placement, the international 10-20 system was used, with 21 to 36 channels applying a Temporal Central Parasagittal (TCP) montage as shown in Figure 17 ([FERRELL et al., 2020](#)).

Moreover, EEGs were recorded with different seizure types like simple partial seizure (**SPSZ**) that occurs in a specific brain locality; complex partial seizure (**CPSZ**) is a simple partial seizure with impaired awareness; focal seizure (**FNSZ**) is a brief seizure that starts in one location of the brain (and may spread), where the patient is fully aware and able to interact;

Figure 17: Temporal Central Parasagittal (TCP) montage, using 22 derivations and 10-20 system



Source: (FERRELL et al., 2020)

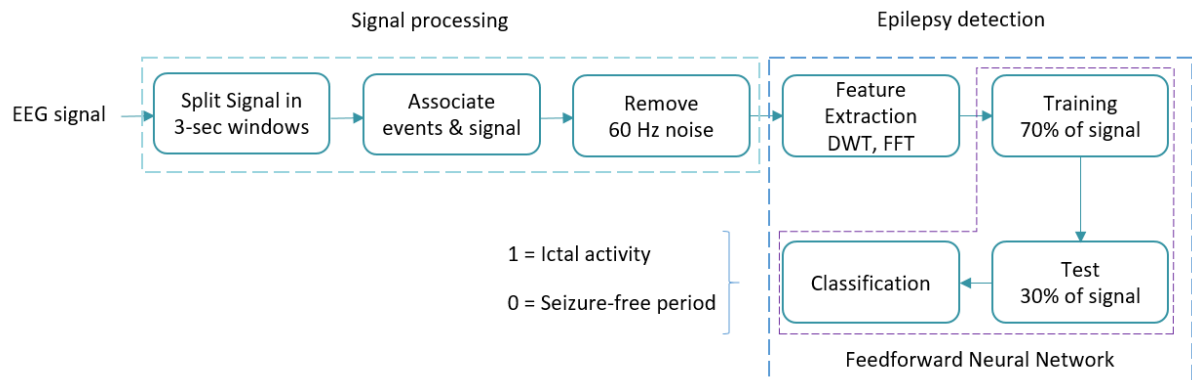
generalized seizure (**GNSZ**) is a seizure occurring in the entire brain; absence seizure (**ABSZ**) is a brief, sudden seizure involving a lapse in attention; tonic seizure (**TNSZ**) presents stiffening the whole body during seizure; clonic seizure (**CNSZ**) involves jerking/shivering of the body; tonic-clonic seizure (**TCSZ**) is a seizure committing loss of consciousness, at first stiffening and then jerking of body (SHAH et al., 2018).

3.2 METHOD 1: EPILEPSY SEIZURE DETECTION BASED ON FEEDFORWARD NEURAL NETWORK WITH BACKPROPAGATION

This section presents the algorithm based on the Feedforward Neural Network (FNN), using the training method of Backpropagation to detect epileptic seizures. This method, illustrated in Figure 18 works with a single EEG channel and consists of two stages. Signal processing and epilepsy detection. In the first stage, the signal is split into a three-second window size. Then all seizure events are associated with the EEG signal and remove the 60 Hz noise. The second stage starts with the input parameters extraction for the neural network via a Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT). These features feed the FNN using 70% of signal to the training process and 30% to validate the training. Lastly, FNN classifies the EEG

in epilepsy or normal activity.

Figure 18: Epilepsy detection algorithm based on FNN model



Source: Author

3.2.1 Signal Processing

In this stage are described the followed steps to process the signal. Furthermore, the implementation of the algorithms to split EEG signal, associate the EEG signal with seizure events, and remove the power line noise are shown. Besides, the DWT and FFT application to obtain the input network.

Split signal

The whole signal is split up into n rectangular windows of three seconds size or 768 samples since the sampling frequency of EEG is 256 Hz. As seen in the implemented Algorithm 1, the n segments are given by the EEG signal length. Obtaining the split EEG signal array.

Associate Seizure events with EEG signal

As described in section 3.1.1 database provides EEG records in .edf files and seizure events (*FNSZ*, *SPSZ*, *CPSZ*, *GNSZ*, *ABSZ*, *TNSZ*, *CNSZ*, *TCSZ*) in .tse files, which detail the brain activity that the patient presents during records, besides, the beginning and end time of each seizure event. With this information, we implement the Algorithm 2 where the EEG signal, previously divided into windows of three seconds size, is associated with seizure events.

Algorithm 1: EEG signal division in 3 second windows

Result: Divides the whole EEG signal into 3 second windows, making the number of samples in each window three times the sampling frequency of the signal

input : EEG signal and sampling frequency

output: EEG windows array

Calculate the total interval dividing the length of the signal by the number of samples in every window;

Define the onset and end of the first window as 1 and the number of samples in one window, respectively;

Append the output array of the first window;

for $i \leftarrow 2$ **to** *total intervals* **do**

$onset \leftarrow end + 1$;

$end \leftarrow i * samples$;

 Use the new onset and end to make the i -th window;

 Append the output array;

end

Source: Author

Algorithm 2: Associate seizure events with the EEG signal

Result: Seizure Events associated with the EEG signal

input : EEG window array, events

Define the function to identify the seizure;

if $onset\ of\ event < onset\ of\ signal < end\ of\ event$

or $onset\ of\ event < end\ of\ signal < end\ of\ event$ **then**

for $k \leftarrow 0$ **to** $size\ of\ list\ of\ events - 1$ **do**

if $list\ of\ events[k] \leftarrow type\ of\ seizure$ **then**

return True;

end

return False;

end

end

```

total windows ← size of EEG window array;
list of events ← ["FNSZ", "SPSZ", "CPSZ", "GNSZ", "ABSZ", "TNSZ", "CNSZ", "TCSZ"];
for  $i \leftarrow 1$  to total windows - 1 do
    for  $j \leftarrow 0$  to size of events do
        Call identify seizure function;
        EEG window array seizure[ $i$ ] ← function(EEG window array[ $i$ ], list of events,
            events [ $j$ ]);
        if EEG window array seizure[ $i$ ] then
            | break
        end
    end
    return the EEG window array with events of seizure associate
end

```

Source: Author

Notch filter

The 60 Hz noise of the power line interference with the EEG signal is removed via a stop-band filter (notch filter). To design the filter is used a 5-th order Butterworth filter with cut frequency $\omega_{c_1} = 59$ Hz and $\omega_{c_2} = 61$ Hz, obtaining the next five repeated complex conjugate zeros:

$$z_{1,2,3,4,5} = 0.09804667 \pm 0.99518182 \cdot i,$$

Moreover, the following five complex conjugate poles:

$$p_1 = 0.12031221 \pm 0.98514456 \cdot i;$$

$$p_2 = 0.11020235 \pm 0.97415126 \cdot i;$$

$$p_3 = 0.09569743 \pm 0.97104127 \cdot i;$$

$$p_4 = 0.07420034 \pm 0.98965168 \cdot i;$$

$$p_5 = 0.08203389 \pm 0.97687108 \cdot i.$$

At length, the gain of the transfer function is $K = 0.9236$. Thus, the digital filter transfer function is represented by (13).

$$H(s) = 0.9236 \frac{(s - z_1)(s - z_2)(s - z_3)(s - z_4)(s - z_5)}{(s - p_1)(s - p_2)(s - p_3)(s - p_4)(s - p_5)} \quad (13)$$

Discrete Wavelet Transform (DWT)

To develop the algorithm proposed in this section, the Daubechies orthogonal family of wavelets from orders 2 to 6 (KULASURIYA; PERERA, 2011) were tested, giving the best accuracy in classification, the 5th order wavelet. Thus, the EEG signal was divided into subbands, using a five-level decomposition wavelet exposed in Section 2.3.1, getting the detail coefficients D1 to D5 and the approximation coefficient A5. However, the coefficient D1 will not use. Table 1 summarizes these coefficients, which have their frequency range nearby to the standard brain waves: *Delta* (δ) 0.5-4 Hz; *Theta* (θ) 4-7 Hz; *Alpha* (α) 8-13 Hz; *Beta* (β) 14-30 Hz and *Gamma* (γ) 30-100 Hz, where is possible to evaluate the brain activity with foreground patterns (e.g., epileptic spikes), and continuous background (DRONGELEN, 2006).

Table 1: Frequency Bands by Wavelet Decomposition

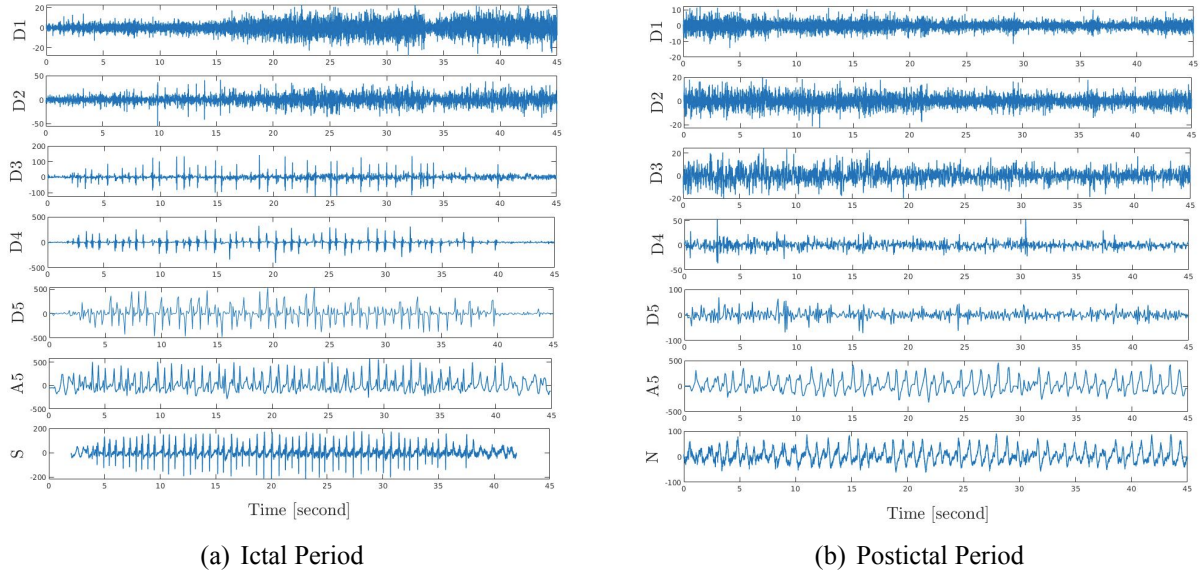
Decomp. Level	Decomposed Signal	Frequency Range [Hz]	Brain Waves
1	D1	64-128	-
2	D2	32-64	<i>Gamma</i> (γ)
3	D3	16-32	<i>Beta</i> (β)
4	D4	8-16	<i>Alpha</i> (α)
5	D5	4-8	<i>Theta</i> (θ)
5	A5	2-4	<i>Delta</i> (δ)

Figure 19 shows the example of EEG signal decomposition via DWT applying an ictal (S) and postictal (N) period. Therefore, illustration 19(a) presents the partition in subbands of the ictal period, i.e., the moment when occurring an epileptic seizure. This episode had a duration of 45 seconds (100 to 145 seconds) taken from a patient who presented a generalized seizure, while illustration 19(b) shows the DWT application in a postictal period (N) segment (155 to 200 seconds) from the same patient. The signal N denotes the moment when the seizure has finished.

3.2.2 Feature Extraction

The parameters to feed FNN are computed for each studied patient and suitable to classify an epilepsy activity due to its behavior is characterized by spikes or sharp waves, which present irregular and unpredictable temporal patterns with a repetition rate from 3 to 6 Hz (SÖRNMO;

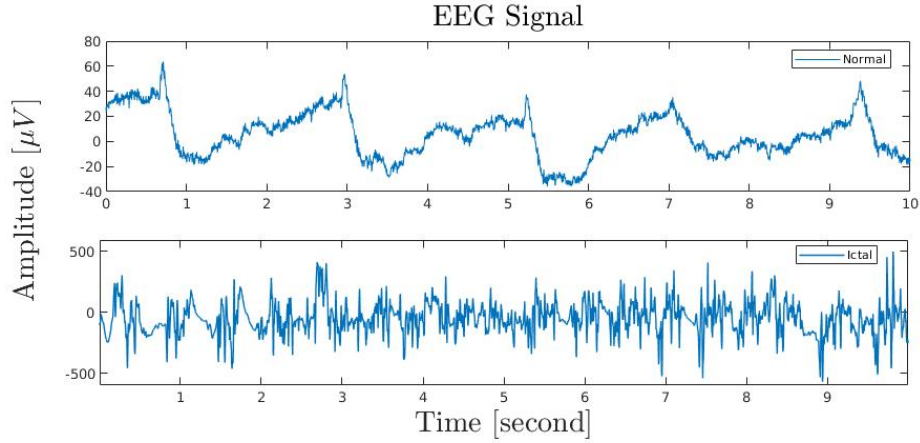
Figure 19: EEG Signal Wavelet Decomposition from a patient with GNSZ; Derivation FP1-F7; 256Hz Sample frequency



Source: Author

LAGUNA, 2005). Note that the amplitude of these transient waves is higher when compared with the continuous background (i.e., normal EEG), as shown in Figure 20.

Figure 20: EEG Signal from patient before and during TCSZ; Derivation FP1-F7; 256Hz sample frequency.



Source: Author

Hence, to determine the input features to train the neural network, the wavelet coefficients from Table 1 were used to compute the following parameters:

- Maximum value of signal.

$$S_{max} = \max[\max(Di), \max(A5)], \quad \forall i = 2, \dots, 5, \quad (14)$$

- Minimum value of signal.

$$S_{min} = \min[\min(Di), \min(A5)], \quad \forall i = 2, \dots, 5 \quad (15)$$

- Standard Deviation of signal.

$$S_{std} = \text{std}[\text{std}(Di), \text{std}(A5)], \quad \forall i = 2, \dots, 5 \quad (16)$$

- Mean Value of signal.

$$S_{mean} = \text{mean}[\text{mean}(Di), \text{mean}(A5)], \quad \forall i = 2, \dots, 5 \quad (17)$$

- Sum of the signal power.

$$S_{power} = \sum_{i=2}^5 \text{rms}(Di)^2 + \text{rms}(A5)^2 \quad (18)$$

Moreover, the FFT of the EEG signal autocorrelation function is applied to obtain Power Spectrum Density (PSD), subsequently are calculated the mean value, maximum value, and minimum value of PSD, used as input parameters of the neural network.

Algorithm 3 shows the feature array implementation, appending the calculated parameters above to feed the neural network.

Algorithm 3: Features Array

Result: Extract signal features using DWT and PSD

input : EEG signal and sampling frequency

output: Feature array

Get the 5 Wavelet decomposed layers of the EEG signal;

Get the PSD;

Get S_{max} ; S_{min} ; S_{std} ; S_{mean} ; S_{power} ; PSD_{max} ; PSD_{min} ; PSD_{mean} ;

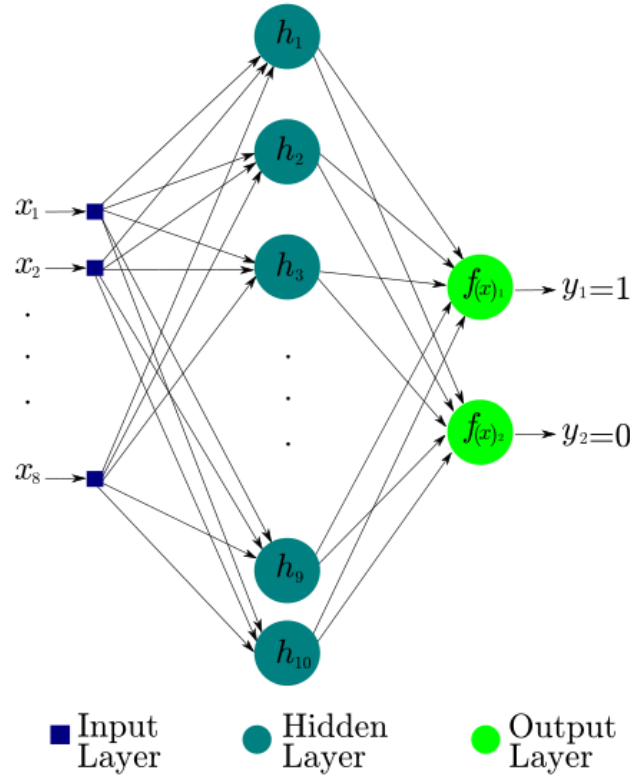
Append those values to the features array;

Source: Author

3.2.3 Feedforward Neural Network with BP Model

As explained in Section 2.4.3, Feedforward Neural Network is one of the most used ANNs in artificial intelligence since it has well-defined layers. Besides, the training process and recall patterns are described by connection forward, but not move backward (HEATON, 2015). For that reason, the backpropagation (BP) method is employed in training FNN for supervised learning. Consequently, the developed model based on Feedforward Neural Network with BP illustrated in Figure 21 uses pattern recognition, where the output consists of a vector with 0 and 1 values. Then, the class which we want to recognize is the ictal activity or '1', so '0' represents a seizure-free period. Furthermore, the weight and bias of the neuronal network with BP are updated via the gradient computed by the Stochastic Gradient Descent (SGD) algorithm by the selection of a training set element randomly (HEATON, 2015).

Figure 21: Feedforward Neural Network model architecture



Source: Author

In this way, the hyperparameters chosen for customizing and training the neural network were as follows. Ten neurons in the hidden layer; 5000 epochs, i.e., the maximum number of iterations to train the network, the test to pick them is shown in the results chapter. Then, the learning rate of 0.01 and momentum of 0.9 was used as default parameters. Besides, it is

assigned a training rate of 0.7 and a testing rate of 0.3, i.e., the software randomly split the EEG into subsets of 70% of signal to train network, and 30% to validate the training process. At last, the sigmoid activation function is used in the hidden layer and the Softmax activation function in the output layer. To implement the FNN model is applied the Python language with the API `keras` from `tensorflow`.

Thence, Algorithm 4 shows how was implemented the FNN model in Python. First, the model is created through the function `model.add` adding the input, hidden, and output layers to the model. Then the model is compiled using `model.compile`, in this step, we assigned the SGD optimizer with learning rate and momentum. Besides, in the training process, the input data is split into set of 70% for training (`X_train`, `y_train`) and 30% to validate (`X_test`, `y_test`), where `X` represents the EEG signal and `y` the labels or events in EEG recording, in this case the seizure types. Later, the model is trained with the function `model.fit`. At length, with the operation `model.predict` the network makes a classification represented in the confusion matrix. The evaluation metrics and confusion matrix will present in the results chapter.

Algorithm 4: Implementation of FNN model in Python 3.8.8

Result: Calls the fit function for the FNN

input : EEG data and labels

Create the FNN model ;

Compile the FNN model;

Splits the input data into sets of 70% for training and 30% for the validation set;

Calls the fit function:

Calls the predict function using the entire set;

Plots the confusion matrix;

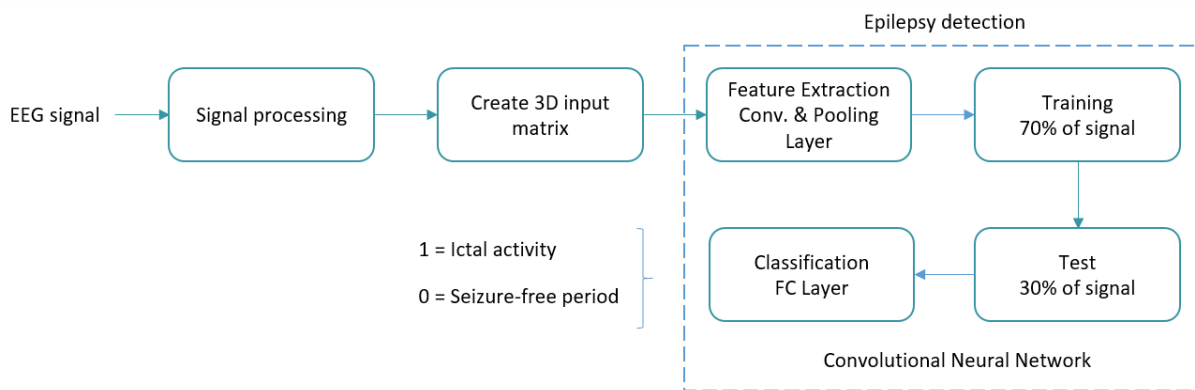
Source: Author

3.3 METHOD 2: EPILEPSY SEIZURE DETECTION BASED ON CONVOLUTIONAL NEURAL NETWORK

This section presents the developed epilepsy detection system based on Convolutional Neural Networks (CNN). This model consists of 8-layers and makes a binary classification, where 1 represents the ictal activity, no matter the epileptic seizure type that presents the patient, so 0 indicates the seizure-free period. The epilepsy seizure detection algorithm illustrated in Figure 22

works on 21 EEG channels and consists of three stages. The first stage is signal processing, which prepares the signal to build the 3D input matrix. The second stage consists of creating the matrix in the time domain, frequency domain via FFT, and time-frequency domain via Short Time Fourier Transform (STFT). The final stage is epilepsy seizure detection via the CNN model, for which the input data is split into two sets, 70% of data to train the model and 30% to validate the training process.

Figure 22: Epilepsy detection algorithm based on CNN model



Source: Author

3.3.1 Signal Processing

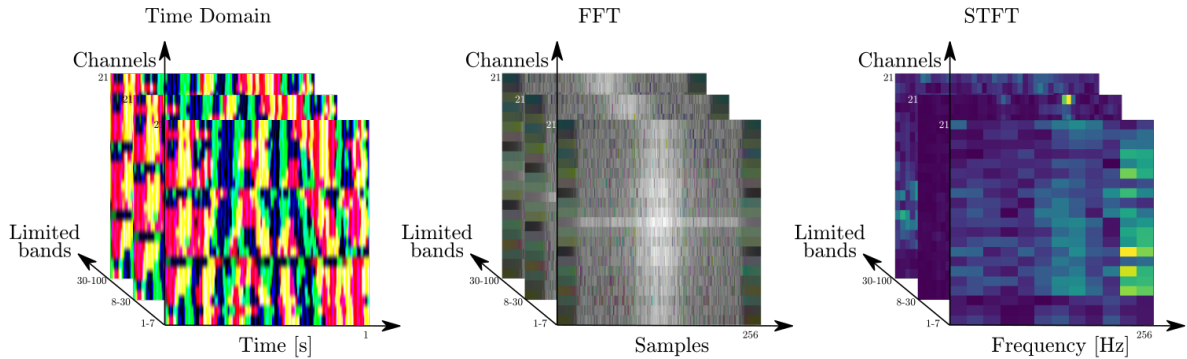
Therefore, the first recorded minute is deleted to remove any instrumentation artifacts in the acquisition of EEG. Besides, to facilitate the epileptic patterns detection, the signal is split into 1-second size rectangular windows without overlap. For this is applied the Algorithm 1 but changing the cut size by one, making the number of samples in each window equal to the sampling frequency of the signal; yet, this way of split signal is not using to implement the Short-Time Fourier Transform (STFT), as shown later. Next, the 60 Hz power line noise is rejected via a notch filter using the same filter design described in section 3.2.1. Later, the signal is filtered into three frequency bands that include the standard brain waves to evaluate the brain patterns such as epileptic spikes and continuous background: 1 to 7 Hz (delta and theta), 8 to 30 Hz (alpha and beta), and 30 to 100 Hz (gamma), obtaining the input in the time domain. Then, applying the Fast Fourier Transform (FFT) to each frequency band is gotten the frequency domain input. Finally, the time-frequency domain input is attained with the STFT implemented with a Hann window, with 50% overlapping and 256 samples per second. Thus, we get three independent inputs that consist of several EEG sessions concatenated after have been processed,

as explained previously, so these sessions are appended in an array with the total time length size (the time sum of all sessions appended), making the same process on the event files of each session. Hence, we obtain an array that contains several EEG records and one event vector to train the network.

3.3.2 3D input matrix

Once the signal is processed, three different inputs will feed the CNN model. The 3D matrix in the time domain, in the frequency domain, and in the time-frequency domain. Figure 23 shows a representation of these inputs. Consequently, for each band-limited, there is a matrix of 21 rows corresponding to the number of EEG channels, for the total time of EEG, in the time domain is illustrated 1 second, 256 samples per second in the frequency domain via FFT, and 1 second and 256 [Hz] in the time-frequency domain via STFT. These matrices represent an input image, which the CNN network uses to train.

Figure 23: Representation of three input types received by CNN model; in time domain filtering in three frequency bands, in frequency domain via FFT and in time-frequency domain via STFT



Source: Author

Algorithm 5 shows how is created the EEG image for each window using the three frequency bands. Whence as inputs, the function receives Gamma (30-100 Hz), Alpha-Beta (8-30Hz), and Delta-Theta (1-7Hz) frequency band array. Then, it is built the three-dimensional matrix creating an array of the image object, initialized with the three frequency bands previously split in windows of 1-second size, applying three auxiliaries arrays (**aux1**, **aux2**, **aux3**). Thence, in the first auxiliary array of 1D is appended the k -th values of each frequency band at the j -th channel of the i -th window, shown as follows:

Algorithm 5: 3D EEG image construction algorithm

Result: Constructs the 3D representations of the EEG windows, using the gama, delta-theta and alpha-beta frequency bands that were decomposed using band-pass filters.

input : Gama, Alpha-Beta, Delta-Theta

output: 3D matrix list, containing the constructed 3D images of the EEG windows

Init list image object;

Init **aux1**, **aux2**, **aux3**, auxiliary arrays;

for $i \leftarrow 0$ **to** *length of image object array* **do**

for $j \leftarrow 0$ **to** *EEG channels* **do**

for $k \leftarrow 0$ **to** *length of EEG window* **do**

aux1 $\leftarrow$ append the k -th values of each frequency band at the j -th channel of the i -th window of the list image object;

aux2 $\leftarrow$ append **aux1**, creating a 3D array;

 clear **aux1**;

end

aux3 $\leftarrow$ append **aux2**;

 Clear **aux2**;

end

 Output array $\leftarrow$ append **aux3**;

 Clear **aux3**;

end

return Output array

Source: Author

$$\mathbf{aux1} = [\gamma_k \quad \alpha\beta_k \quad \delta\theta_k]$$

Then, in the second auxiliary array is added the values of each frequency band, creating a matrix for one channel such as seen:

$$\mathbf{aux2} = \begin{bmatrix} \gamma_{(1,1)} & \alpha\beta_{(1,1)} & \delta\theta_{(1,1)} \\ \gamma_{(2,2)} & \alpha\beta_{(2,2)} & \delta\theta_{(2,2)} \\ \vdots & \vdots & \vdots \\ \gamma_{(256,256)} & \alpha\beta_{(256,256)} & \delta\theta_{(256,256)} \end{bmatrix}$$

Next, in the third auxiliary array is appended **aux2**, creating a 3D matrix for one window of 256 samples, such as seen next:

$$\mathbf{aux3} = \begin{array}{cccc} \delta\theta_{(1,1)} & \delta\theta_{(1,2)} & \cdots & \delta\theta_{(1,256)} \\ \delta\theta_{(2,1)} & \delta\theta_{(2,2)} & \cdots & \delta\theta_{(2,256)} \\ \vdots & \vdots & \ddots & \vdots \\ \delta\theta_{(21,1)} & \delta\theta_{(21,2)} & \cdots & \delta\theta_{(21,256)} \end{array} \begin{array}{cccc} \alpha\beta_{(1,1)} & \alpha\beta_{(1,2)} & \cdots & \alpha\beta_{(1,256)} \\ \alpha\beta_{(2,1)} & \alpha\beta_{(2,2)} & \cdots & \alpha\beta_{(2,256)} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha\beta_{(21,1)} & \alpha\beta_{(21,2)} & \cdots & \alpha\beta_{(21,256)} \end{array} \begin{array}{cccc} \gamma_{(1,1)} & \gamma_{(1,2)} & \cdots & \gamma_{(1,256)} \\ \gamma_{(2,1)} & \gamma_{(2,2)} & \cdots & \gamma_{(2,256)} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{(21,1)} & \gamma_{(21,2)} & \cdots & \gamma_{(21,256)} \end{array}$$

At last, aux3 is appended to the output array, getting the 3D matrix list, which contains the constructed 3D images of the EEG windows or the 3D input matrix in the time domain.

Later, to the output array obtained in Algorithm 5 is applied the FFT, normalizing the values in the range of 0 to 256. Thus, the frequency response of image 3D is obtained to feed the CNN model.

Finally, to obtain the 3D input matrix in the time-frequency domain, the STFT was applied to each band limited, which returns the STFT of the signal in function of time and frequency for 21 EEG channels. Like this, we obtained a 3D matrix per band. Then these matrices are appended and formed a list of matrices, normalizing values in the range of 0 to 1.

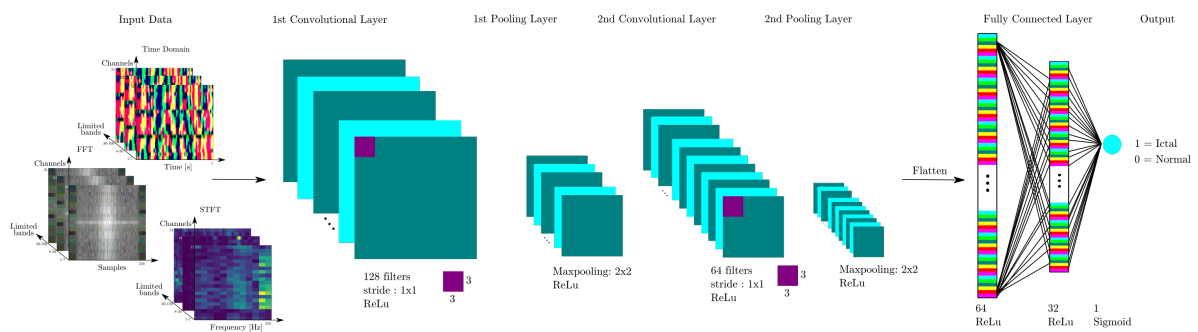
3.3.3 Convolutional Neural Network Model

Section 2.4.4 has shown that the Convolutional Neural Networks are used for pattern recognition in images. However, in the last ten years, the researchers applied them to process EEG records. The advantage of using a CNN is that while the training process occurs, the weights are computed automatically, i.e., it is not necessary to define "manually" these parameters when the network is customized.

Whence, the CNN model illustrated in Figure 24, consists of two 2D convolutional layers, with 128 and 64 filters, respectively, both applying a 3x3 kernel size, to reduce the computational cost and the number of weights for backpropagation, besides, it is employed a stride of one in x and y directions. Next, each convolutional layer is followed by a max-pooling layer over a 2x2 region and a stride of two for downsampling the image in half. Then, the last max-pooling layer output is flattened, converting the 2D structure into a vector to enter into fully connected layers. Thus, it is created three fully connected layers with 64, 32, and 1 neuron. Moreover, the acti-

vation functions Rectified Linear Unit (ReLU) and Sigmoid are used to build our CNN model. Since an image is naturally nonlinear, the ReLU function is used after the convolutional layer to increase the nonlinearity, breaking up the imposed linearity when the image is convolved. ReLU function after max-pooling and fully connected layers provide robustness to the model. At last, the sigmoid activation function is applied to the output layer to estimate the probability of a binary event like seizure-free period or ictal activity occurs, due to the output is a probability value between 0 or 1, classifying the probabilities higher than 0.5 as ictal activity.

Figure 24: CNN model architecture, which consists of two convolutional layers, each one followed by a max-pooling layer. Then, the output is flatted and passed by three fully connected layers. Finally, the network classify the signal into 1 = ictal activity or 0 = seizure-free periods. The model receives three inputs one at time; in the time domain, frequency domain, and time-frequency domain



Source: Author

The model is optimized according to the binary cross-entropy loss, applying the Adam optimizer, beginning with a 0.0001 learning rate adjusted throughout the training. Additionally, the validation set accuracy is evaluated while training the model. Then, it is possible to assess the learning process, analyzing the learning curves, which will explain in the next chapter.

The training algorithm consists in to split the EEG signal randomly into training and test sets. 70% of EEG data to train the network divided in turn into training data and target data. And, 30% of the EGG signal is used to validate the training process. In addition, 20 epochs are applied to train the model and 32 training samples per iteration, known as batch size. The summarize of the model is presented in Table 2, which was implemented with `keras` and `tensorflow` libraries in Phyton language.

Therefore, Algorithm 6 shows how was implemented the CNN mode training process in Python. The model is created using the function `model.add` adding convolutional, max-pooling, and fully connected layers on the model. Then, the model is compiled by `model.compile` in this step, we assigned the learning rate, the optimizer, and metrics evaluation. In the training

Table 2: Summary of the eight layer that are part of the CNN model

Layer Type	Output Shape	Kernel Size	Stride	Activation
Input	21 x 400250 x 3	-	-	-
Conv2D	19 x 400248 x 128	3x3	1	ReLU
MaxPool2D	9 x 200124 x 128	2x2	2	ReLU
Conv2D	7 x 200122 x 64	3x3	1	ReLU
MaxPool2D	3 x 100061 x 64	2x2	2	ReLU
Fully Connected	64	-	-	ReLU
Fully Connected	32	-	-	ReLU
Fully Connected	1	-	-	Sigmoid
Trainable Parameters: 83649				

process, the input data is split into set of 70% for training (X_{train} , y_{train}) and 30% to validate (X_{test} , y_{test}), where X represents the EEG signal and y the labels or events in EEG recording, i.e., the seizure types, the model is trained using the function `model.fit`. Finally, with the function `model.save` we save the model with the update weights. Thus, we obtain the model already trained to test it.

Algorithm 6: Implementation the CNN training process in Python 3.8.8

Result: Calls the fit function for the CNN and saves CNN model

input : EEG images and the label of each image from train set

Create the CNN model;

Compile the CNN model;

Splits the input data into sets of 70% for training and 30% for the validation set;

Calls the fit function;

Saves the CNN with updated weights;

Source: Author

In Algorithm 7 presents how is implemented the test process in Python. To use the the trained model, the model is loaded using `tf.keras.models.load_model(network_name)`. Then, applying the function `model.predict` the network makes a classification, which is presented in the confusion matrix. The evaluation criteria and results presented by the confusion matrix will show in the next chapter.

Algorithm 7: Implementation test process of CNN in Python 3.8.8

Result: Calls predict function for CNN and display the results

input : EEG images and the label of each image from test set

Load the CNN model trained;

Calls the predict function using the entire set;

Plots the confusion matrix;

Source: Author

4 RESULTS

This chapter presents the performance results to evaluate the techniques previously explained in chapter 3, applying Feedforward Neural Network with BP and Convolutional Neural Network. To make the experiments were chosen eight seizure patients from the TUH-SC database, shown in Table 5 who presented some seizure types. Since this work aims the epilepsy seizure detection, all seizure events are classified as ictal activity. Thus, both network models classify the EEG into two classes, 1 for the ictal event and 0 for the seizure-free period. The FFN model used one EEG channel from which the features are obtained via DWT and FFT, thus getting the input in time and frequency domain to feed the model, while the CNN model used 21 EEG channels and three bands limited to build the input 3D matrix, obtaining three different inputs to train the model. First, the 3D matrix in the time domain. Second, the time domain input is transformed to the frequency domain via FFT. At last, using STFT is obtained a third 3D matrix in the time-frequency domain.

Section 4.1 presents the experimental protocol, where is explained, the training cases applied to each model, the database used in the training and test process, also its specifications, the evaluation metrics, and learning curves applied to evaluate the performance of the techniques used. Section 4.2 shows the epilepsy seizure detection results achieved for both models and training cases tested.

4.1 EXPERIMENTAL PROTOCOL

Two training cases were made to evaluate the performance of both detection methods. In **case 1**, one model per patient was created, trained with the training set of each patient individually, i.e., we have **eight models**. In **case 2**, **one training set** was built whit the training sets from patients 1, 4 and 6 detailed in Table 5, which contains several sessions with different seizure types to train a **single model**. Finally, the created models were tested on the test set that consists of one session per patient did not include in the training set. Note that the training algorithm for both FNN and CNN models consists of splitting the input into two subsets: 70% of the signal will be used to train the network, and the remained 30% to validate the training process. Table 3 presents a summary of the architectures developed, the input types which the networks receive for their respective processing and training cases.

Table 3: Experimental protocol

Network Architecture	Input type	Processing	Training
FNN	8 features in time and frequency domain	DWT, FFT	case 1
CNN	3D matrix in time domain	filtering 3 bands limited	case 2
	3D matrix in frequency domain	FFT	
	3D matrix in time-frequency	STFT	

4.1.1 Database description

From the TUH-SC database described in section 3.1.1 used to develop both FNN and CNN models, eight seizure patients were chosen, each one with several sessions, obtaining a total of 74.1 hours of EEG recordings collected with the specifications detailed in Table 4. Although the EEGs have more than 21 channels, in the EEG specification table, we put 21 since the CNN model works with 21 derivations, additionally because the others have EKG, EMG, and other electrode information.

Table 4: EEG recordings specifications

Number of Channel:	21
Electrodes placement:	International 10-20 system
Resolution:	16 bits
Sample frequency:	256 Hz
Filter analogical:	128 Hz Low Pass
Montage:	Temporal Central Parasagital (TCP)

Table 5 show the summary of the patients chosen, the experimental group consists of three women and five men between 24 to 62 years old, who presented the different seizure types explained in section 3.1.1. The chosen database consist of 40 complex partial seizures (**CPSZ**), 79 focal seizures (**FNSZ**), 20 generalized seizures (**GNSZ**), 17 tonic seizures (**TNSZ**), and 51 combined seizures (**FNSZ/GNSZ**).

Besides, this experimental group was divided into two sets. The training set involves many sessions for each patient, whereas the test set contains only one session per patient. Thus, the training process has more data.

4.1.2 Evaluation metrics

Both models make a binary classification, where the first class represents the events that we want to identify named **Seizure**; wherefore, the second class was named **Seizure-free**. When applied both models on the data set previously labeled is possible to see how our model classifies this

Table 5: Summary of eight Epileptic Seizure Patients chosen from Temple University Hospital Seizure Corpus database

Patient	Age	Sex	Seizure Type	Training set		Test set	
				Num Seizure	Time[h]	Num Seizure	Time[s]
1	60	F	CPSZ	19	10.96	1	601
2	43	M	FNSZ	37	10.18	1	601
3	52	M	CPSZ	18	4.50	2	514
4	24	F	TNSZ	16	4.99	1	365
5	59	M	GNSZ	19	5.37	1	601
6	62	M	FNSZ/GNSZ	23	14.30	1	702
7	39	F	FNSZ/GNSZ	24	10.09	3	699
8	59	M	FNSZ	40	13.66	1	601

data. In this way, a confusion matrix illustrated in Figure 25 is obtained. True positive (TP) is the number in which the model made a correct prediction about ictal activity on EEG data; true negatives (TN) are times that the model made the right prediction about seizure-free activity in the brain. Consequently, false-positive (FP) and false-negative (FN) are considered errors of detection.

Figure 25: Confusion matrix for a binary classification between the classes seizure and seizure-free, comparing the true values (True label) with the estimate values by the network (Predicted label)

True label	Seizure-free	True Negative	False Positive
	Seizure	False Negative	True Positive
		Seizure-free	Seizure
		Predicted label	

Source: Author

The metric most used to evaluate a model performance is *accuracy*, which indicates the

percent of observations that a classifier can classify correctly and is defined by (19).

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \cdot 100\% \quad (19)$$

Moreover, it is possible to calculate the *error* rate (20), to analyze the percent mistakes our classifier made.

$$error = \frac{FP + FN}{TP + TN + FP + FN} \cdot 100\% \quad (20)$$

Since we are interested in epileptic seizure detection, we will evaluate the true positive rate or *recall* that indicates relevant results in our research. Defined by its arithmetic expression:

$$recall = \frac{TP}{TP + FN} \cdot 100\% , \quad (21)$$

Furthermore, the *precision* defined in (22) indicates how accurate are the retrieved data or whether the search results include too many mistakes.

$$precision = \frac{TP}{TP + FP} \cdot 100\% . \quad (22)$$

We can reduce the number of FP increasing *precision* but decreasing the positives results, i.e., reduce the *recall*. In the same way, if we want to reduce the number of FN will be necessary to decrease precision. For epilepsy seizure detection, we will put more emphasis on recall. One metric that allows making a relation between *recall* and *precision* is the F-score. The performance will be better whether this parameter is near 100%. Its arithmetic equation is:

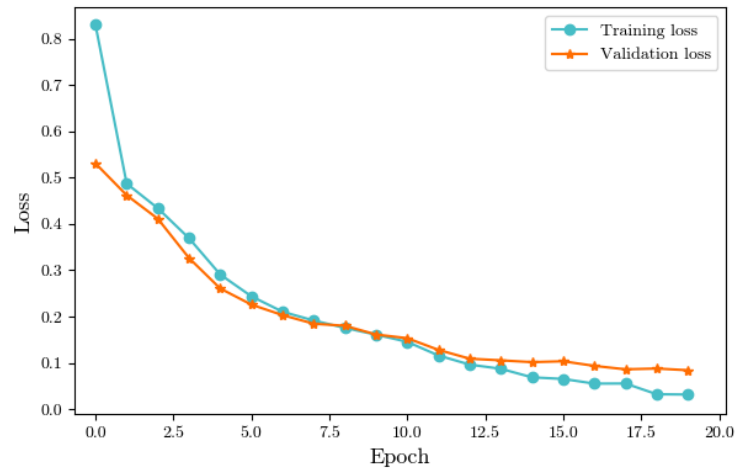
$$F\text{-score} = \frac{2 \cdot precision \cdot recall}{precision + recall} \cdot 100\% . \quad (23)$$

4.1.3 Learning Curves

Loss and accuracy curves or learning curves are widely using to provide important information about the performance of the incremental learning model. With the loss curve, it can diagnose if the model is appropriately learning. In the learning process, we can find two problems. Overfitting refers to a model that learns very well the training dataset, including statistical noise or random fluctuations. In a loss curve, it is possible to detect overfitting of the model when the training and validation loss decreases with experience to a point and begins to increase again. On the other hand, underfitting refers to a model that cannot learn the training dataset, so if the

training loss remains flat regardless of training or the training loss continues decreasing until the end of training without stabilizing, the model is underfitting (BROWNEE, 2019). In Figure 26 it can see a good fit due to the training and validation loss curve decrease until stabilizing, and the mean square error obtained between both curves is the order of $1e^{-3}$.

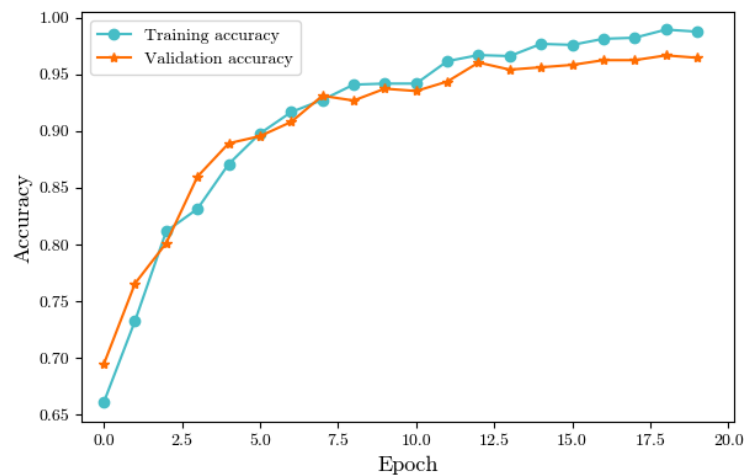
Figure 26: Example graphic of loss curve



Source: Author

The accuracy curve presents the classification performance of the model. Such as seen in Figure 27 the model shows a good learning performance since the training accuracy curves increase along with epochs until stabilizing the same behavior occurs on the validation set.

Figure 27: Example graphic of accuracy curve



Source: Author

4.2 PERFORMANCE RESULTS

Before beginning the network training, the number of epochs for each model was chosen based on the training time and error detection.

4.2.1 Epoch selection of the Feedforward Neural Network with BP model

To achieve the best performance in the FNN model was modified two parameters of the neural network. The number of hidden neurons from 5 to 20 neurons and the number of epochs from 2000 to 7000, obtaining the results of training time expressed in minutes and detection error in almost 10 minutes of EEG records, shown in Table 6. For 5, 10, and 20 hidden neurons, the better performance was with 5000 epochs since this parameter has a training time approximate of 5 minutes and achieved the lowest error. Thus, the epoch number chosen was 5000. Additionally, comparing the results achieved by 5, 10, and 20 neurons in 5000 epochs, both training time and error did have not much difference, so the neurons number picked was ten to reduce the computational cost.

Table 6: Epoch selection for the FNN model

Hidden Neurons	Epochs					
	2000		5000		7000	
	Time [min]	Error [%]	Time [min]	Error [%]	Time [min]	Error [%]
5	2,01	6,54	5,06	6,14	6,96	6,30
10	2,09	6,62	5,44	5,85	6,94	6,03
20	2,08	6,53	4,97	5,70	6,84	5,80

4.2.2 Epoch selection of the Convolutional Neural Network model

In the CNN model, the tested epochs were 20, 50, and 100, in approximately 10 EEG recorded minutes per patient. As seen in Table 7 while the epoch number increases, the training time and error increase too. For that reason, the picked epoch number was 20 since this parameter achieved the best performance and the lowest training time around 3 minutes in about 10 minutes of EEG. On the other hand, the total training time with 20 epochs for the CNN model trained with the set conformed by training sessions of patients 1, 4, and 6 was 2,74 hours since the total time of EEG records is about 30 hours.

Table 7: Epoch selection for the CNN model

Patients	Epochs					
	20		50		100	
	Time [min]	Error [%]	Time [min]	Error [%]	Time [min]	Error [%]
1	4,26	2,13	10,23	1,32	20,47	3,82
2	3,85	0,99	9,21	1,62	18,42	4,69
3	1,73	0,27	4,08	0,84	8,16	2,43
4	1,74	1,97	4,00	5,70	8,00	16,49
5	1,72	0,00	4,08	2,68	8,16	7,76
6	5,05	1,15	12,19	2,53	24,37	7,33
7	3,68	0,98	8,84	0,66	17,67	1,91
8	3,26	0,69	7,70	0,98	15,40	2,84
Average	3,2	1,02	7,54	2,04	15,08	5,91

4.3 EPILEPSY SEIZURE DETECTION RESULTS

4.3.1 Feedforward Neural Network with BP model

This section shows the performance results of the Feedforward Neural Network with BP model to classify the EEG signal in the epileptic seizure and seizure-free period. Table 8 shows an example of extracted features, using the detail coefficients D2, D3, D4, D5, and approximation coefficient A5 to compute the input parameters like the standard deviation, the signal power's sum, maximum value, minimum value, and mean value of the signal. And it is used FFT to estimate the power spectral density, computing the maximum, minimum, and average value of PSD. Here, it is possible to distinguish the difference between the obtained parameters for the ictal and seizure-free period in the same patient.

Table 8: Example Input Parameters Extraction

Parameters	Seizure-free period	Ictal period
DWT		
Standard Deviation	60.14	83.45
Mean	4.58	5.66
Maximum	447.07	722.09
Minimum	-335.78	-502.11
Summation Power	21237.39	71828.76
FFT		
PSD Mean	1.28	4.61
PSD Maximum	315.53	187.73
PSD Minimum	0.003	0.012

Besides, as explained in section 3.2.1, the EEG signal was decomposed into five levels

by fifth-order Daubechies wavelet (db5), which gave the best response to improve the ANN classifier performance as it presents 99.8% accuracy, whereas db2, db3, db4, and db6 obtain an accuracy of 98.7%, 98.3%, 99.3%, and 98.7% respectively.

Hence, the epilepsy seizure detection results are shown below for the FNN model trained and tested for each study patient applying the training case 1, obtaining the performance detailed in Table 9 and as we can see, the network was not able to detect any seizure event in patients who presented focal seizures (patient 2 and 8) and combined seizures (patient 6). Although the individual performance for the other patients is acceptable, the performance general is low, achieving 57.5% of accuracy, 49.8% of recall, and 50% of precision. Besides, the classification error of 42.5%, and the F-score is 49.5%.

Table 9: FNN model performance

Patient	accuracy	recall	precision	error	F-score
1	91,8	71,4	69,0	8,2	70,2
2	-	-	-	100	-
3	94,2	57,9	84,6	5,8	68,8
4	86,1	98,0	87,0	13,9	92,2
5	94,0	99,5	94,3	6,0	96,8
6	-	-	-	100	-
7	94,0	71,4	65,2	6,0	68,2
8	-	-	-	100	-
Average	57,5	49,8	50,0	42,5	49,5

Due to the results in training case 1 presented the ictal activity detection problem in three EEG recordings, training case 2 was not applied because the model tendency is the same. Therefore, to improve these results was decided to test a more complex architecture network like the Convolutional Neural Network.

4.3.2 Convolutional Neural Network model

This section shows the performance results of the ictal activity detection algorithm based on CNN fed with three input signals in the time domain, in the frequency domain, and time-frequency, using eight EEG recordings from the TUH-SC database.

This method was developed to improve the results presented in section 4.3.1. Therefore, Table 10 shows the epilepsy seizure detection results on the time-domain signal for each analyzed patient using the training case 1. However, the general performance compared with FNN did not improve as expected. Besides, persist the problem observed in the previous method, it

is not possible to detect any seizure event in patients 2, 6, and 8. Hence, the got results with this input were: accuracy of 57.6%, even recall of 44.1%, and precision of 43.8% were lower than the FNN model. Finally, the error maintains similar to the FNN model in 42.4% and F-score of 43%.

Table 10: CNN model performance using a Time Domain input

Patient	accuracy	recall	precision	error	F-score
1	88,4	29,0	41,9	11,6	34,3
2	-	-	-	100	-
3	87,5	93,4	93,0	12,5	93,2
4	94,2	55,6	43,5	5,8	48,8
5	98,7	77,8	77,8	1,3	77,8
6	-	-	-	100	-
7	91,8	96,8	94,2	8,2	95,5
8	-	-	-	100	-
Average	57,6	44,1	43,8	42,4	43,7

As can be seen in Table 11, the results of epilepsy detection for each patient with input in the frequency domain using the training case 1 still present the ictal activity detection problem in the same three patients. However, it shows an increase in accuracy, recall, precision, and F-score, obtaining 58.2%, 44.4%, 45.1%, and 44.4%, respectively. Besides, the error achieved is 41.8%. In the epilepsy detection method based on CNN with both inputs in the time and frequency domain, training case 2 did not apply since the model tendency is the same. For that reason, the last method to obtain the 3D input matrix via STFT is tested.

Table 11: CNN model performance using a Frequency Domain input (FFT)

Patient	accuracy	recall	precision	error	F-score
1	95,1	64,5	85,1	4,9	73,4
2	-	-	-	100	-
3	89,8	97,2	92,2	10,2	94,6
4	98,6	94,4	81,0	1,4	87,2
5	95,8	5,6	11,1	4,2	7,4
6	-	-	-	100	-
7	86,3	93,1	91,8	13,7	92,4
8	-	-	-	100	-
Average	58,2	44,4	45,1	41,8	44,4

Here was applied the STFT to obtain the input matrix, as explained in section 3.3.2, the filtered signal in three frequency bands enters in function `stft` from `scipy.signal` Python

library, which auto returns a 3D matrix, which contains STFT of the EEG signal as a function of time and frequency. Thus, Table 12 shows the performance results of the CNN model with time-frequency domain input applying the training case 1. The main success of this method was that it was able to detect ictal activity in all patients, and so, it is possible to see a considerable difference in the global results compared to previous methods, achieving an accuracy of 95.3%, recall of 81.6%, a precision of 92.5%, and F-score of 85.7%, besides a lowest error of 4.7%.

Table 12: CNN model performance using a Time-Frequency Domain input (STFT), training case 1

Patient	accuracy	recall	precision	error	F-score
1	96,5	71,0	97,8	3,5	82,2
2	99,1	90,9	100,0	0,9	95,2
3	91,2	100,0	91,2	8,8	95,4
4	97,1	83,3	71,4	2,9	76,9
5	99,3	84,2	94,1	0,7	88,9
6	96,1	75,0	100,0	3,9	85,7
7	93,6	98,8	94,3	6,4	96,5
8	89,9	50,0	90,9	10,1	64,5
Average	95,3	81,6	92,5	4,7	85,7

Since the results of the CNN model with input in the time-frequency domain using training case 1 were better than the methods presented previously, besides that the model was able to detect ictal activity in all patients, we proceed to test training case 2. Note that in case 1, we have one CNN model per patient, trained with the sessions of each one, whereas in case 2, we have one single CNN model trained with one training set conformed by the sessions of patients 1, 4, and 6 that include all seizure types present in the database. At last, the trained models were tested with the test set shown in Table 5.

Thus, Table 13 shows a decrease in the performance of this final test, obtaining an accuracy, recall, precision, and F-score of 78.1%, 76.9%, 66.2%, and 65.4%, respectively, and an error of 21.9%, higher than in case 1. However, if we evaluate only the results of the patients used to train the model, it shows a significant increase in the performance, with the accuracy of 96.8%, recall of 82%, a precision of 86%, and F-score of 83.8%. Moreover, the error of 3.2% is the lowest of all methods reported in this research.

Consequently, Table 14 indicates the summary of the results achieved by both FNN and CNN models. As can be seen for training case 1, the best performance was for the CNN model with the input in the time-frequency domain acquired via STFT, and using this method, the ictal activity was detected in the whole experimental group, achieving accuracy, recall, and

Table 13: CNN model performance using a Time-Frequency Domain input (STFT), training case 2

Patient	accuracy	recall	precision	error	F-score
1	96,3	75,8	90,4	3,7	82,5
2	85,2	81,8	39,1	14,8	52,9
3	85,3	88,7	94,8	14,7	91,7
4	97,7	83,3	78,9	2,3	81,1
5	33,9	57,9	3,0	66,1	5,8
6	96,3	87,0	88,8	3,7	87,9
7	61,4	56,5	99,7	38,6	72,1
8	68,3	84,0	35,0	31,7	49,4
Average	78,1	76,9	66,2	21,9	65,4
1, 4, 6^a	96,8	82,0	86,0	3,2	83,8

^a Average between performances results of patients 1, 4 and 6.

precision over 80% and an error less than 5%, which is acceptable. In training case 2, since it was possible to apply only in the last method, it was made a comparison between the global results and the achieved results evaluating only the patients used in the training process, wherefore this situation (average between patients 1, 4, and 6) obtained the best results reported in this work. Overall, these results prove that the CNN model developed has better results creating an individual model, i.e., one model per patient or when the future data of the trained model for some people correspond to these same people. In other words, the CNN model learned the "brain behavior" of each person.

Table 14: Compare performance between FNN and CNN models

Model	Input Type	accuracy	recall	precision	error	F-score
case 1						
FNN	8 features in time and frequency domain ^a	57,5	49,8	50,0	42,5	49,5
	3D matrix in time domain ^a	57,6	44,1	43,8	42,4	43,7
CNN	3D matrix in frequency domain (FFT) ^a	58,2	44,4	45,1	41,8	44,4
	3D matrix in time-frequency (STFT) ^a	95,3	81,6	92,5	4,7	85,7
case 2						
CNN	3D matrix in time-frequency (STFT) ^a	78,1	76,9	66,2	21,9	65,4
	3D matrix in time-frequency (STFT) ^b	96,8	82,0	86,0	3,2	83,8

^a Average of the eight patients performance results

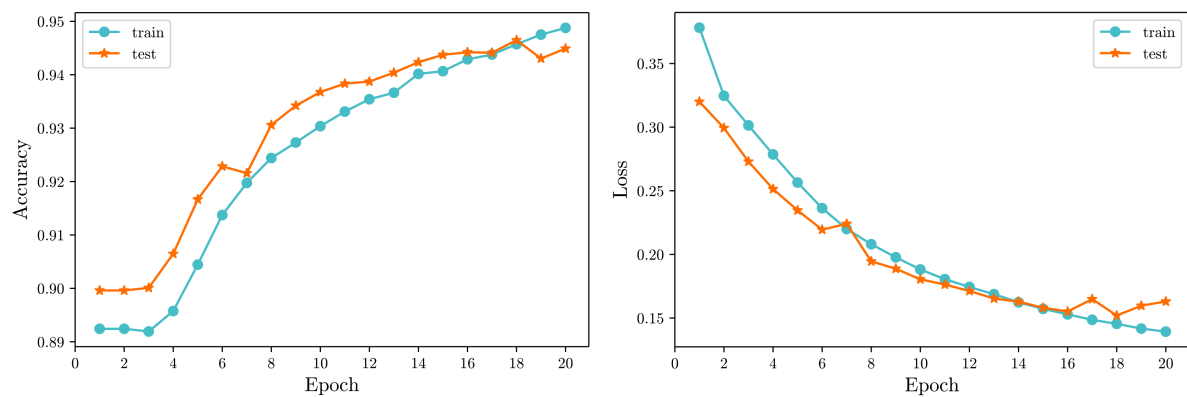
^b Average between performance results of patients 1, 4 and 6

As explained previously, learning curves are widely used to diagnose the performance of a model that presents incremental learning. Therefore, analyzing the loss curves for the CNN model trained for each patient (training case 1) presented in Figure 36 on Appendix A, we can

see that the model is underfitting for patients 2, 6, and 8, for both inputs in time and frequency domain. For that reason, the model was not able to learn the epileptic seizure patterns in these patients. Besides, the models of patients 1 and 4 with the input in the frequency domain are overfitting. As a consequence, validating the presented results, all models that applied the input in the time-frequency domain presented a good fit. Besides, Figure 37 on Appendix A shows the classification performance of each model. The models with underfitting present an error in performance since they did not increase along with experience. Furthermore, patients 1 and 5 with the input in the time domain have fluctuations so that the accuracy does not stabilize. Thus, the best performance was achieved by models with the input in time-frequency because the learning accuracy increases along with epochs until stabilizing, and the same behavior occurs on the validation set (orange line).

On the other hand, Figure 28 shows the accuracy and loss curves of the CNN model with input in time-frequency for training case 2, which presents low overfitting. For this reason, it achieves a better performance in patients used in the training process, which is demonstrated in the seizure predictions made by the CNN model illustrated in Appendix B, here we note that the better performance was in patients 1, 4, and 6, as saw in Table 14. However, since the model got to make predictions for other patients, we can say that the network generalized the acquired knowledge.

Figure 28: Learning curves to CNN model trained with training set from patients 1, 4 and 6 (case 2) using the input in time-frequency domain via STFT

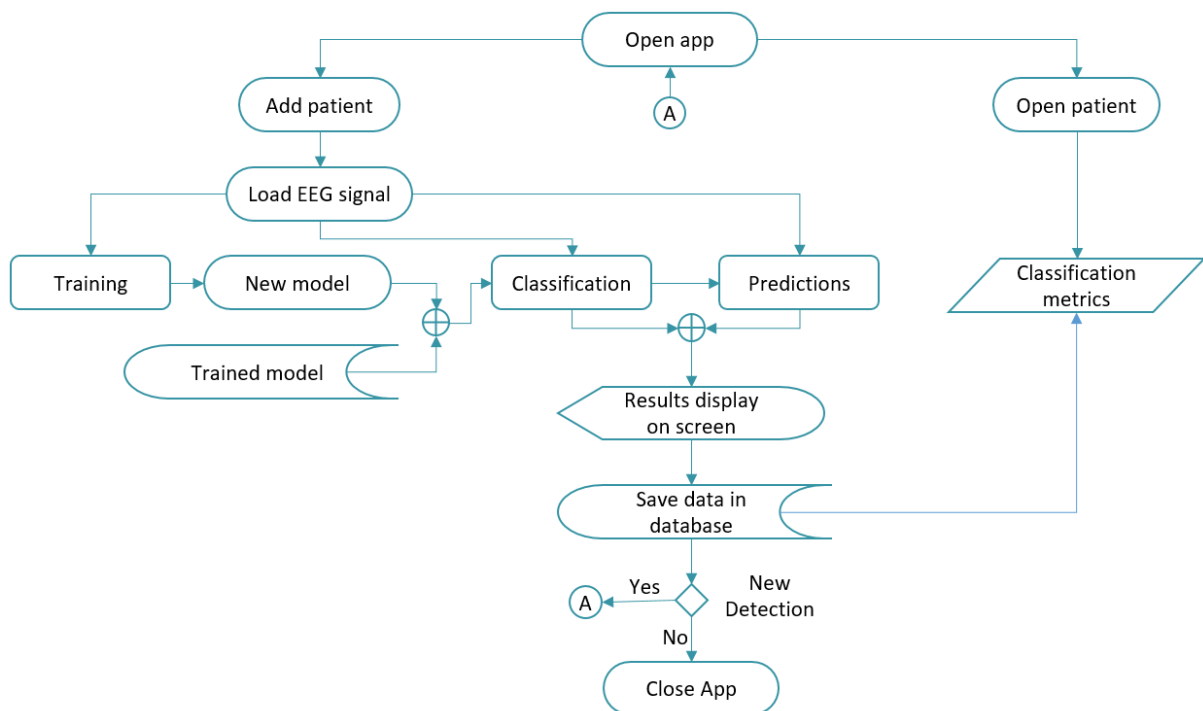


Source: Author

5 EPILEPSY DETECTOR SOFTWARE

This chapter describes the prototype of the developed system for epileptic seizure detection using the CNN model with the input in the time-frequency domain, which achieved better performance results. The EPILEPSY DETECTOR software implemented in the open-source language Python consists of two main tasks called Add patient and Open patient as shown in Figure 29. The add-patient phase corresponds to a friendly interface, where the user can enter the patient's data together with the EEG study. Besides, it will have the option of training a new model or using a CNN model already trained to classify the EEG and obtain the predictions done by the model, resulting in the epilepsy detection performance visualization in the user interface, after that the epilepsy seizure detection results for each patient are saved in a database, that later we can access in the open patient phase.

Figure 29: Flowchart of EPILEPSY DETECTOR system operation



Source: Author

Since the EPILEPSY DETECTOR system currently allows to detect ictal activity in EEG records using CNNs and save the performance metrics acquired. A future improvement of this system would be embedded software in a customized wearable device that sends a message alarm to familiars or friends to help the person with epilepsy. Another possible application for this software would be to aid the medical staff in monitoring an individual patient, observing

seizure frequency or duration.

5.1 EPILEPSY DETECTION SYSTEM INTERFACE

This section presents the implemented pages for the interface of the EPILEPSY DETECTOR system, which consists of the following pages:

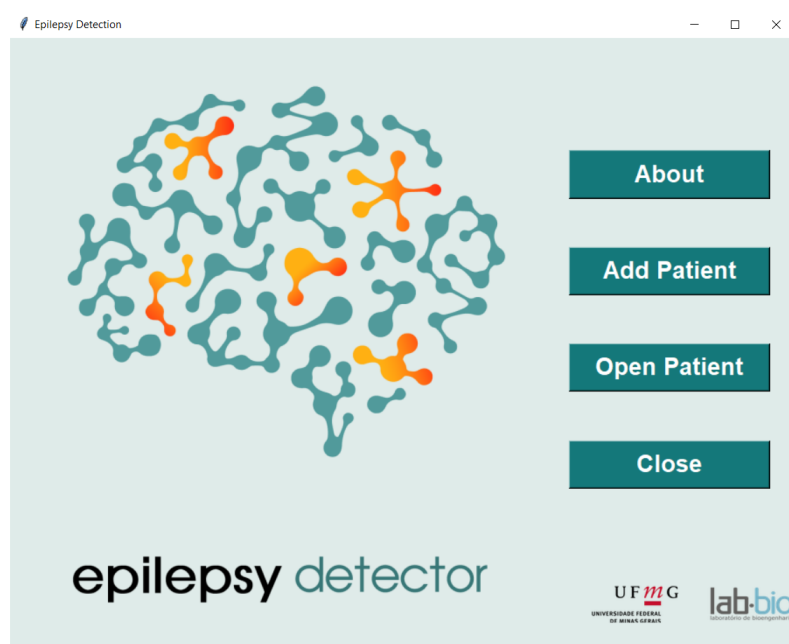
- Home page;
- About page;
- Add patient page;
- View patients page;
- Classification data page;

each one with specific functionality, designing a simple, practical, and intuitive application. These pages are described below.

5.1.1 Home page

As shown in Figure 30, the Home page has a simple look and contains only the buttons that will give access to the About page, Add Patient, and Open Patient pages, and has a Close button to exit from the app.

Figure 30: Home Page

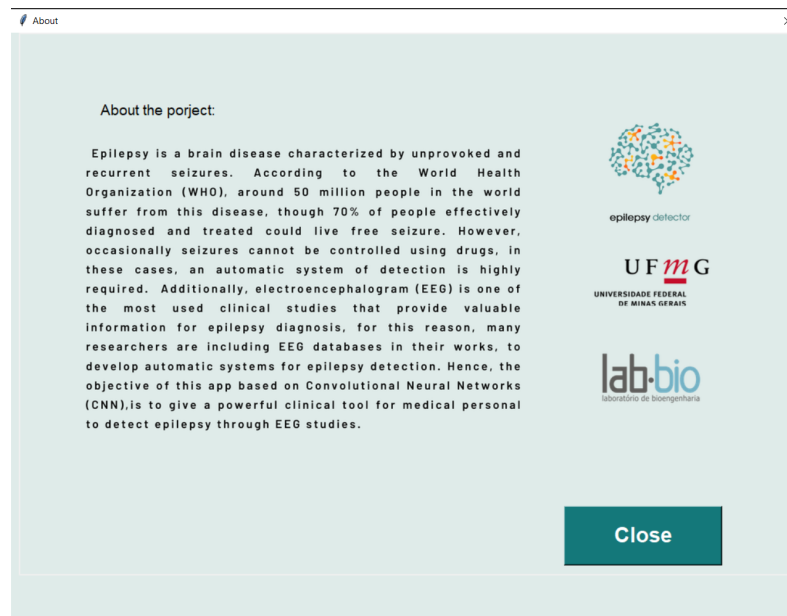


Source: Author

5.1.2 About page

Figure 31 presents the About page, where the project aim and technique used for epilepsy seizure detection is detailed. Moreover, it has a Close button to exit from this window and return to the Home page.

Figure 31: About Page



Source: Author

5.1.3 Add patient page

The purpose of this page presented in Figure 32 is to add the principal information of a patient, like identification code, age, gender, and some extra information, besides loading the EEG record for subsequence analysis. In this way, we have clean, search, delete and change options for search, registration, or modification of patient data. On the other hand, the training, classification, and prediction buttons administer the main functions of the epilepsy seizure detection system. Thus, when the user runs the **Training** function, the system creates a new model trained with the loaded EEG records. Then, executing the **Classification** function, it is possible to choose a trained model to detect an ictal activity on preloaded EEG, displaying a confusion matrix on the Results page and autosaving the accuracy, recall, and precision metrics obtained in the classification process in a database. At last, the **Predictions** function shows the ictal activity identified on EEG along time, on the Results page

Figure 32: Add patient page

Cod	Age	Gender	Info	Accur.	Recall	Precision	File
1	59	Male	focal seizure	68.27	35	35	00011077_s001_x006
2	39	Woman	generalized/focal seizure	61.41	99.69	99.69	00010062_s007_x000
3	39	Woman	generalized/focal seizure	61.41	99.69	99.69	00010062_s007_x000
4	23	Woman	tonic seizure	33.95	57.89	3.05	00008479_s002_x006
5	59	Male	generalized seizure	33.95	3.05	3.05	00008479_s002_x006
6		Male		33.95	57.89	3.05	00008479_s002_x006
7		Male		96.31	75.81	90.38	00006514_s010_x009
8		Male		96.31	75.81	90.38	00006514_s010_x009

Source: Author

5.1.4 View patient page

The patient view page shown in Figure 33 consists of search, clean, and delete options, which allow searching the results of patients via the identification code or delete a saved patient. Moreover, we can generate a report with the patient's data and detection performance metrics.

Figure 33: View patient page

Cod	Age	Gender	Info	Accur.	Recall	Precision	File
1	59	Male	focal seizure	68.27	35	35	00011077_s001_x006
2	39	Woman	generalized/focal seizure	61.41	99.69	99.69	00010062_s007_x000
3	39	Woman	generalized/focal seizure	61.41	99.69	99.69	00010062_s007_x000
4	23	Woman	tonic seizure	33.95	57.89	3.05	00008479_s002_x006
5	59	Male	generalized seizure	33.95	3.05	3.05	00008479_s002_x006
6		Male		33.95	57.89	3.05	00008479_s002_x006
7		Male		96.31	75.81	90.38	00006514_s010_x009

Source: Author

5.1.5 Results page

As explained above, the Results pages indicate the performance achieved by the system to detect ictal activity on EEG records. Thence, Figure 34 presents the results of the classification process, displaying the confusion matrix that links up the true events with the events predicted by the system, besides the accuracy, recall, and precision metrics, autosaving these values in a database.

Figure 34: Classification page



Source: Author

Finally, Figure 35 shows the prediction graphs of seizure events identified on EEG along the time, where we can note the onset and end events.

5.2 EPILEPSY DETECTION SYSTEM DATABASE

5.2.1 Working with data

For future analysis of the results obtained by the system, the designed interface is integrated with a SQL database in which the user can search a patient, besides edit or delete data. Therefore, the database is created with the data given by the user when registering a new patient. Thus, there are mandatory and optional data for the correct system operation and generation of results.

Mandatory data

The user must provide two files that will be used in the classification process. These files

Figure 35: Predictions page

Source: Author

consist of an (.edf) file, which contains sessions collected EEG per patient informing date, sample frequency, at last, the number of used channels. Then, a (.tse) file that has a summary of seizure events presented by the patient, reporting each ictal activity at the start and end time of the event.

Optional data

The user can furnish additional data, like the age, gender, and other further information of the patient. These data will show on the report header created by pressing the "Reports" button present in the upper corner within Add and View patient pages. A PDF document will be generated containing all patient data and performance metrics data, except for result images. This file will open in the PDF viewer of the user's computer or the web browser.

5.2.2 Manipulating the Database

As stated earlier, there are three options for data manipulation. These options are used to access more appropriately the required information, avoiding errors and misuse of the saved content.

Search option

The search option uses the patient's ID information to look for in the database, where only

the patient with such identification will display on the interface. Once the patient was found, there is the option to edit or delete the data that present any error. Then, if the information is complete, is it possible to generate a report.

Editing option

The editing option takes into account possible errors when adding the patient to the database. For security reasons, it is not possible to change the data obtained by the deep learning algorithm or the names of the patient's files. However, the fields that can be changed are the age and gender of the patient.

Option to delete

Finally, the principal cause of deleting a patient from the database would be if the files with the EEG signals and events have been sent in the wrong way, later the user has the option of creating that patient again, loading the EEG sessions, and classifying the signal through the detection system, having confidence information for analysis.

6 CONCLUSION

In this work was developed an automatic seizure detector based on Machine Learning techniques. To achieve the main aim of this study was analyzed the performance of two ANN architectures. Feedforward Neural Network with the training method of backpropagation working with a single EEG channel and Convolutional Neural Network, which used 21 EEG channels. So as that, the signal was processed to acquire the input to both models, for the eight training parameters of the FNN model were used DWT and FFT, whereas the CNN model was created using three inputs in the time domain, in the frequency domain via FFT and in the time-frequency domain using STFT. Moreover, both models split the input data into two subsets, 70% to train model and 30% to validate the training. Subsequently, the experimental group to validate both models consists of eight EEGs from Temple University Hospital Seizure Corpus (TUH-SC) database. Besides, to evaluate the performance was applied two training cases. For case 1, a model was created per patient. In case 2, one training set was built, which contains several sessions with different seizure types, to train one single model.

Hence, the performance results for training case 1 were: The FNN and CNN model with both in time and frequency domain inputs achieved accuracy over 55%, recall, precision, and F-score over 44%, and error over 40%, while the CNN model with the time-frequency domain input shows the best results for this training case, obtaining an accuracy of 95.3%, recall of 81.6%, a precision of 92.5%, F1-score of 85.7%, and error of 4.7%. For this reason, training case 2 was applied only to this last method, obtaining an accuracy, recall, precision, F1-score, and error of 78.1%, 76.9%, 66.2%, 65.4%, and 21.9% respectively. However, evaluating the results from the patients used to train the model is achieved the best performance of the two training cases, showing an accuracy of 96.8%, recall of 82%, a precision of 86%, and F1-score of 83.8%. Moreover, the error of 3.2% is the lowest of all methods reported in this research. Therefore, the CNN model with input in the time-frequency domain via STFT obtained the best performance in training cases 1 and 2. The results reported in this study confirm the network's ability to learn how to classify whether there exists or not an ictal activity, regardless of the seizure type.

This study proves that the CNN model developed has better results creating a model individual, i.e., one model per patient or when the future data of the trained model for some people correspond to these same people. In other words, the CNN model learned the "brain-behavior" of each person. Even so, both models meet the objective of detecting ictal activity in EEG

recordings from patients, which the network knows. Thus, the CNN model trained was used to develop a prototype of an aid application that makes it easy to monitor an epilepsy patient.

6.1 SUGGEST FOR FUTURE WORKS

The detection of epilepsy has been a major research topic since a decade. Besides, the application of techniques of machine learning is commonly used for this purpose. For future work, the development of a wearable device is a potential improvement for this work. However, at present, the detection field still presents some untackled problems, like real-time monitoring and possible EEG mount avoidance or EEG channel reduction. In addition, an interesting approach would be to use a novel architecture, like a liquid neural network, which is capable of adapting its behavior on the fly. This type of system could be very useful in medical diagnostics. The researchers drew inspiration from the worm's nervous system with only 302 neurons, designing a neural with parameters that can change over time.

References

- ACHARYA, U. R.; OH, S. L.; HAGIWARA, Y.; TAN, J. H.; ADELI, H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. **Computers in Biology and Medicine**, 2018. ISSN 18790534.
- AL-OMAR, S.; KAMALI, W.; KHALIL, M.; DAHER, A. Classification of EEG Signals to Detect Epilepsy Problems. **2013 2nd International Conference on Advances in Biomedical Engineering, ICABME 2013**, p. 5–8, 2013.
- ALHUSSEIN, M.; MUHAMMAD, G.; HOSSAIN, M. S. EEG Pathology detection based on deep learning. **IEEE Access**, IEEE, v. 7, p. 27781–27788, 2019. ISSN 21693536.
- AZAMIMI, A.; SAUFIAH, A.; RAHIM, A.; IBRAHIM, A.; EEG, A. Development of EEG-based Epileptic Detection Using Artificial Neural Network. **2012 International Conference on Biomedical Engineering (ICoBE)**, IEEE, n. February, p. 605–610, 2012.
- BEAR, M. F.; CONNORS, B. W.; PARADISO, M. A. Neurônios e Glia. In: **NEURO-CIÊNCIAS Desvendando o Sistema Nervoso**. fourth. [S.l.]: Artmed, 2017. cap. 2, p. 23–54.
- BERZAL, F. **Redes Neuronales & Deep Learning**. Granada: [s.n.], 2018. 803 p. ISBN 1-0903-3688-8. Disponível em: <<http://deep-learning.ikor.org>>.
- BESIO, W. G.; MARTÍNEZ-JUÁREZ, I. E.; MAKEYEV, O.; GAITANIS, J. N.; BLUM, A. S.; FISHER, R. S.; MEDVEDEV, A. V. High-Frequency Oscillations Recorded on the Scalp of Patients With Epilepsy Using Tripolar Concentric Ring Electrodes. **IEEE Journal of Translational Engineering in Health and Medicine**, Institute of Electrical and Electronics Engineers Inc., v. 2, 2014. ISSN 21682372.
- BRONZINO, J. D. Principles of Electroencephalography. In: BRONZINO, J. D. (Ed.). **The Biomedical Engineering Handbook**. Third edition. Boca Raton: CRC Press / Taylor and Francis Group, 2006. cap. 26, p. 26–1; 26–12.
- BROWNLEE, J. **How to use Learning Curves to Diagnose Machine Learning Model Performance**. 2019. [Online]. Available: <<https://machinelearningmastery.com/learning-curves-for-diagnosing-machine-learning-model-performance/>>. [Accessed: 29-Oct-2020]. Disponível em: <<https://machinelearningmastery.com/learning-curves-for-diagnosing-machine-learning-model-performance/>>.
- CHAIBI, S.; BOUET, R.; JUNG, J.; LAJNEF, T.; SAMET, M.; BERTRAND, O.; KACHOURI, A.; JERBI, K. Development of Matlab-Based Graphical User Interface (GUI) For Detection of High Frequency Oscillations (HFOs) in Epileptic Patients. **Espa 2012**, p. 56–62, 2012.
- CHAN, A. M.; SUN, F. T.; BOTO, E. H.; WINGEIER, B. M. Automated Seizure Onset Detection for Accurate Onset Time Determination in Intracranial EEG. **Clinical Neurophysiology**, International Federation of Clinical Neurophysiology, v. 119, n. 12, p. 2687–2696, 2008. ISSN 13882457. Disponível em: <<http://dx.doi.org/10.1016/j.clinph.2008.08.025>>.
- CHUI, C. K. **Wavelets: A Mathematical Tool for Signal Analysis**. Texas: SIAM, 1997. 229 p. ISBN 0898713846.

CONRADSEN, I.; BENICZKY, S.; WOLF, P.; TERNEY, D.; SAMS, T.; SORESENSEN, H. B. Multi-modal Intelligent Seizure Acquisition (MISA) System - A New Approach Towards Seizure Detection Based on Full Body Motion Measures. **Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009**, p. 2591–2595, 2009.

DAMAYANTI, A.; PRATIWI, A. B.; MISWANTO. Epilepsy detection on EEG Data Using Backpropagation, Firefly Algorithm and Simulated Annealing. In: **Proceedings - 2016 2nd International Conference on Science and Technology-Computer, ICST 2016**. [S.l.]: Institute of Electrical and Electronics Engineers Inc., 2017. p. 167–171. ISBN 9781509043576.

DAOUD, H.; BAYOUMI, M. A. Efficient Epileptic Seizure Prediction Based on Deep Learning. **IEEE Transactions on Biomedical Circuits and Systems**, IEEE, v. 13, n. 5, p. 804–813, 2019. ISSN 19409990.

DORAI, A. Automated Epileptic Seizure Onset Detection. **2010 International Conference on Autonomous and Intelligent Systems, AIS 2010**, IEEE, p. 1–4, 2010.

DRONGELEN, W. van. **Signal Processing for Neuroscientists**. [S.l.]: Elsevier Academic Press, 2006. 320 p. ISBN 13:978-0-12-370867-0.

_____. _____. Second edi. [S.l.]: Elsevier Academic Press, 2018. 723 p. ISBN 9780128104828.

EPILEPSY FOUNDATION. **Refractory Epilepsy (Difficult to Treat Seizures)**. 2014. [Online]. Available: <<https://www.epilepsy.com/learn/refractory-epilepsy-difficult-treat-seizures>>. [Accessed: 8-July-2019].

FERRELL, S.; MATHEW, V.; REFFORD, M.; TCHIONG, V.; AHSAN, T.; OBEID, I.; PICONE, J. **Electrode Location and Channel Labels**. Philadelphia, Pennsylvania, 2020. 17 p. Disponível em: <https://www.isip.piconepress.com/publications/reports/2020/tuh{_}eeg/electrod>.

FISHER, R. S.; ACEVEDO, C.; ARZIMANOGLU, A.; BOGACZ, A.; CROSS, J. H.; ELGER, C. E.; ENGEL, J.; FORSGREN, L.; FRENCH, J. A.; GLYNN, M.; HESDORFFER, D. C.; LEE, B. I.; MATHERN, G. W.; MOSHÉ, S. L.; PERUCCA, E.; SCHEFFER, I. E.; TOMSON, T.; WATANABE, M.; WIEBE, S. ILAE Official Report: A Practical Clinical Definition of Epilepsy. **Epilepsia**, v. 55, n. 4, p. 475–482, 2014. ISSN 15281167.

GAUTAM, S.; SRIYA, S.; CHAUHAN, T. Focal and Non-Focal Epilepsy Detection Using EEG Signals via Empirical Mode Decomposition. In: **2015 International Conference on Signal Processing and Communication, ICSC 2015**. [S.l.]: Institute of Electrical and Electronics Engineers Inc., 2015. p. 452–455. ISBN 9781479967612.

GOODFELLOW, I.; BENGIO, Y.; COURVILLE, A. **Deep Learning**. [S.l.]: MIT Press, 2016. <<http://www.deeplearningbook.org>>.

GUO, L.; RIVERO, D.; DORADO, J.; RABU, J. R.; PAZOS, A. Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks. **Journal of Neuroscience Methods**, v. 191, p. 101–109, 2010.

HAYKIN, S. **Neural Networks - A Comprehensive Foundation**. second. Ontario, Canada: Prentice Hall PTR, 1999. 823 p.

HEATON, J. **Artificial Intelligence for Humans, Volume 3: Deep Learning and Neural Networks**. [S.l.]: Heaton Research, Inc., 2015. 268 p. ISBN 9781505714340.

HELDBERG, B. E.; KAUTZ, T.; LEUTHEUSER, H.; HOPFENGARTNER, R.; KASPER, B. S.; ESKOFIER, B. M. Using Wearable Sensors for Semiology-independent Seizure Detection - Towards Ambulatory Monitoring of Epilepsy. In: **Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS**. [S.l.]: Institute of Electrical and Electronics Engineers Inc., 2015. v. 2015-Novem, p. 5593–5596. ISBN 9781424492718. ISSN 1557170X.

HUGLE, M.; HELLER, S.; WATTER, M.; BLUM, M.; MANZOURI, F.; DUMPELMANN, M.; SCHULZE-BONHAGE, A.; WOIAS, P.; BOEDECKER, J. Early Seizure Detection with an Energy-Efficient Convolutional Neural Network on an Implantable Microcontroller. **Proceedings of the International Joint Conference on Neural Networks**, v. 2018-July, 2018.

JAGTAP, P. T.; BHOSALE, N. P. IOT Based Epilepsy Monitoring using Accelerometer Sensor. In: **2018 International Conference on Information, Communication, Engineering and Technology, ICICET 2018**. [S.l.]: Institute of Electrical and Electronics Engineers Inc., 2018. ISBN 9781538655108.

JALLON, P.; BONNET, S.; ANTONAKIOS, M.; GUILLEMAUD, R. Detection System of Motor Epileptic Seizures Through Motion Analysis with 3D Accelerometers. **Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009**, IEEE, p. 2466–2469, 2009.

KHAN ACADEMY. **Overview of neuron structure and function (article)**. Khan Academy, 2015. Disponível em: <<https://www.khanacademy.org/science/biology/human-biology/neuron-nervous-system/a/overview-of-neuron-structure-and-function>>.

KIM, T.; ARTAN, N. S.; SELESNICK, I. W.; CHAO, H. J. Seizure Detection Methods Using A Cascade Architecture For Real-Time Implantable Devices. **2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Osaka, Japan, 3-7 July, 2013**, IEEE, p. 1005–1008, 2013.

KRISHNAN, P. T.; BALASUBRAMANIAN, P. Automated EEG Seizure Detection Based on S-Transform. **2016 IEEE International Conference on Computational Intelligence and Computing Research, ICCIC 2016**, IEEE, p. 1–5, 2017.

KULASURIYA, K. A.; PERERA, M. U. Focal epileptic seizure forecasting in EEG signals using wavelet transform and artificial neural networks. **Proceedings - 2011 IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2011**, p. 296–301, 2011.

KUSMAKAR, S.; KARMAKAR, C. K.; YAN, B.; O'BRIEN, T. J.; MUTHUGANAPATHY, R.; PALANISWAMI, M. Automated Detection of Convulsive Seizures Using a Wearable Accelerometer Device. **IEEE Transactions on Biomedical Engineering**, IEEE, v. 66, n. 2, p. 421–432, 2019. ISSN 15582531.

LASEFR, Z.; REDDY, R. R.; ELLEITHY, K. Smart Phone Application Development for Monitoring Epilepsy Seizure Detection Based on EEG Signal Classification. In: **2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference**,

UEMCON 2017. [S.l.]: Institute of Electrical and Electronics Engineers Inc., 2018. v. 2018-Janua, p. 83–87. ISBN 9781538611043.

LIU, X.; AIMIN, J.; XU, N. Automated Epileptic Seizure Detection in EEGs Using Increment Entropy. **Canadian Conference on Electrical and Computer Engineering**, IEEE, p. 1–4, 2017. ISSN 08407789.

MOORE, J.; ZOURIDAKIS, G. Evoked Potentials. In: **Biomedical Technology and Devices**. Boca Raton: CRC Press, 2004. cap. 5.

PEDRAM, M. Z.; SHAMLOO, A.; ALASTY, A.; GHAFAR-ZADEH, E. MRI-Guided Epilepsy Detection. In: **2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)**. [S.l.: s.n.], 2015. p. 4001–4004.

RAJOUB, B. Characterization of biomedical signals: Feature engineering and extraction. In: **Biomedical Signal Processing and Artificial Intelligence in Healthcare**. Elsevier Inc., 2020. cap. 2, p. 29–50. ISBN 9780128189467. Disponivel em: <<http://dx.doi.org/10.1016/B978-0-12-818946-7.00002-0>>.

RASHID, M. or; AHMAD, M. Epileptic Seizure Classification using Statistical Features of EEG Signal. In: **International Conference on Electrical, Computer and Communication Engineering, February 16-18, 2017. Bangladesh**. [S.l.: s.n.], 2017. p. 308–312. ISBN 9781509056262.

SAYEED, A.; KOUGIANOS, E.; MOHANTY, S. P.; ZAVERI, H. An Energy Efficient Epileptic Seizure Detector. **2018 IEEE International Conference on Consumer Electronics (ICCE)**, IEEE, p. 1–4, 2018.

SAYEED, M. A.; MOHANTY, S. P.; KOUGIANOS, E.; ZAVERI, H. A Fast and Accurate Approach for Real-Time Seizure Detection in the IoMT. In: **2018 IEEE International Smart Cities Conference (ISC2)**. [S.l.]: IEEE, 2018. ISBN 9781538659595.

SAZGAR, M.; YOUNG, M. G. Overview of EEG, Electrode Placement and Montages. **Absolute Epilepsy and EEG Rotation Review**, p. 3–11, 2019.

SCHAD, A.; SCHINDLER, K.; SCHELTER, B.; MAIWALD, T.; BRANDT, A.; TIMMER, J.; SCHULZE-BONHAGE, A. Application of a Multivariate Seizure Detection and Prediction Method to Non-invasive and Intracranial Long-term EEG recordings. **Clinical Neurophysiology**, v. 119, n. 1, p. 197–211, 2008. ISSN 13882457.

SCHEFFER, I. E.; BERKOVIC, S.; CAPOVILLA, G.; CONNOLLY, M. B.; FRENCH, J.; GUILHOTO, L.; HIRSCH, E.; JAIN, S.; MATHERN, G. W.; MOSHÉ, S. L.; NORDLI, D. R.; PERUCCA, E.; TOMSON, T.; WIEBE, S.; ZHANG, Y. H.; ZUBERI, S. M. ILAE Classification of the Epilepsies: Position Paper of the ILAE Commission for Classification and Terminology. **Epilepsia**, v. 58, n. 4, p. 512–521, 2017. ISSN 15281167.

SCHIRRMESTER, R.; GEMEIN, L.; EGGENSPERGER, K.; HUTTER, F.; BALL, T. Deep learning with convolutional neural networks for decoding and visualization of EEG pathology. **2017 IEEE Signal Processing in Medicine and Biology Symposium, SPMB 2017 - Proceedings**, v. 2018-Janua, p. 1–7, 2017.

SHAH, V.; WELTIN, E. von; LOPEZ, S.; MCHUGH, J. R.; VELOSO, L.; GOLMOHAM-MADI, M.; OBEID, I.; PICONE, J. The temple university hospital seizure detection corpus. **Frontiers in Neuroinformatics**, v. 12, n. November, p. 1–6, 2018. ISSN 16625196.

SÖRNMO, L.; LAGUNA, P. **Bioelectrical Signal Processing in Cardiac and Neurological Applications**. [S.l.]: Elsevier Academic Press, 2005. 689 p. ISBN 0124375529.

SORNMO, L.; LAGUNA, P. The Electroencephalogram – A brief background. In: **Bioelectrical Signal Processing in Cardiac and Neurological Applications**. [S.l.]: Elsevier Academic Press, 2005. cap. 2.

TATUM, W. O.; HUSAIN, A. M.; BENBADIS, S. R.; KAPLAN, P. W. **Handbook of EEG Interpretation**. [S.l.]: Demos Medical Publishing, 2007. 289 p. ISBN 9781933864112.

TORRES, C. V. Epilepsia. **Medicine (Spain)**, v. 11, n. 73, 2015.

WORLD HEALTH ORGANIZATION. **Epilepsy, A Public Health Imperative**. 2019. [Online]. Available: <https://www.who.int/mental_health/neurology/epilepsy/report_2019/en/>. [Accessed: 2-Dec-2020].

ZANDI, A. S.; JAVIDAN, M.; DUMONT, G. A.; TAFRESHI, R. Automated Real-Time Epileptic Seizure Detection in Scalp EEG Recordings Using an Algorithm Based on Wavelet Packet Transform. **IEEE Transactions on Biomedical Engineering**, v. 57, n. 7, p. 1639–1651, 2010. ISSN 00189294.

ZAZZARO, G.; CUOMO, S.; MARTONE, A.; MONTAQUILA, R. V.; TORALDO, G.; PAVONE, L. EEG Signal Analysis for Epileptic Seizures Detection by Applying Data Mining Techniques. **Internet of Things**, Elsevier B.V., n. xxxx, p. 100048, 2019. ISSN 25426605. Disponível em: <<https://doi.org/10.1016/j.iot.2019.03.002>>.

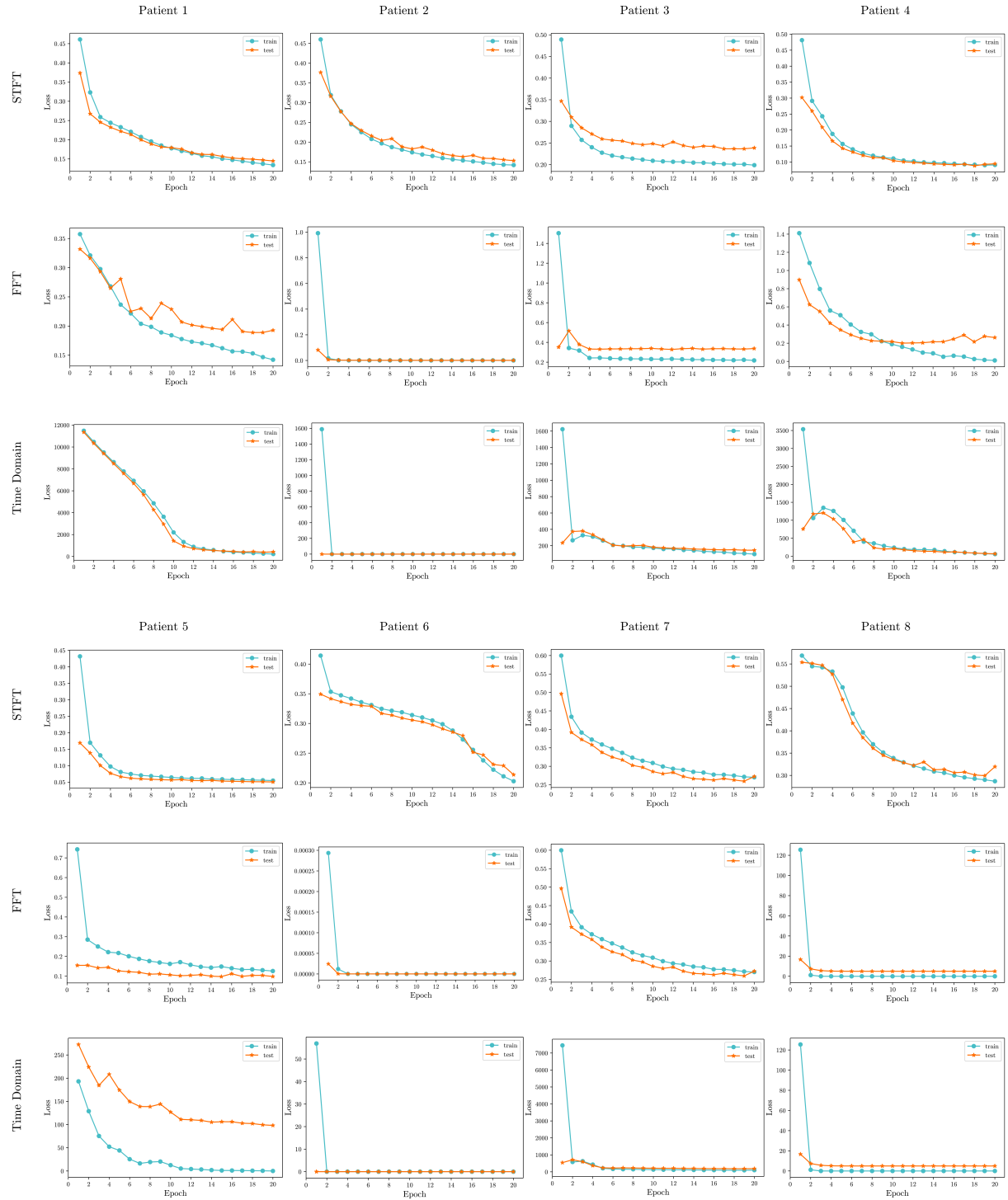
ZHANG, T.; CHEN, W. LMD Based Features for the Automatic Seizure Detection of EEG Signals Using SVM. **IEEE Transactions on Neural Systems and Rehabilitation Engineering**, v. 25, n. 8, p. 1100–1108, 2017. ISSN 15344320.

ZHOU, M.; TIAN, C.; CAO, R.; WANG, B.; NIU, Y.; HU, T.; GUO, H.; XIANG, J. Epileptic seizure detection based on EEG signals and CNN. **Frontiers in Neuroinformatics**, v. 12, n. December, p. 1–14, 2018. ISSN 16625196.

Appendices

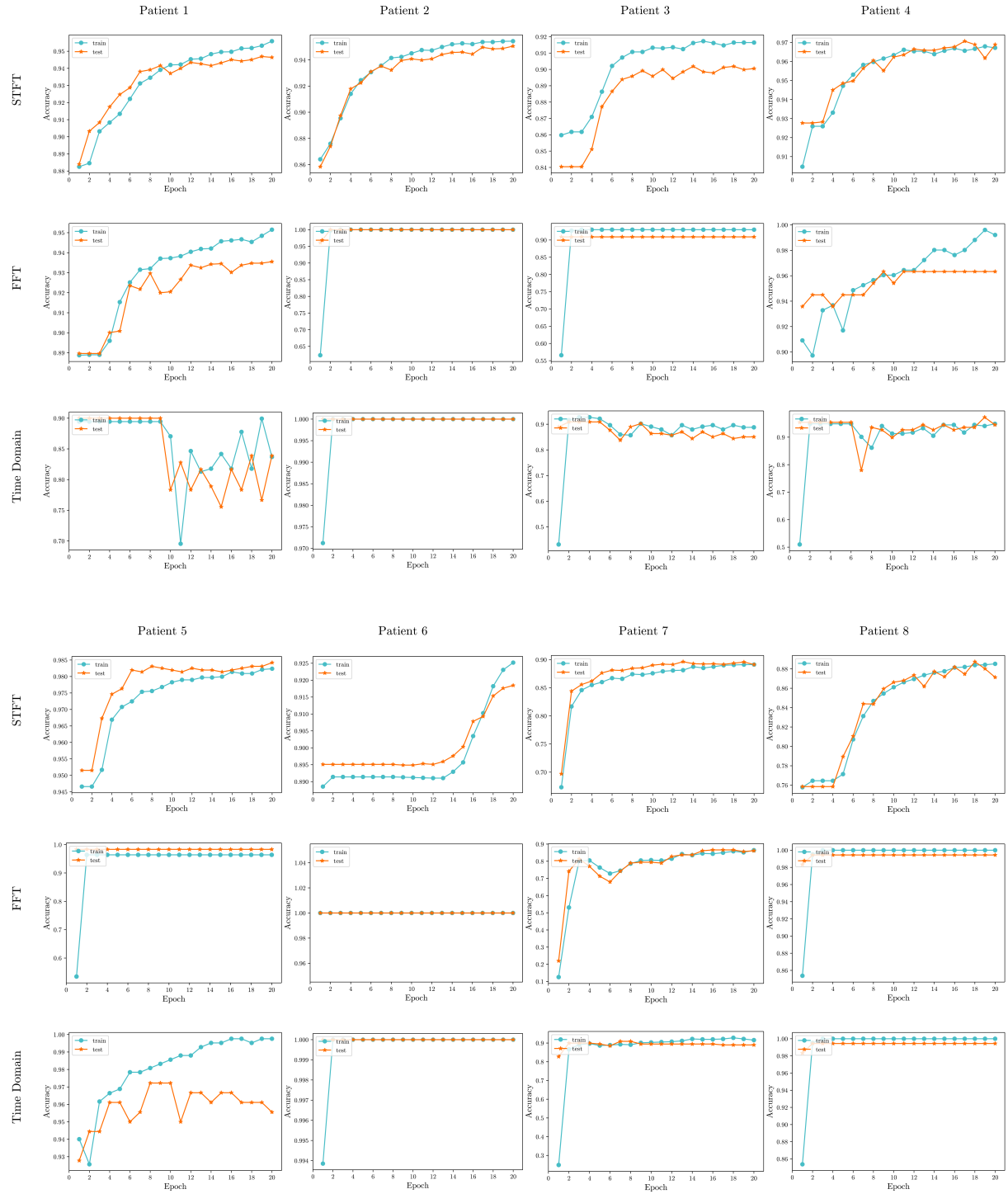
Appendix A LEARNING CURVES TRAINING CASE 1

Figure 36: Loss curves to CNN model trained for each patient (case 1) using input in time domain via filtering three limited bands, frequency domain via FFT and time-frequency domain via STFT



Source: Author

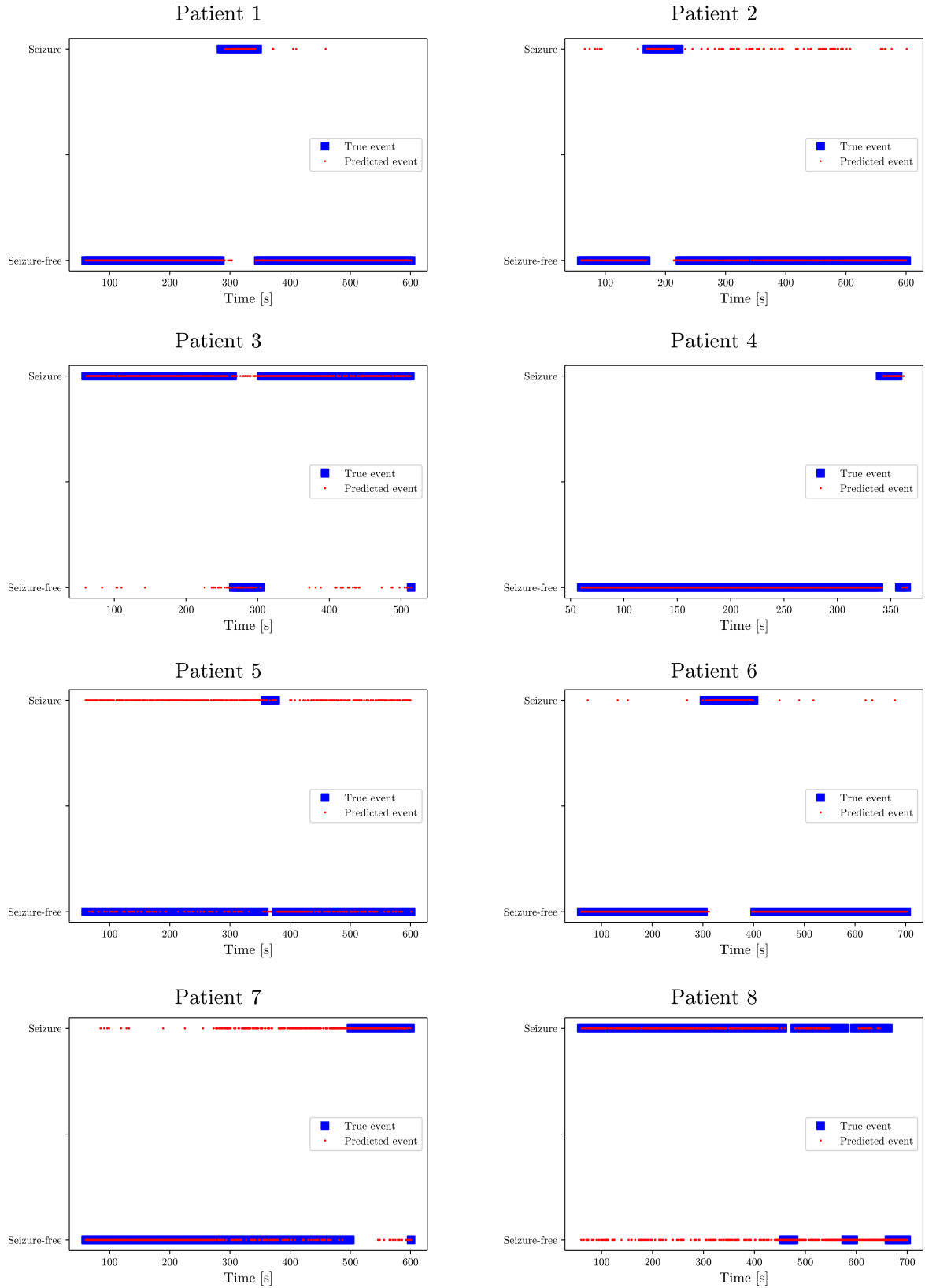
Figure 37: Accuracy curves to CNN model trained for each patient (case 1) using input in time domain via filtering three limited bands, frequency domain via FFT and time-frequency domain via STFT



Source: Author

Appendix B SEIZURE PREDICTIONS TRAINING CASE 2

Figure 38: CNN model Predictions (case 2); the blue lines represent the true events, and red lines are the prediction made by the model obtaining the best predictions for patients 1, 4 and 6



Source: Author

Appendix C AUXILIARY ALGORITHMS

Algorithm 8: Image normalization

Result: Takes the images FFT and normalizes the values in a range of 0 to 255

```
for  $i \leftarrow 0$  to length of image array do  
    Take the FFT of the  $i$ -th image;  
    Normalize the values to be between 0 and 255;  
    Append the output array;  
end
```
