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# THESIS

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## Time-scale analysis and classification of electroencephalographic signals (EEG): Application on remote--surveillance of epilepsy

## Analyse temps-échelle et classification des signaux Electroencéphalographique (EEG): Application à la télésurveillance de l'épilepsie

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**« And He gave you of all that you asked for, and if you count the Blessings of Allâh, never will you be able to count them. Verily, man is indeed an extreme wrong-doer, a disbeliever. »**

[Quran. chapter: Ibrahim, verse 14]

# Dedication

*My family.*

*My professors.*

*My friends and colleagues.*

*All whom supported me to accomplish this dissertation.*

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***All praise is due to Allah alone.***

# Abstract

Electroencephalography (EEG) stands as a cornerstone in non-invasive brain activity monitoring, offering invaluable insights with high temporal resolution. This dissertation focuses on harnessing EEG for the detection of epileptic activity, specifically targeting the precise delineation of epileptic zones responsible for abnormal electrical patterns within the brain. The meticulous mapping of these zones is pivotal for assessing patients with pharmacoresistant epilepsy, paving the way for targeted seizure-free interventions. Thus, this dissertation introduces two complementary subsystems: the Representative EEG Channel Creator (RECC) and the Seizure Affected EEG Channel Detector (SAECD). The RECC contributes to enhanced dimensionality reduction with up to 93.75%, improving the efficiency of epilepsy pattern detection with a sensitivity of 98.46%. Upon a positive response from the RECC indicating epileptic EEG, the SAECD subsystem is activated. Leveraging the Energy-to-Shannon-Entropy ratio and a k-means clustering approach, SAECD precisely localizes the epileptogenic focus and traces the path of seizure diffusion within the brain with a promising average silhouette range of [51.21-88.18]%. In addition to the innovative subsystems introduced, this study places a particular emphasis on the selection of an appropriate mother wavelet. The careful choice of this latter plays a crucial role in enhancing the accuracy and efficiency of the proposed epilepsy detection system. In addition to advanced signal processing techniques, this research incorporates engineered features. These latter are strategically designed to capture nuanced aspects of epileptic activity, contributing to the overall robustness and effectiveness of the proposed methodology. Furthermore, the dissertation embraces the realm of telemedicine with the introduction of Epileptica, an asynchronous application designed for remote access to the results generated by the developed EEG-type-independent system. This telemedical platform enhances accessibility to critical information, supporting neurologists in making informed decisions regarding patient care and the suitability for seizure-free surgery.

**Keywords:** Electroencephalography, EEG dimensionality reduction, epilepsy detection, epileptogenic focus detection, time–scale analysis, wavelet transform, mother wavelet selection, classification, telemedicine, client-server architecture.

# Résumé

L'électroencéphalographie (EEG) constitue une pierre angulaire dans le suivi non invasif de l'activité cérébrale, offrant des informations précieuses avec une haute résolution temporelle. Cette thèse se concentre sur l'exploitation de l'EEG pour la détection de l'activité épileptique, ciblant spécifiquement la délimitation précise des zones épileptiques responsables des anomalies électriques dans le cerveau. La cartographie minutieuse de ces zones est essentielle pour l'évaluation des patients atteints d'épilepsie pharmacorésistante, ouvrant la voie à des interventions ciblées et sans crises. Ainsi, cette thèse propose deux sous-systèmes complémentaires : le Representative EEG Channel Creator (RECC) et le Seizure Affected EEG Channel Detector (SAECD). Le RECC contribue à une réduction dimensionnelle accrue jusqu'à 93,75%, améliorant l'efficacité de la détection des motifs épileptiques avec une sensibilité de 98,46%. En cas de réponse positive du RECC indiquant un EEG épileptique, le sous-système SAECD est activé. En s'appuyant sur le ratio Énergie/Entropie de Shannon et une approche de regroupement par k-means, le SAECD localise précisément le foyer épileptogène et retrace la diffusion des crises dans le cerveau avec une silhouette moyenne prometteuse allant de [51,21 à 88,18] %. En plus des sous-systèmes innovants proposés, cette étude accorde une attention particulière à la sélection d'une ondelette mère appropriée. Ce choix minutieux joue un rôle crucial dans l'amélioration de la précision et de l'efficacité du système de détection d'épilepsie proposé. En complément des techniques avancées de traitement du signal, cette recherche intègre des caractéristiques conçues sur mesure. Ces dernières sont stratégiquement élaborées pour capturer des aspects subtils de l'activité épileptique, renforçant la robustesse et l'efficacité globale de la méthodologie développée. Par ailleurs, cette thèse s'inscrit dans le domaine de la télémédecine avec l'introduction d'Epileptica, une application asynchrone permettant un accès à distance aux résultats générés par le système développé, indépendant du type d'EEG. Cette plateforme télémédicale améliore l'accessibilité aux informations critiques, soutenant les neurologues dans la prise de décisions éclairées sur les soins aux patients et l'adéquation à une intervention chirurgicale visant l'absence de crises.

**Mots clès:** Electroencéphalographie, réduction dimensionnelle de l'EEG, détection de l'épilepsie, détection du foyer épileptogène, analyse temps-échelle, transformation en ondelettes, sélection de l'ondelette mère, classification, télémédecine, architecture client-serveur.

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# Introduction

Understanding the functional mechanism of the body's control center (the brain) has become within reach due to electroencephalography, this non–invasive technique represents an important step to carry out for the diagnosis and prescription of neurodegenerative pathologies and abnormalities such as; Epileptic seizures, which represent the studied subject in the present thesis.

Epilepsy is a serious neurological disorder defined as electrical discharges of a group of neurons within the brain. It is typified by chronic and unexpected seizures. These latter, are difficult to be managed by medical staff. Latest statistics show that 1% of the population, both sexes and all ages, are affected by this chronic disease [14]. As presented previously, electroencephalography allows the recording of waveform series known as EEG. This signal describes the electrical activity status within the brain. Nevertheless, owing to the erratic occurrence of epileptic seizures, visual analysis of EEG signals remains insufficient. And therefore, mathematical processing and classification of EEG signals are required for the assistance of epilepsy diagnosis and for the bested understanding of its ambiguous reasons.

Electroencephalogram-based brain activity exploration for diagnosis aid in epilepsy syndrome has been introduced as a research area in the early 70s. Prior *et al* [15] developed a Cerebral Function Monitor device that serves in unsupervised long–term EEG monitoring, this latter, was qualified to recognize the tonic-clonic epileptic seizures through the surveillance and the detection of high augmentation in the magnitude of the recorded EEG signal.

After that, in 1974, Babb *et al* [16] designed a seizure detector electronic circuit. It has been installed in the neurological ward to be used while monitoring and recording the EEG signals of four patients. Among 66 ictal reports observed by both medical staff or the developed detector; 28 recorded epileptic seizures were detected by the ward's nurses, while, the implemented seizure detector recorded about 64 ictal epochs. From the nurse's report, two seizures were wrongly recorded as ictal activity, while the proposed circuit succeeded in identifying 46/64 epileptic seizures, 20 of which were not notified either by the nurses non by patients, which confirms the performance of the implemented seizure detector circuit.

Two years later, Gotman *et al* [17], performed a computerized system for epileptic seizures recognition. This system was implemented on the basis of two characteristics of EEG signal–half–wave namely; magnitude and duration. These attributes combination was proposed to typify EEG spikes and sharp waves, which helps in

ictal activity detection and quantification. The developed system was as well able to exclude the artifacts known as spike–like or sharp wave–like forms (eye blinks, muscle potentials, alpha activity...etc). In summary, Gotman's automatic model detected and determined the zones of epileptogenicity with a high level of reliability. And therefore, this latter was of great impact on clinical electroencephalography.
Six years later, Gotman took the name of the avant-garde, since he supported the idea of computerized epilepsy detection systems and he developed a dynamic one (patient–independent). His proposed technique depends upon the location of sudden inconstancy in the EEG signals rhythmic bustle that spans [3-20] Hz of the frequency range. To assess the proposed system, several tests have been conducted. The final results demonstrate that this latter was not able to identify ictal episodes with high-frequency noise and low magnitude. The effectiveness of the devised algorithm can thus only be observed in the case of EEGs with a frequency range of less than 20 Hz.
A few years later, the method previously mentioned was modified and applied to a larger EEG collection with 5303 hours of recordings. The two primary goals of this improved approach were to enhance the specificity value of the implemented system and to consider a significant temporal context of electroencephalographic data. Nevertheless, since this method's main flaw was the detection delay drawback, it could not be applied in a real-time application. [18].
In 1993, Qu *et al* [19] proposed a novel automatic detection system of ictal activity within EEG signals based on k nearest neighbors classifier performance. This system is a static model (patient-specific approach) that has enhanced the efficiency of abnormal brain activity detection because single–patient EEG registrations were of less incoherence for both ictal and normal activities. This proposed system was updated several times [20, 21] to overcome the issue of latency detection. However, the main limitation of such static automatic models appears when testing unseen data. Usually, the algorithm performance decreases because it has been developed based on specific patient characteristics, and consequently, it can not adapt in the case of a new patient with unseen features.
A short while later, several researchers invested in this field by implementing a variety of epileptic seizure detection models. Below is a brief presentation of these ictal activity recognition systems; In 2005, Kannathal *et al* [22] studied the human brain's high complexity through spectral, renyi, kolmogorovsinai, and approximate entropies, they aimed through this study to compare between these latter effects on epilepsy detection within Bonn EEG signals. To achieve their purpose, they applied the adaptive neuro-fuzzy inference system (ANFIS) for normal and seizure signals classification, and as consequence, they affirmed on the basis of the obtained accuracy of 90% that, the entropies can highly differentiate between normal and abnormal brain activity.
Moreover, Jahankhani *et al* [23] extracted four statistical attributes namely; mean, maximum, minimum, and standard deviation from the wavelet coefficients of Bonn ictal and normal EEG signals, these features were used as input for the Multilayer Perceptron Network (MLP) as well as the Radial Basis Function Network (RBF) classifiers, the effectiveness of their applied neural network model was qualified in

terms of apprenticeship performance and classification correct rate, in summary, their findings (97%, 98% for MLP and RBF respectively) ensured that the built scheme has the potential to identify the EEG signals epileptic abnormalities and outperforms remarkably the ANFIS model previously cited.

Later, Subasi [24] classified epileptic epochs and normal ones from the same Bonn EEG database by applying a combination of wavelet transform-based statistical attributes extraction and a mixture of expert models, and to enhance the efficiency of his developed model, Subasi has used the gating function together with his expert networks outputs. Finally, he evaluated the approach based on the obtained accuracy values and certified that using this mixture of experts provides a higher accuracy rate in comparison to utilizing the stand-alone neural network.

Two years later, Ocak *et al* [25] carried out a new study on the same Bonn EEG signals, in which they explored the regularity and complexity of this data via the approximate entropy (ApEn) of specific Discrete Wavelet Transform (DWT) coefficients, their findings reveal that; firstly, the ApEn values decrease in seizure periods in comparison to seizure-free ones and therefore, they achieved a considerable correct rate of 96%. Secondly, they re-followed the same steps excluding the step of pre-processing with DWT resulting in less performance of 73%, which confirms that the EEG signals are of considerable non–stationary nature. In summary, the obtained 96% of accuracy represents a hopeful achievement and gain in processing time when comparing it with the various entropies used in [22], however, the results obtained when applying the mixture of experts model proposed by Subasi [24] remains favorable.

In the same year, Polat *et al* [26] published their hybrid diagnosis decision-making system, based on the well-known Fast Fourier Transform (FFT) together with the decision tree classifier applied on Bonn EEG signals. The declared results underline the effectiveness of their hybrid model in the interpretation of the studied EEG signals with a precision of 98.72%. Consequently, their system can be used reliably as an assistance tool for epileptic activity recognition.Nevertheless, in the state of the art, the obtained results of epileptic seizure detection show that the wavelet transforms analysis is more efficient in terms of capturing pertinent characteristics from signals of non–stationary and non–linear nature such as the electroencephalogram signals. Since it utilizes scale–varying basis functions for energy estimation and local features extraction from the processed signal. Besides that, it provides preferable time-frequency localization when compared to the short-time Fourier transforms approach. Therefore, and since we are developing systems for seizure detection based on wavelets, the published research to be presented and discussed in the following parts will consider three primordial points namely; the **appropriate mother wavelet** for correct detection of epileptic activity, the necessary **decomposition levels** to detect the brainwaves of clinical interest and the **adequate classifier** to build a robust and adaptive model for epilepsy detection. Starting with the study of Panda *et al* [27] in which they applied a time–scale analysis on Bonn EEG signals employing Daubechies mother wavelet with order 02 (db2), and they stopped the DWT–based EEG decomposition process at five–levels to begin the feature extraction phase, finally an SVM model for epilepsy detection was built.

The suggested model's greatest accuracy of 91.2% was obtained after removing all computed features and preserving only the energy of each DWT coefficient individually, which reduced processing time to 0.5 seconds. In synopsis, the entire epilepsy detection process is encouraging, however, due to the complexity of the studied pathology, the proposed algorithm needs to be improved in terms of the appropriate mother wavelet and distinguishing features extraction, since when comparing the Subasis's [24] results with an error rate of 0.02 using db4 mother wavelet with four statistical attributes and Panda's result with an error rate of 0.09 and they unmentioned the reason behind their selection of db2 mother wavelet, we conclude that the choice of the processing mother wavelet and the features to be extracted are of great effect on epilepsy detection performance even if the used classifiers are various.

On the other hand, Khan *et al* [28] followed the same system as in Panda's study *et al* [27] (relative energy values computed from specific discrete wavelet transform (DWT) sub-bands), but they used db4 instead of db2 mother wavelet and linear discriminant analysis as a classifier, their model was evaluated employing five subjects, with multiple EEG channels; 23, 24 and 26 as stated in each subject annotations. They attained a classification accuracy of 91%, after an apprenticeship phase with 80% of the data, This result is identical to the one provided by Panda's model, although they changed the mother wavelet and used the same as Subasis's work [24]. Consequently, the extracted features are of high influence on the performance of the detection process and that has been confirmed by Lui *et al* [29] who carried out a db4 five–level decomposition approach and relative energy as a feature, as in [28], however, they added more significant features namely; The fluctuation index (estimation of the intensity of a decomposed sub-band), variation coefficient and relative amplitude, these characteristics besides the relative energy improved the detection performance to 95.33% of the correct rate, with an SVM classifier. In conclusion, the suggested algorithm is determined to be resilient when compared to the models previously mentioned because it functions well on long-range EEGs.

In a study by Zainuddin *et al* [30], wavelets, neural network models along with several activation functions and different feature extraction techniques were examined in the operation of classifying ictal and normal activity. As a result and based on their final accuracy of 98.66%, it was concluded that the method was effective. The Morlet wavelet, according to the authors, is the optimum wavelet function to use for such complex detection. In addition, the db4 was also shown to be more suitable than the db2 mother wavelet. The overall error rate achieved supported the created model's ability to help neurologists in the process of diagnosis. The proposed model's advantage is its ability to detect other neurodegenerative diseases, such as Alzheimer's and Parkinson's. However, it had to be applied to epileptic seizure prediction, which is an interesting application because it requires the classifier to distinguish between pre-ictal and normal EEGs.

Additionally, the performance of applying recurrence quantification analysis based-characteristics extraction from theta, delta, alpha, beta, and gamma sub-bands obtained at four–levels Daubechies four (db4) mother wavelet, was investigated by Niknazar *et al* [31] to build a dynamical system that serves in the identification of normal, interictal, and ictal cases. The implemented algorithm was applied to the same Bonn dataset. Where seventy percent of the data points (70%) of each group ( 140 samples for both Healthy and interictal groups and 70 observations of the seizure group) were randomly selected for the training phase of Error–Correcting Output Codes (ECOC). The rest of the samples (60 samples for both Healthy and interictal and 30 samples for the abnormal group) represent the test data. As a consequence, they reached an error rate of 0.0133, which proves the effectiveness of their model. Nevertheless, the authors declare that the model needs to be more simplified and retested on other datasets.

Recently, a study by Shoaib *et al* [32] for seizure detection within CHB–MIT EEG signals has been accomplished. They proposed a system that processes directly the compressed signals to avoid reconstruction time and to conserve energy. After using the wavelet energy as a characteristic to typify the EEG signal, the SVM was used to evaluate the evidence of their proposed system. Their findings showed that their approach affects negatively the sensitivity by 4%.

One year later, Zabihi *et al.* [33] aimed to address several deficiencies in the state of the art, namely; chaos false impression and surrogate data processing implementation. To this end, they proposed a new method to catch the underlying dynamics of epileptic activity and hence to recognize and differentiate them from the non–ictal segments in an evident way. Seven (07) attributes were extracted from 23 EEG channels based on their suggested Poincaré mapping strategy. Then they employed the Naive Bayes and LDA classifiers to quantify the effectiveness of their approach. A hopeful accuracy result of 94% and 93% for the Naive Bayes and LDA respectively was obtained. However, it remains insufficient in comparison to the aforementioned epilepsy recognition findings.

Afterward, Hasan *et al.* [34] proposed a novel approach for seizure detection through Wavelet and Hilbert transforms. Statistical characteristics such as; mean, minimum, and maximum of absolute values of coefficients besides the average power and std were extracted. This combination was applied to the Bonn database for evaluation with the knn classifier. As a result, they obtained accuracies of 100% and 96% for the used A—E and B—E datasets, while the Hilbert transform results reached 100% in accuracy, sensitivity, and specificity for both datasets.

A year later, Chen *et al.* [35] accomplished a study for seizure recognition based on wavelet analysis, Fourier spectra–based shift–invariant attributes extraction, and the k–nearest neighbors for the classification phase of seizure and non–seizure epochs, their experimental findings show that the developed method attained a perfect correct rate of 100%, for the overall experiments applied on Bonn EEG database. In summary, the obtained results are optimal. Moreover, the authors declare that their proposed model is faster in terms of computational time. However, the 100% as result in both works [34, 35] may be a sign of an overfitting issue, especially when, the developed system is tested on one database only, while such a perfect result necessitates to be re-evaluated on a large number of observations to ensure this typical evidence.

Building a trustworthy model for seizure recognition required a careful selection of mother wavelet, decomposition level, and features, Abbasi and Esmaeilpour [36] evolved a new method to improve the exactness of prediction and classification of various states of Bonn EEG signals namely; healthy, paroxysmal, and pre–epileptic cases, firstly, they parsed the EEG signals into sub-bands in several categories through the discrete wavelet transform (db4 mother wavelet) then they computed statistical attributes like; maximum, minimum, mean and standard deviation for each resulting sub-band. A correct rate, sensitivity, and specificity of 98.33, 100, and 97.1% respectively were reached using a multilayer perceptron (MLP) as a classifier.

Latterly, Solaija *et al.* [37] utilized the Dynamic Mode Decomposition (DMD) of EEG signals to reveal the ictal activity with 87% sensitivity. Their built model attained this result after dividing the data equally (50%) between the apprenticeship and test phases. These low findings assert that such non–stationary signals like EEG necessitates more potent processing tools such as wavelet transform. Zhang *et al.* [38] computed 24 features from the TUH EEG Corpus database, which contains 22 EEG channels for each record, to apprenticeship and validate their SVM–based epilepsy recognition model at 99.4% accuracy. Even though the error rate reached is favorable, their model was built using the overall 22 EEG channels for every patient. As a consequence, it may conduct into an overfitting issue.

More recently, various approaches and combination of features were computed, citing; the Fourier–Bessel series expansion [39, 40], Taylor–Fourier filter bank [41]. Nevertheless, all these models were tested separately on Bonn EEG Database and the CHB–MIT EEG Scalp Database, even though they provide encouraging performance values, they remain scanty when taking into account the few number of signals employed for the experimentation. Therewith, they treat all handy EEG channels, disregarding the fact that utilizing such sizeable number of EEG channels could have a unfavorable effect on the automatic epilepsy detection performance, due to the complexity of multi–channels systems in comparison of those with limited number of channels. Thus, a trustworthy EEG channel selection approach, distinctive features and classifier design, decrease the computational cost, offers faster results and eliminate possible over–fitting resulting from processing all available channels.

Minimized classification errors with reduced computational time can be achieved by using EEG effective channel selection [42]. Several techniques of EEG electrode selection have been introduced in several studies. These methods in general fall under two categories, namely; static and dynamic channels selection [43], the static ones select a fixed channels for seen and unseen data, whilst other approaches are based on a dynamic selection of EEG channels.

Signal statistic characteristics like variance and entropy, can be computed and efficiently employed for channel selection. This approach provides four trends for relevant EEG channel selection, where the common thread is that, they are all based on EEG signal statistics. Duun–Henriksen *et al.* [44] developed various channel selection schemes based on a mixture of statistical criteria namely; **variance–based selection** (The three channels at maximum variance were kept for signal classification), **difference in variance–based selection** (channels were chosen based on the minimum difference of variance.). After channel selection, a feature extraction process based on wavelet transform was applied on the pertinent channels, then a non–linear radial basis kernel–based support vector machine (SVM) was used for seizure detection on iEEG data with 59 ictal epochs and 1419 h, recorded from 10 patients. Finally, their results show that, the appropriate channel selection method is the one based on maximum variance during ictal activity, which reached a sensitivity of 96 % using three channels.

Faul [45] applied another statistical measure, which is the probability of a seizure in a channel provided by the real–time EEG analysis for event detection (REACT) system developed by Temko et al [46] as a mean for pertinent channel selection, aiming to decrease the computational effort, He affirmed that this latter (computational efforts) can be minimized up to 65 % with no influence on the seizure detection performance (96%, 94% for both used databases).

A new dynamic channel selection system for multichannel EEG data classification was proposed by [47]. The purpose behind developing such method, is to facilitate the avoidance of data artifacts for the multiple channels, and the selection of pertinent ones (channel(s)) for each segment. The proposed method was inspired from the multiple classifier behaviour concept, which, enables the dynamic identification of needed channels and provide more precise results in comparison to the traditional static models.

A solid and patient–specific sequential forward search system (RSS–SFSM) for effective channel selection was implemented by [48] who performed two strategies for attributes extraction, four classifiers with several parameters, and two channel selection systems, to identify epileptic–seizure and seizure–free epochs. They employed the fewest number of EEG electrodes and obtained the least possible error rate, they tested their model on a well–known CHB–MIT dataset.

More recently, Moctezuma and Molinas [49] developed a multi–objective optimization approach for electroencephalographic (EEG) relevant channel characterization on the basis of non–dominated sorting genetic algorithm (NSGA) for seizure and seizure–free classification. They evaluated their model on EEG signals that have been recorded from 24 patients and collected to form the public and well known CHB-MIT database. They started by decomposing these EEG signals(each channel) into several frequency bands by means of two processing methods namely; the empirical mode decomposition (EMD) and the discrete wavelet transform (DWT), after that for each of th resulting sub–band four attributes (energy and fractal dimension values) were extracted. The resulting feature vectors were then used to address two unconstrained aims by NSGA–II or NSGA–III; to enhance classification correct rate and to minimize the number of the processed EEG channels. Their findings have shown a perfect accuracies of up to 100% when using one single EEG channel. Interestingly, when processing all available EEG channels, the accuracies achieved were lower in comparison to the ones reached when only effective EEG channels were kept by NSGA–II or NSGA–III. consequently, the obtained results are hopeful and confirm the fact that epileptic seizures can be correctly detected by means of few electrodes.

The challenge of reducing EEG data dimensionality through feature selection continues to be a focus of ongoing research. Numerous techniques, such as the Hilbert

Transform, Hessian Local Linear Embedding [50], PCA, ICA, K-PCA, and isometric feature mapping [51], have been explored in recent years to enhance EEG analysis across various applications, including Alzheimer's disease diagnosis, motor imagery BCI, sleep stage classification, and epilepsy diagnosis.

In their study, Chen*et al.* [52] applied an autoregressive moving average model to analyze EEG dynamics, achieving 93% and 94% accuracy rates on the publicly available Bern-Barcelona and CHB-MIT EEG databases, respectively. Their approach also demonstrated efficiency in processing time, taking only 0.317 seconds with an SVM classifier.

In another investigation, Wail*et al.* [53] developed a method for detecting epileptic seizures using 54 different mother wavelets within the discrete wavelet transform (DWT). Several statistical features were extracted from the resulting DWT coefficients, and a Genetic Algorithm (GA) was employed to reduce the feature space. The study found that an Artificial Neural Network (ANN) performed better than other classifiers for epilepsy detection, though the specific mother wavelet most suitable for the analyzed EEGs was not identified. To enhance classification performance and reduce processing time, Zubair *et al.* [54] introduced subpattern PCA and cross subpattern correlation dimensionality reduction techniques. By utilizing DWT in EEG recordings, they identified features characterizing epileptic episodes, achieving 97% and 98% accuracy for the SPPCA and SUBXPCA methods, respectively.

Keyvan *et al.* [55] introduced a technique aimed at reducing EEG data in a patient-specific manner by selecting the most informative and relevant intracranial EEG (iEEG) channels. This method was designed to lower computational demands, achieving an average data reduction of 68%.

Amiri *et al.* [56] recently developed a method for automated seizure detection in EEG signals. Their approach employed the adaptive short-time Fourier transform alongside sparse common spatial pattern (sCSP) to pinpoint channels with epileptic activity. A linear classifier was then utilized to differentiate between seizure and non-seizure epochs in the CHB-MIT EEG Scalp database, yielding an impressive accuracy of 98.81% while also reducing computational time.

On the other hand, now days, digital telecommunication technologies (television, internet, fiber optics, computers, smart phones, satellite...etc) are filling our homes, offices, cars, and even our streets, they are a part of our daily lives, in way that their ubiquity often goes unremarkable. Therefore, the advancement of these technologies is an obvious confirmation that we are living in the midst of a dramatic information and communications revolution that is radically reshaping the way we live, work, provide services, learn, spend leisure time. Automatically, the classical health care is also changing, where the effectiveness of this technological advancement on health industry can be seen in the flourishing field of telemedicine, which provides health care services remotely.

The telemedecine has notably changed and improved storage, retrieval, and use of biomedical information in several medical fields, particularly in neurosciences, where, this latter application in epileptology was proposed two decades ago [57]. Nevertheless, up to now, the literature has recorded few remote neuro–applications

and thus the tele–epileptology is yet far from being standard.
Telemedecine offers virtual environment for neurologists collaboration known also as tele–expertise. Remote consultation and surveillance of epileptic patients by their medical staff, independently to their physical presence [58]. Thus, distant patients and urgent cases, can benefit of remote high–quality medical services. Tele–EEG, represents a telemedicale EEG analysis environment that manages local patient database, including EEG data files [59]. Remote real–time video–EEG consultation [60]. Besides, the smart phone applications for epilepsy care, such as epilepsy society app and my epilepsy diary [61].
Moreover, diagnosis of epileptic troubles in children, frequently require the intervention of pediatric neurologist (epileptologists), and that represents such an impossibility for those living in rural zones and under socioeconomic levels [62]. To address this issue, the University of Kansas Center for Telemedicine and Tele–health (KUCTT), represents an example from real life of applying remote pediatric neurology, this clinic organized each Tuesday per a month from 1:00 pm to 4:00 pm, a synchronized (real–time) videoconferencing equipment, which consists of an expert (pediatric neurologist), an on–site manager, who guarantees the appropriate functioning of the tele–session, and assists the camera positioning for a precise and correct examination, besides a distant manager who aids the patient and his family in the use of this technology [63].
In addition, few recent studies addressed this geographic issue through an implementation of modern telemedical channel for EEG transmission and classification into normal or epileptic recordings, which helps in speedily and accurately diagnosing patients without obliging them or their doctors to travel [64]. Multiple–input, multiple–output orthogonal frequency–division multiplexing System for transmission of electroencephalogram signals and linear discriminant analysis for their classification, has been recently joined to form a telemedical application [65].
Edward Molina *et al.* [66] developed a system designed to significantly reduce the time neurologists need to spend analyzing EEGs for epilepsy diagnosis, cutting the time required by about 65–75%. This system is also applicable in a tele-health setting.
In a study by Athar *et al.* [67], an encrypted EEG data classification and recognition system was developed utilizing the Chaotic Baker Map and Arnold Transform algorithms in conjunction with Convolutional Neural Networks (CNNs). The method involves first converting the EEG time series from each channel into a 2D spectrogram image, which is then encrypted using the Chaotic Baker Map and Arnold Transform. These encrypted images are subsequently processed by CNN-based Transfer Learning (TL) models. The experimental results demonstrated that this approach, when applied to the publicly available CHB-MIT dataset, yielded satisfactory performance using the GoogLeNet model with the encrypted EEG images.

Upon a comprehensive examination of the mentioned studies, it is evident that utilizing wavelet analysis for non-stationary signals, such as EEG, proves to be an effective approach in epilepsy detection with consistently high accuracy values. However, the scrutiny of these cutting-edge research papers has brought to light three primary research gaps.

Firstly, there exists a potential risk of generating misleading high accuracy and overfitting issues when processing multichannel EEG signals from all available channels. This not only introduces a high-dimensional dataset but also poses computational challenges, leading to increased processing time.

Secondly, there is a notable need for a paradigm shift in the field, emphasizing not only the detection of epileptic seizures but also the precise identification of their source. Such a shift is paramount for advancing patient care, as pinpointing the source facilitates more effective seizure control measures and opens avenues for ictal-free surgical interventions.

Thirdly, it's noteworthy that all the referenced telemedical systems cater to 60% of epilepsy patients who can achieve complete control with drug therapy. However, 40% of individuals with epilepsy face the challenge of pharmacoresistant epilepsy, denoting an inability to achieve seizure control through initial medication trials. This subset of patients may become candidates for seizure-free surgery, underscoring the critical need for precise localization of the epileptogenic focus as a primary treatment consideration. Thus, there is a growing demand for asynchronous telemedicine applications specifically tailored to the needs of this pharmacoresistant category. The development of telemedicine tools that allow timely and flexible interactions between healthcare providers and patients with drug-resistant epilepsy becomes essential for optimizing their care and treatment outcomes.

In the pursuit of addressing the aforementioned gaps in existing research, our thesis endeavors to make significant contributions to the field of epilepsy detection. The primary objective of this study is to surmount the challenges inherent in current methodologies, particularly those associated with multiple EEG-channel techniques. Our innovative approach centers on the development of an EEG-type-independent system for epilepsy detection, integrating wavelet transform alongside supervised and unsupervised machine learning techniques. The focal points of our research involve tackling issues related to high dimensionality and achieving precise localization of the epileptogenic focus. Our proposed system comprises two synergistic subsystems: the Representative EEG Channel Creator (RECC) and the Seizure Affected EEG Channel Detector (SAECD). The RECC is dedicated to enhancing the dimensionality reduction of EEG data, thereby facilitating improved and expedited epilepsy pattern detection. Subsequently, upon a positive response from the RECC indicating an epileptic EEG, the SAECD subsystem is activated. This subsystem employs the Energy-to-Shannon-Entropy ratio and a k-means clustering approach to pinpoint the epileptogenic focus and map the path of seizure diffusion within the brain. To validate the effectiveness of our proposed system, comprehensive evaluations and comparisons with existing studies are conducted. Through these assessments, we aim to demonstrate the efficiency and advancements offered by our novel approach in epilepsy detection.

Furthermore, our study aligns with the critical need for asynchronous telemedicine applications, particularly tailored to individuals with pharmacoresistant epilepsy. As a part of our broader objectives, the second goal involves the creation of a dedicated telemedicine platform named Epileptica. This platform is specifically designed to cater to individuals facing pharmacoresistant epilepsy. The results of epileptogenic focus detection (EFD) provided by our innovative SAECD subsystem can be seamlessly relayed to healthcare professionals through the Epileptica telemedical application. This asynchronous application, serves to support neurologists in determining whether a patient is a viable candidate for seizure-free surgery, thereby enhancing patient care and treatment outcomes.

The five chapters that make up this thesis provide pertinent details about our research area. These latter are arranged in the following way:

**Chapter 01**

This chapter offers a concise overview of the structural aspects of the human brain, delves into electroencephalography (EEG) as a method for observing brain activity, and explores the impact of ictal activity on EEG recordings.

**Chapter 02**

This chapter centers on the concept of time scale analysis through the application of wavelet transform, emphasizing its efficacy in analyzing non-stationary signals, particularly the EEG datasets under investigation.

**Chapter 03**

This chapter offers an in-depth exploration of significant features in EEG signals, along with an overview about current classification methods. Special emphasis is placed on the features proposed in this study to augment the efficacy of detecting epileptic seizure and epileptogenic focus circumscription.

**Chapter 04**

This chapter provides a concise discussion of telemedicine, outlining its applications, advantages, and its notable impact on the field of neurosciences, particularly in the domain of epileptology.

**Chapter 05**

This chapter comprises two integral parts, each delineating sophisticated methodologies and cutting-edge technologies in the domain of epilepsy detection and characterization.

In the initial part, a comprehensive exposition unfolds, elucidating the adopted approach for epilepsy detection and epileptogenic focus circumscription. This involves meticulous considerations in mother wavelet selection, the extraction of engineered features, and the reduction of EEG dimensionality. The strategic amalgamation of these elements aims to achieve heightened accuracy and sensitivity in discerning epileptic patterns within electroencephalogram (EEG) signals.

The second part introduces an asynchronous client–server application named "Epileptica." Engineered to facilitate remote access to the outcomes of epileptogenic region detection, Epileptica stands as our contribution in investing technology into the realm of epilepsy research. This technologically advanced application enhances accessibility and collaboration, fostering the seamless dissemination of critical information pertaining to the detection results of epileptogenic regions.

**Appendix A** represents a user-friendly application crafted within the MATLAB graphical user interface (GUI) environment, aimed at optimizing both ease of use and operational efficiency in the domains of epilepsy detection and the precise circumscription of epileptogenic focus.

**Appendix B**

Provides further facts and information regarding the programming language used to create Epileptica in addition to the communication protocol.

**Appendix C**

Lists the scientific works that were accomplished in conjunction with this thesis study on a national and international level.

# Chapter I

# Neurology & Electroencephalography: a Brief Introduction

Significant endeavors have been dedicated to the exploration of the human brain, an intricately interconnected organ that exercises comprehensive control over the various facets of our physiological functions, consciousness, actions, thoughts, and desires. This overarching dominion over human cognition and behavior is orchestrated through a diverse array of cerebral activities encompassing electrical, metabolic, chemical, and hemodynamic processes [68].

The brain constitutes of billion nerve cells called neurons, connected to each other within a sophisticated cerebral network. During their function, these neurons generate an electrical activity, which can be recorded and visualized under the form of a complicated graph called electroencephalogram (EEG). Its name (EEG) is related and taken from the term Electroencephalography, which is a technique that serves to measure and record the potentials resulted from the brain neurons activity. This latter, represents the first step to be performed for a medical diagnosis in neurology field, in order to clearly understand the brain mechanism and recognize its dysfunctions.

This chapter is divided into four principal sections. The first **Section I.1**; Brain anatomy, offers a succinct introduction of the fundamental concepts of the human brain anatomy and physiology. More detailed information about the central nervous system and the cerebral neurons network function are presented in **section I.2**. While the emphasis will be on the human brain electrical dysfunction, disorder or also called brain chaos: The epilepsy. Its international clinical definition, besides the types of seizures and their consequences on the patient body are introduced in **section I.3**. Finally **section I.4**, was reserved for the Electroencephalography, which is a reliable technique for the identification and diagnosis of normal brain function and its diseases.

## I.1 Brain anatomy

The human brain, the most sophisticated organ of the entire body, resides within the cranial vault that provides it protection. Its weight increases from birth until adulthood. The average weight for an adult is about 2% of the body weight [1400 to 1800 grams] [69].

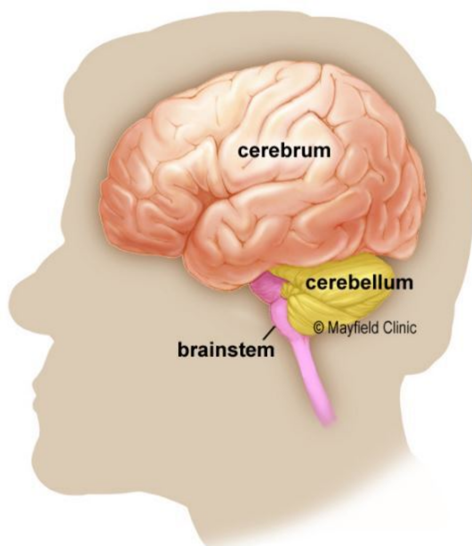



Figure I.1: The human brain. Source [70]

### I.1.1 Brain components

The human brain consists of three principal components; the cerebrum, the brainstem and the cerebellum [71] as illustrated in Figure I.1.

**The cerebrum** occupies a large part of the brain and consists of two halves (hemispheres) bathed in the cerebrospinal fluid. These latter are joined by inter–hemispheric commissures and the diencephalon. Each hemisphere is divided into four lobes namely; frontal, temporal, parietal and occipital, delimited by fissures (lateral, pre–occipital, calcarine and parieto–occipital fissures) [72].

**The cerebellum** or regulator, situated directly under the cerebrum. This latter, is responsible for maintaining the balance and coordinating voluntary movements.

**The brainstem** represents the lower extension of the brain, placed in front of the cerebellum and connected to the spinal cord. It is composed of three structures namely: the mid brain, pons and medulla oblongata. It acts as a connection station, transmitting messages between several parts of the body and the cerebral cortex.

### I.1.2 Brain lobes

The brain hemispheres are divided through fissures into lobes; frontal, temporal, parietal and occipital. Each lobe is composed of several areas and responsible of specific functions. However, there is a very complex relation between lobes and the left and right hemispheres [72].

**Frontal lobe**

Represents the largest brain lobe. It is the source of reasoning and responsible for various functions; planing Behavior, personality, problem solving, speech, writing and self awareness...etc. Besides it enables voluntary motor coordination (motor strip).

**Parietal lobe**

The Parietal lobe is responsible of sensory perceptions awareness; touch, pain and temperature. It decodes words, languages, visions, sensory and memory...etc. Moreover it ensures the visual perception.

**Temporal lobe**

This lobe as the parietal one is also involved in the perception of sensory strip. It plays a pivotal role in various principal functions, including memory formation, auditory processing, language comprehension, and aspects of emotion regulation.

**Occipital lobe**

Situated at the back area of the hemispheres. This lobe is responsible of decoding information from the visual system; light, color...etc.

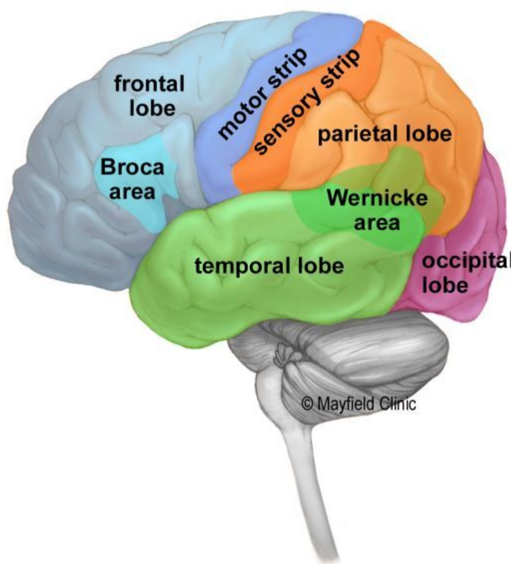



Figure I.2: The human brain lobes. Source [70]

## I.2 Central Nervous System (CNS)

The central nervous system or nervous axis (neural) is composed of the brain and the spinal cord. The white and gray substances represent the two types of tissue of this system. The gray matter is made up of the cell body of neurons, it represents the superficial part of the spinal cord. While the white matter, fills the internal part of the brain and contains axons and dendrites which ensure the transmission of information. These latter (information) will be interpreted and processed in the gray matter [68, 72].

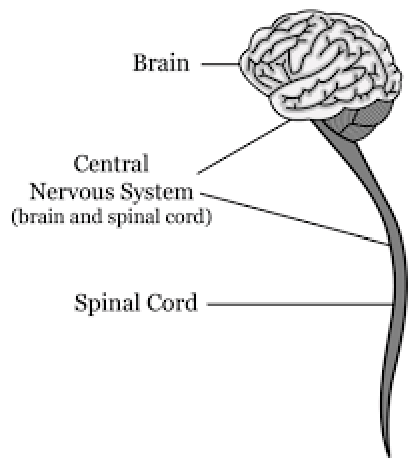



Figure I.3: The central nervous system (CNS): Brain and Spinal cord. Source [73]

The brain contains approximately 100 billion nerve cells known as "neurons" Figure I.5, which form an integrated and very exact unitary network cable that maintained the electrical charge of the brain. Neurons are of various shapes and sizes but of common characteristics and all consist of three elementary parts: the soma (cell body), the axon and the dendrites as shown in the Figure I.4. Their electrochemical aspect enable them to transmit electrical messages to each other along distances [68, 72].

The cell nucleus represents the heart of the soma. The axon is the slender portion or the long outlet of the neuron that connects its nucleus with the dendrite of the next neuron. The dendrite is the shorter structure of the neuron with umpteen receptors. The synapses represent the intermediaries or the biases by which the neurons communicate with each other as shown in Figure I.5 [75].

The axon–dendrite link enables neurons communication. The axon is the transmitter of nerve impulses throughout its extension until the synaptic termination. The neuron produces chemical substances in the synaptic cleft (space separating two nerve cells) depending on the frequency of the nerve flow arriving. These substances are called the neurotransmitters and carried by vesicles. When the nerve impulse arrives, they will be released in the synaptic melt (extra-cellular medium)

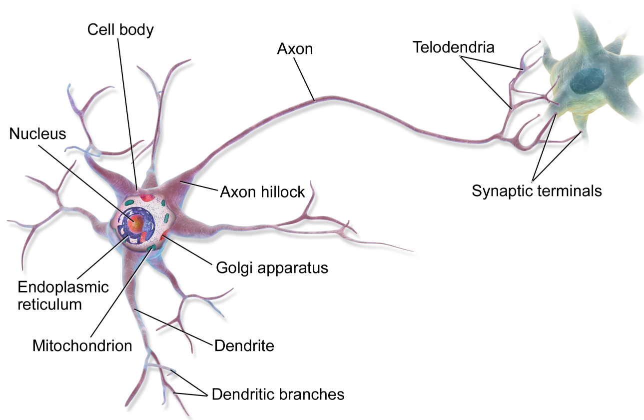



Figure I.4: Neuron anatomic structure. Source [74]

to inhibit or activate the receptor neuron at its cellular body. Then the nerve impulse continue its way by the same procedure from one neuron to the other until the required destination [75–77].

The inter–neuron communication system explained in the previous paragraph represents the normal electrical flow, its dysfunction or alterations in neurons synchronization due to an abnormal excitation of a large number of nerve cells causes a neurological pathology known as **epilepsy**, which will be detailed in the next section.

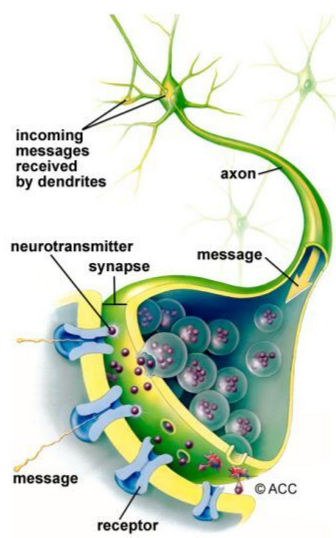



Figure I.5: Neuron and synapse: Neurotransmission. Source [70]

## I.3 Epilepsy

Recently, the epidemiology studies have disclosed that around 70 million peoples worldwide suffer from the epilepsy disease. With 85% of them belonging to the third world countries. The epilepsy, as defined by the World Health Organization, has its name derived from the Greek word 'epilambanein,' which conveys the idea of an attack or behaving violently and harshly during a brief seizure. The epilepsy is a clinical status typified by the incidence of the paroxysmal phenomena (seizures) which corresponds in pathophysiology to transient excitation of the cerebral nerve cells [78]. The epilepsy is also defined as a neurological disease that affects all or a part of nerve cells. These epileptic seizures are characterized by a sudden repetitive abnormal electrical discharges, which leads to an abnormal and uncontrollable behavior [79]. The electroclinical analysis of the epileptic seizures established in 1981 an international classification of epileptic seizures into two broad categories; generalized or partial seizures (Focal) as shown in Figure I.6 [80].

(a) Focal seizure

(b) Generalized seizure

Figure I.6: Types of epileptic seizures. Source [81]

### I.3.1 Generalized Epileptic Seizures

The epileptic seizure is called generalized if the two cerebral hemispheres are affected by a paroxysmal discharge that leads to a loss of consciousness. There are more then four types of generalized seizures [82].

#### Absence seizures

This type of seizures known also as petit mal, often affects children under the age of 10. An absence means a loss of consciousness for a few seconds accompanied by almost with eyes movements: eyelids shaking in case of typical absences while the atypical absences are characterised by Limb movements. These absences can occur from one to several times during the day [82].

**Myoclonic seizures**

Myoclonic seizures are characterized by muscle contractions translated into a strong and uncontrolled shaking of the limbs: arms and legs [82].

**Atonic seizures**

These atonic seizures called also drop seizures, affect almost; the trunk, jaws and head, resulting in traumatic sudden falls, due to the unexpected loss of muscle tone. Within a few seconds the person regains consciousness if the fall has not caused complications that requires other procedures [82].

**Clonic seizures**

The clonic seizures represent an exceptional case of myoclonic seizures, in addition to all the complications engendered by this latter (myoclonic seizure), it stimulates the salivary gland [82].

**Tonic–clonic seizures**

The tonic–clonic seizures or grand mal seizures, are the most complicated type of epileptic seizure. It starts by person falling and consciousness loss, then limbs stiffening, rolled back eyes, breathing stop about 10 seconds. Then limbs tremulations about 30 seconds with urine loosening. This status represents a 3rd level of coma [82].

## I.3.2 Focal Epileptic Seizures

In this type of seizures, the paroxysmal discharge does not affect the entire brain but a particular part recognized in neurology field as "Epileptogenic zone". There are two types of partial (focal) seizures [82];

**Simple partial seizures**

The simple partial seizure affects a small area of the brain. During this latter, the person keeps his consciousness but without being able to control the effects caused by the affected area of the brain. simple partial seizures can affect movement (eyes and head), emotions and sensations (hallucinations) [82].

**Complex partial seizures**

This type of seizure is generally located in the temporal lobe and recognized as psychomotor seizures. The person with this attack may lose or remain approximately conscious, can behave in a strange way or walk aimlessly. The complex partial seizure lasts up to a minute or two [82].

### I.3.3 Epilepsy Diagnostic

The first means that serves to directly highlight the epileptic activity and enables its exploration and diagnosis is the **Electroencephalogram (EEG)**. The electroencephalography is a technique that serves to directly record the electrical activity produced within the human brain. this technique will be explained in the next section [83].

## I.4 Electroencephalography

Electroencephalography is a technique used to visualize and record the brain's electrical activity, producing a tracing commonly known as an electroencephalogram (EEG). The origins of this invention trace back to 1929, when Dr. Hans Berger, a German psychiatrist, first recorded brain activity using a rope galvanometer and a set of electrodes strategically placed on the scalp [84].

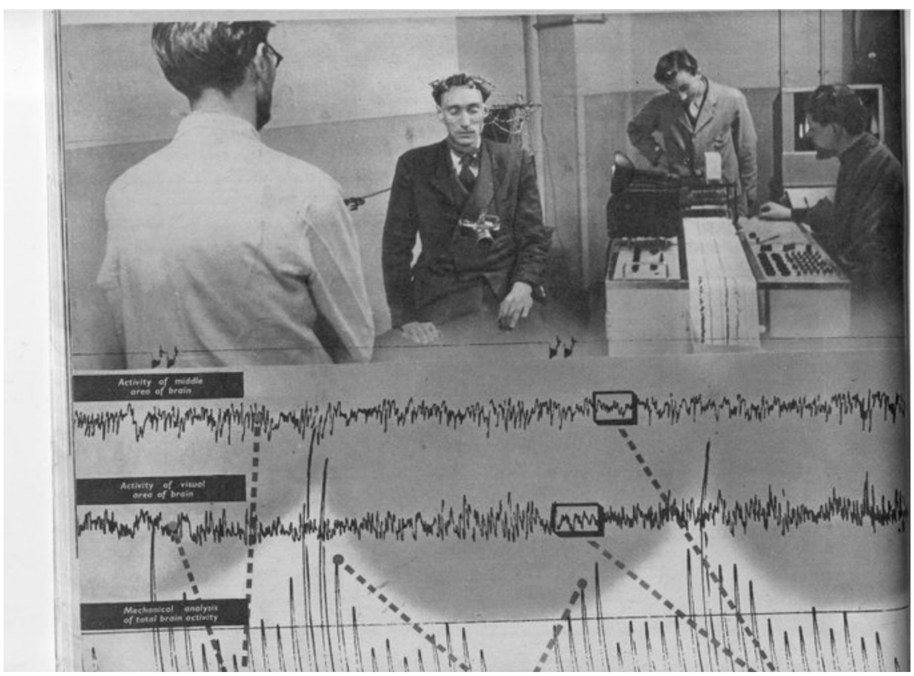



Figure I.7: The electroencephalography (first recording of brain electrical activity by Berger). Source [85]

Since the 1950, the electroencephalogram has been established as the first examination to be carried out for neurological abnormalities diagnosis [86].

### I.4.1 Electroencephalogram (EEG)

The term electroencephalogram reflects the graphical translation of the electrical activity generated in the brain nerve cells. This signal is beneficial to study and explore the brain activity and to diagnose and recognise the neurological disorders such as; epilepsy, autism, Alzheimer..etc. The EEG signal represents the difference in potential resulting from some electrodes suitably placed on the scalp, it is of the order of some micro–volts, where the age and the status of the examined person generates modifications on the obtained EEG tracing. Berger's first EEG recording shows that its aspect changes according to the person's state of consciousness( sleep, awake, closed eyes..etc.). Studying the brain electrical activity, through the electroencephalogram records, divulges that the EEG potentials of humans are of complex aperiodic and unpredictable aspect, with irregular eruptions of oscillations, which are categorized in nominated bands called brain waves, namely; $\delta$ [0–4] Hz, $\theta$ [4–8] Hz, $\alpha$ [8–16] Hz, $\beta$ [16–32] Hz and $\gamma$ [32–64] Hz [87, 88].

#### Delta Brain Wave

During the deep sleep, the neurons do not process any information, they are stimulated by a periodic and constant nervous flow, which makes the synchronization strong, this activity is reflected on the electroencephalogram by a slow rhythm of low frequency [0-4] Hz and a high amplitude, recognized as Delta brain wave [88].

#### Theta Brain Wave

The Theta brain wave represents the dominant rhythm during the hypnagogy status (daydreaming), it occurs in the EEG signal with a frequency of [4–8] Hz and a magnitude almost greater than 20 microvolts [88].

#### Alpha Brain Wave

The Alpha rhythm reflects the phase between consciousness and subconsciousness. It is a regular rhythm obtained during a state of relaxation with closed eyes, disappears once they are open. The Alpha rhythm is characterized by a frequency between [8–16] Hz and an amplitude of [30–50] microvolts. Its source is the occipital lobe and cortex [88].

#### Beta Brain Wave

This fourth rhythm appears during a full physiological neurons activity status such as problem solving, decision making and information processing ... etc. Its source is the temporal, occipital and frontal lobes. The beta rhythm is typified by a frequency between [16–32] Hz and an amplitude of [10–30] microvolts [88].

**Gamma Brain Wave**

The gamma waves [<31]Hz can be generated from any part of the brain. These latter, reflect the synchronized processing of information from different regions of the brain [88].

### I.4.2 Electroencephalogram Acquisition

A specific number of small size discs known as electrodes are neatly and accurately placed on several locations of the scalp surface with interim glues. Then each pair of electrodes are connected to an amplifier and an electroencephalogram recording machine. At the end, the brain electrical activity is visualized as wavy lines on a computer screen. EEG recordings, according to their application, can be about 1 to 256 electrodes, each pair of electrodes represents one channel and produces a signal, consequently, the electroencephalogram is of multi–channels recordings [89].

**Electrodes**

The electrodes, Figure I.8 are small conductive elements attached to a digital recorder. They ensure restricted and stable contact with the scalp. The EEG electrodes are of various types, namely: disposable, reusable and needle electrodes [89].

**Disposable Electrodes**

Disposable EEG electrodes, shown in Figure I.8a, are widely employed, due to their quick and easy application. However, they are are of a large size, which decreases their performance within scalp regions with thick hair. These discs are attached to a cable or wire that connects to a recording device. These small electrodes consist of a silver chloride rod, covered with an artificial foam wrapped in a fabric (thread or cotton) forming the tampon. The use of a rubber helmet helps to keep them straight on the scalp. To ensure the continuity of the electrical transmission During the electroencephalography examination, it is necessary to regularly soak saline water carefully (an electrolytic liquid 10g of single / L), an overdose of salt can cause complications for some sensitive skins.

**Reusable Electrodes**

Reusable EEG electrodes, Figure I.8b, are of small size in comparison of the disposables discs, consequently, they overcome the thick hair impediment. These latter, can be constructed with several metals that easily conduct current such as gold, silver and tin, which make them more costly, but they are almost durable. As the disposables discs, the reusable electrodes They are maintained with headbands, and they have to be cleaned guardedly after each use.

(a) Disposable electrodes

(b) Reusable electrodes

(c) Needle electrodes

Figure I.8: Types of electrodes (discs) for EEG acquisition. Source [90]

**Needle Electrodes**

These electrodes, Figure I.8c, are employed for intercranial (subcutaneous) application, their needle ends in silver or in stainless steel, allows them to be introduced at a well–defined extension of [0.5–1] cm in the thickness of the scalp. Needle electrodes are often used in cases of deep comas, hence the need for conductive elements which ensure optimum quality of electrical contact and almost constant. These discs are expensive and they can also be used in case of brain surgery.

### The International 10–20 Electrode System

The electrodes placement over the scalp is an important point, to insure that, the brain electrical activity is recorded correctly. The Jasper system for placement of electrodes on the scalp was introduced in 1958 [91] and standardized by the international neurology organization under the famous nomenclature **The 10–20 system**. In this system each electrode has a name and a number, while the **10** and

**20** refers to the distances between adjacent electrodes, which is either 10% or 20% of the hole font–back or right–left of the skull. From where the first Fronto–polar point is at a distance of 10 % of the nasion and the inion, as well as the last point located at the occipital lobe. The other points which follow are at a distance of 20% from each other. A specific name (one or two letters) that represents the lobe on which the electrode is placed; (F) (P) and (O) for frontal, parietal, occipital lobe respectively, with (C) which designates the center and (Fp) for frontopolar. The number is used to identify the position of this electrode on one of the hemispheres; pair for right hemisphere, odd for left hemisphere. An EEG signal is recorded from the difference between the voltages at two discs. The EEG signal can be monitored with the several montages, Figure I.10

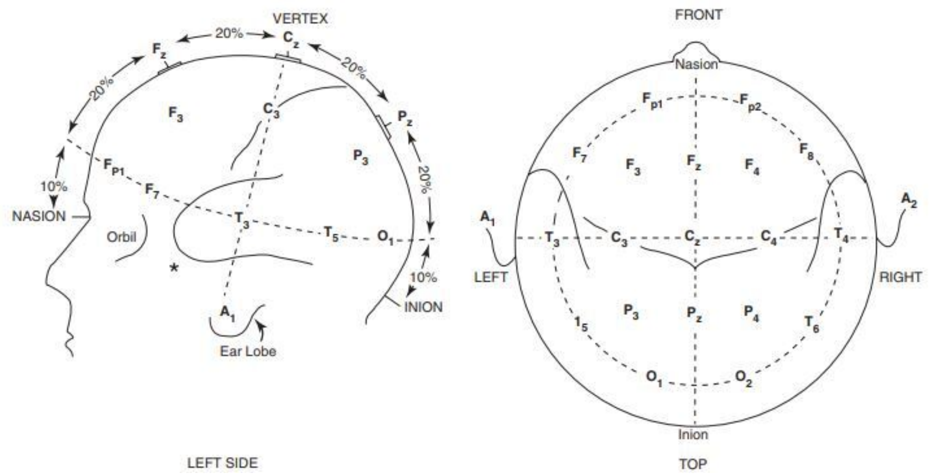


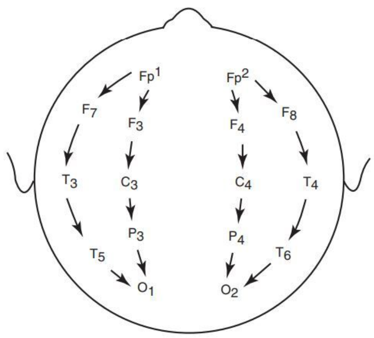

Figure I.9: The international 10–20 system for positioning electrodes on the scalp. Source [92]

### Bipolar Montage

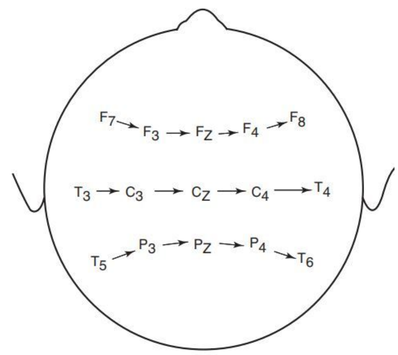
In the bipolar montage, the potential difference is estimated by the sum between two active electrodes; no reference or neutral electrode. The bipolar montage performs a cerebral exploration from front to back as in Figure I.10a, which is called the longitudinal bipolar montage and from the right to the left side as in Figure I.10b, which is known as transversal bipolar montage [89, 93].

### Referential montage

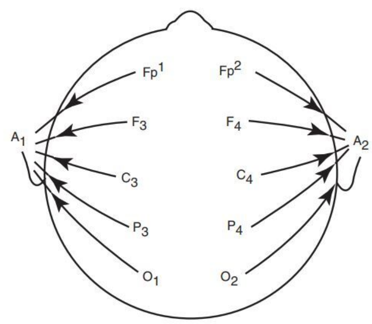
In this montage, an electrode is selected to be used as reference (neutral electrode), then each channel represents the difference between an other electrode and this reference. The choice of the disc to be used as reference is not specified, the midline positions are usually selected, due to the fact that they do nit apply any amplification of the signal in one side of brain (hemisphere) regarding the other hemisphere. Moreover, we can find the well known **linked ears** reference as shown in Figure I.10c, which represents the average of discs linked to earlobes and mastoids [89, 93].




(a) Longitudinal bipolar montage




(b) Transverse bipolar montage




(c) Referential ear montage

Figure I.10: Types of EEG montages. Source [94]

**Average Reference Montage**

In this type of montage, the outputs of the employed amplifiers are summed and averaged, the resulting signal from this operation is utilized as reference for each of the placed electrodes [93].

**Laplacian montage**

The Laplacian montage, consists to make up a channel by taking the difference the difference between a disc (electrode) and a weighted average of the remaining encirclement electrodes [89, 93].

The EEG signals can be viewed via an EEG monitoring device in whatever montage desired.

**Electroencephalography exam**

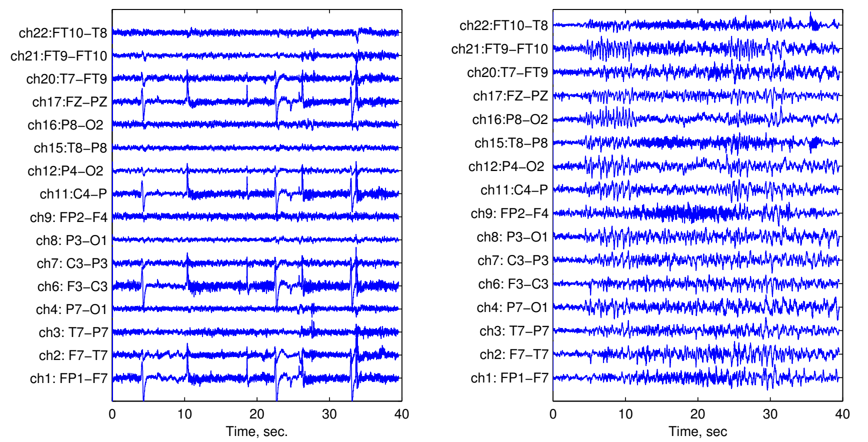
Before placing the electrodes it is necessary to strip the scalp with a paste, recognized as "conductive paste", going through this step is necessary to reduce the impedance skin–electrodes to less than 5000 ohms, this rule has been standardized for the electroencephalogram exam [89, 95]
When placing the electrodes on the scalp, it is of primary importance to ensure that they are symmetrical and at same distance from front to back and from right to left, respecting the distances standardized by the union of neurological societies « 10–20 system » detailed previously.
All electrodes are attached to an input box via a connection wire.
The EEG signals are in the order of a few microvlots, hence the need to go through an amplification system to visualize them.
The noise generated by the electric current can be eliminated by an analogical filter of 50 Hz.
An analog to digital conversion, with a sampling frequency suitably chosen while respecting Shannon's theorem. Then a system for viewing and recording the collected signals.

## I.5 Electroencephalogram Data

The robustness and efficiency of algorithms can be evaluated using a well–collected database. For this reason, data used in this analysis were chosen based on results from recent research studies that reported successful seizure classification with satisfying accuracy values [88, 96].

### I.5.1 CHB–MIT Scalp EEG Database

,
The CHB–MIT Scalp EEG Database was assembled at Boston Children's Hospital. It is made up of pediatric EEG recordings from patients with stubborn epileptic seizures. These patients were monitored for few days following anti–epileptic medications in order to typify their seizures and evaluate their candidacy for surgical intervention. 23 subjects (5 males, aged from 3 up to 22 years old; and 18 females, aged from 1.5 up to 19 years old). Case chb–21 was recorded from the same female patient (chb–01) after 1.5 years). Case chb–24 was appended to the collection in Dec. 2010 [97].
Due to the employed hardware limitations, some gaps between successively numbered EEG.edf files were resulted. Consequently, signals were not recorded in this duration. Generally, the gaps are approximately, about 10 seconds or less, but in some cases, they can be more longer [97].
Recordings original dates and subjects personal information, (protected health information (PHI)), has been replaced with substituted ones. The majority of numerical EEG.edf recordings are exactly of one hour. While, those appertaining to case chb–10 are two hours long, besides; chb–04, chb–06, chb–07, chb–09, and chb–23




(a) Non–seizure (b) Seizure

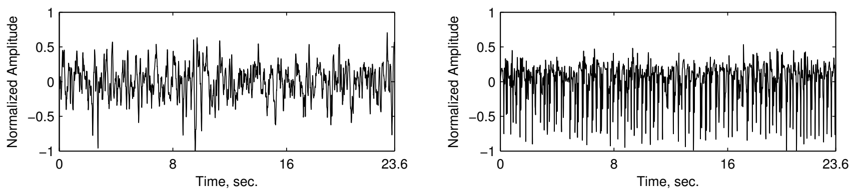
Figure I.11: CHB–MIT EEG Scalp Database: a, Record No.01–01, b, Record No.01–03 (16–Channels), (No EEG signals in channels: 05,10,13,14,18, and 19)

files, in which recordings last four hours long. Note that, files containing epileptic seizures periods are shorter [97].
The 10–20 International system of EEG electrode placement was adopted during the recording of EEG signals of this database. Electrodes are carefully placed over the scalp according to pick up the electrical cerebral activity, which contains significant information about the neurological condition of the brain [97].

Electroencephalograms of the CHBMIT Scalp EEG database were sampled at 256 Hz. This sampling frequency is sufficient to fulfill the Nyquist–rate criterion towards the spectral bandwidth of EEG signals. Signals without epileptic seizures are called non–seizure records and seizure records are those containing one or more epileptic seizures [97].
In Records-with-seizures, the starting ([) and end (]) of each epileptic seizure is annotated in an additional and accessible seizure annotation file. Furthermore, in some records, belonging to case chb–09, other signals are also recorded, such as vagal nerve stimulus (VNS) signal [97].
This database includes EEG signals ranging from 16 common channels to nearly 23 channels. As seen in Figure I.11, we processed these typical channels in each EEG data file.

### I.5.2 Bonn database

This EEG database was gathered from an epilepsy center in Germany [98]. This latter, is made up of Five sets (namely; A to E), each comprise 100 EEG segments of




(a) Normal (b) Seizure

Figure I.12: Bonn EEG Database: a, Set(A),Record N001,b, Record Set(E), Record S001, (single–channel)

one–channel and 23.6–sec duration. These segments were picked out and segmented from long term multiple–channels EEG recordings, after a visual analysis of artifacts such as muscle activity and eye movements.
Sets A and B contain segments recorded from five healthy volunteer subjects, using superficial EEG electrodes placed according to the standardized electrode placement scheme. The volunteers were in an awake state, relaxed and with open eyes (A) and closed eyes (B), respectively.
Sets C, D, and E were collected from a diagnosis archive of pre–surgical EEG recordings of five patients, whom had attained a full epileptic seizures control after an operation of hippocampal resection. Segments in set C and D are an out–of–seizure recordings they contained seizure free intervals and only set E, contained ictal activity.
Bonn EEG signals were recorded using a 128–channel amplifier system, with an average common reference and a sampling rate of 173.61 Hz. Where, the band–pass filter settings were 0.53–40 Hz (12 dB/oct).

In our study, for seizure detection goal, normal (set A) and abnormal (set E) EEG were processed as explained within Table I.1.

Table I.1: *Databases description*

| | **Bonn** | | **CHB–MIT** | | **Total** |
|---|---|---|---|---|---|
| | **Normal** | **Seizure** | **Normal** | **Seizure** | |
| **subsets** | A | E | / | / | |
| **Subjects** | (05) subjects | (05) patients | 23 patients( following anti–epileptic medicines) | | |
| **T. of Electrodes** | Superficial | within the skull | / | | |
| **N. of signals** | 100 | 100 | 24 | 24 | |
| **Sampling frequency (Hz)** | 173.61 | 173.61 | 256 | 256 | |
| | | | | | **248** |

## I.5.3 EEG Contribution in Epilepsy Diagnosis

Since the invention of the electroencephalogram (EEG) in 1929 by Berger, it has established itself as an essential tool in the diagnosis and confirmation of suspension of epilepsy. Since it offers significant details concerning the brain activity background and epileptiform discharges (like spikes and sharp waves), which makes the evaluation of this pathology possible and orientates the prescription of anti–epileptic medication besides when to discontinue these latter [86].

In 1993, Luders et al [99], defined The epileptogenic area or epileptogenic zone as the part of cortex, that is responsible of seizures starting, before its diffusion in local part or the hole brain, and whose disconnection or removal through surgery leads to seizure freedom. Nevertheless, this definition does not take into consideration the time factor influence on this area, ie. in the literature there is an undeniable evidence that the epileptogenic area, can changes over the time and do not keep a static zone in the brain such as the benign focal seizures in children, which start from the occipital area, then this epileptogenic area migrates to the temporal lobe, to disappear at the end in adulthood. This dynamic concept of this area renders the detection of epileptic seizures source more complicated [100]

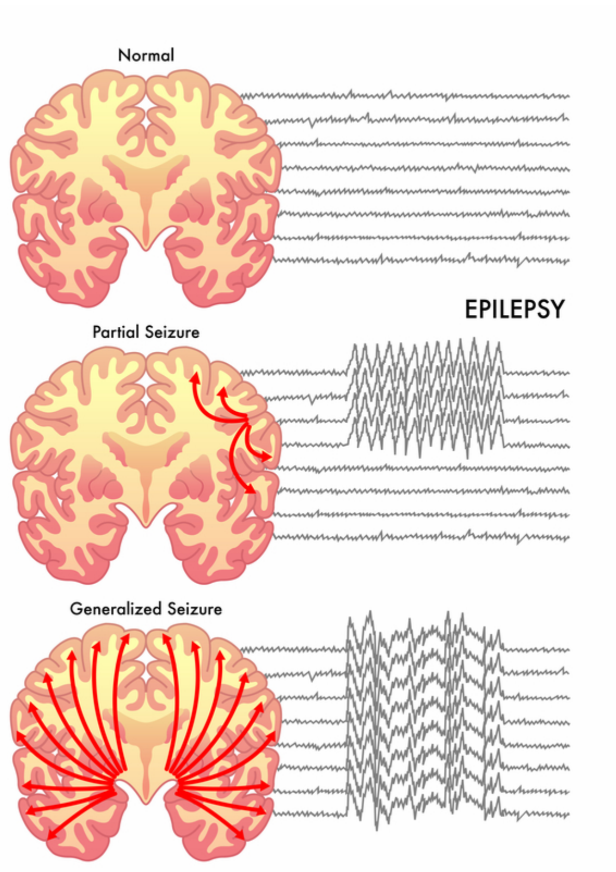



Figure I.13: Relation between epileptic seizures and EEG signal aspect.Source [101]

The EEG aspect helps detecting epileptogenic area as shown in Figure I.13, (ie. if epilepsy is focal, the spikes and sharp waves in a particular area of the EEG, can refer to where the epileptic seizures are coming from in the brain or their inception point for example: parietal lobe). As well as the generalized epilepsy (ie. the spikes and wave discharges propagates over both brain hemispheres, which can be seen in all recorded EEG channels.

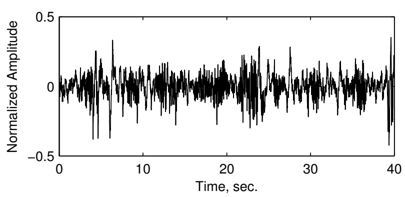
Seizure EEG signal(ictal), can be divided into 4 elementary segments [102], as shown in Figures I.14;

**Ictal EEG**. Which represents the period during the epileptic seizure (please refer to Figures I.12b and I.11b).

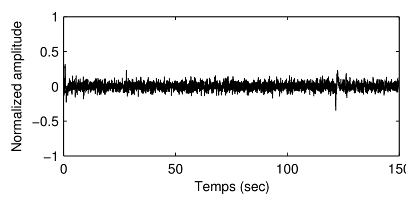
**Pre–ictal EEG**. This EEG segment as shown in Figure represents the period that precedes the seizure incidence.

**Post–seizure EEG**. The postictal slowing effect as shown in Figure I.14b occurs after an epileptic seizure (generalized or localized), it lasts an average of 65 minutes before returning to baseline.

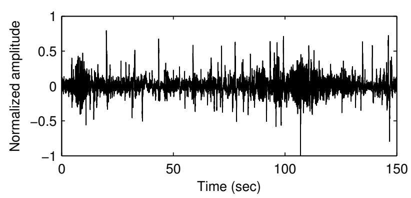
**Inter–ictal EEG**. The termination of a seizure initiates the postictal state, which lasts until the patient recovers to baseline. Thus the Postictal-transition-to-baseline is known as interictal epochs.




(a) Pre-ictal epoch




(b) post-ictal epoch




(c) inter-ictal epoch

Figure I.14: CHB-MIT ictal EEG's epochs.

## I.6 Conclusion

During this preliminary chapter, we have introduced some basic notions of the anatomy and physiology of the human brain. An important part was devoted to represent the Electroencephalography technique, which allows the recording of cerebral electrical variations, resulting from the summation of different potentials produced during a synchronized processing of information by one or a group of nerve cells. Thus, the EEG signals are a unique and essential tool for medical diagnosis of epilepsy. However, it is often complicated to detect the small changes in the aspect of this latter, by a poor visual interpretation. Thus it is obviously substantial to use more powerful tools such as; the signal processing techniques. These precise means provide enough information to help doctors to establish a reliable, quick and accurate diagnosis. The next chapter offers an overview of time–scale signal processing theory.

# Chapter II

# Time–Scale Analysis: Theory of wavelets.

In order to study and control the neurological phenomenon called; brain disorder or epilepsy, we usually have to process the recorded data or the digital measurement known as electroencephalogram (EEG) and extract the information sought. As mentioned in Chapter., the electroencephalography is a technique that serves in measuring the electrical activity within brain nerve cells (neurons) [84]. This graphic recording represents for the neurologist the first step to perform for diagnosis and medicines prescription [86]. Nevertheless, it remains insufficient in some critical status, due to the complicated aspect of the EEG signal and its non–stationary nature [103].

A more precise analysis of EEG signal for epilepsy detection and prediction such as: identifying the epileptogenic area[1], seizure type, duration, severity and pre–ictal phase[2] unseen changes, requires a powerful tool based on non–stationary signal processing techniques, known as time–scale analysis: wavelet transform [104].

This chapter is divided into two principal sections. The first **Section II.1**; Signals: Theory and Classification, which offers a succinct introduction about signals definition, theory and their classification. More emphasis and detailed information about wavelets-based signal processing methods is presented in **section II.2**.

## II.1 Signals: Theory and Classification

We are surrounded by various physical events, including audio, visual, electrical, and mechanical phenomena. The variation of each through the time is called; a Signal. Signals can carry and convey several information [105].

[1]The epileptogenic area: the part of cortex, that is responsible of seizures starting, before its diffusion in local part or the hole brain [99].

[2]Pre–ictal phase: the period that precedes the seizure incidence [102].

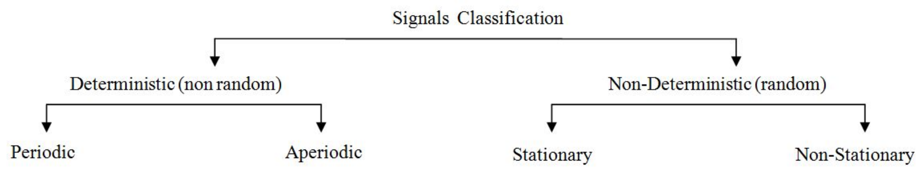



Figure II.1: Signals Classification. Source [106]

In mathematics field, a signal can be defined as a function of one independent variable (time) at minimum. And can be represented graphically via a horizontal and vertical axis (x–axis, y–axis) [105].

In electrical engineering world, the signal is defined as an electrical or electromechanical encoded data. Which is the case in biomedical engineering field. However, this definition remains global since there are so many types of signals and classifying them as shown in Figure II.1 depends on their physical or mathematical properties. These properties play a significant role in signals analysis and decoding for pertinent information extraction [105].

- **Deterministic signals**

A signal is said or classified as deterministic, if it is completely and exactly defined through a mathematical function or formula. In other words, deterministic signals stay invariant when studied over determined and equal ranges of time. Realistic and veritable deterministic signals are infrequent due to the unknown and uncontrollable factors that may influence the aspect of a signal [107].

The category of deterministic signals can be either divided into; Periodic an Aperiodic.

A signal is periodic, Figure II.2, if and only if it satisfies the condition shown in II.1

$$Y(t) = Y(t + T) \tag{II.1}$$

Where; T represents the time period.

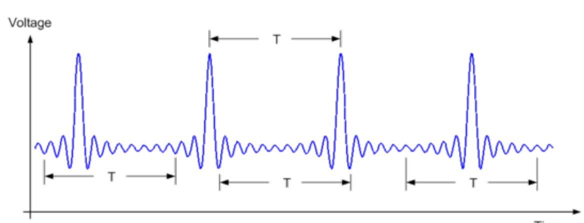



Figure II.2: Deterministic signal: Periodic.

While a signal is characterized as aperiodic if its time function does not exhibit repetition within a specified and finite time interval. In other words, aperiodicity denotes the absence of a regular and recurring pattern over a specific and precise period of time.

- **Non–Deterministic signals**

Signals classified as non–deterministic are also called random signals. According to their name, they are of unpredictable and irregular aspect and their evolution can not be defined or depicted through a mathematical equation. Thus, they can be processed and modelled via stochastic or probabilistic terms. This global class of signals can be divided into two categories: stationary and non–stationary signals [107] as shown in Figure II.1.

A signal is said to be stationary if its frequency or spectral content besides its statistical proprieties are invariant with respect to time (i.e. whose statistical properties, such as mean, variance, and auto-correlation, do not change over time). A Single or Multi–tone sine wave of constant frequency are an example of such signal. A signal that do not satisfy these conditions. i.e frequency and statistical proprieties change through time, is classified as non–stationary signal.

Non–stationary signals are composed of multiple frequencies and their amplitude changes during their propagation in time, which makes their aspects more complicated and their evolution in time unpredictable. Biomedical signals as; electroencephalogram (EEG) as shown in Figure II.3, electromyogram (EMG), electrocardiogram (ECG)...etc, are an example of real life non–stationary signals recorded from determined organs of human body.

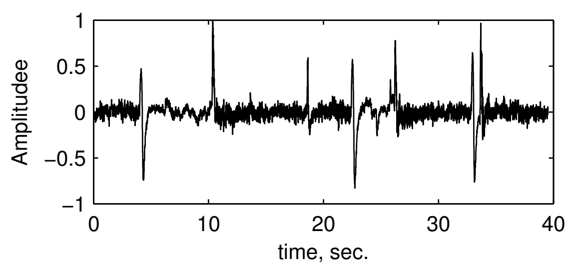



Figure II.3: Non–stationary signal: Electroencephalogram (CHB–MIT normal EEG signal, Record No.01–01, Channel: F1–F7))

The processing of such non-stationary signals necessitates specific mathematical approaches and tools, enabling the determination of their principal features through signal transformation operations. The fundamental method involves conducting the well-known Fourier transform analysis. Nevertheless, Fourier transform analysis offers the appropriate frequency spectra presentation for stationary signals only. Thus for signals of changeable characteristics over time, one of the most valid approaches of processing and capturing both time and frequency changes, is the wavelet transform [108].

# II.2 Wavelet Transform

## II.2.1 Background

Essentially, the transition from a temporal representation to a frequency representation is carried out using the Fourier transform. The Fourier transform of a function, denoted f(t), plays a determining role in quantifying its irregularities and revealing information about its frequency components. It is important to note however, that this transformation completely omits considerations of temporal location.

To enable the localization of the information provided by the Fourier transform within time, Denis Gabor introduced a technique for time-frequency representation in 1940s known as Short–Time Fourier Transform (STFT) [109]. This method involves dividing the input signal into several fixed-length ranges or windows. Subsequently, each range is analyzed independently using traditional Fourier analysis.

This sliding Fourier transform or STFT, represents a significant class of local decomposition of time–frequency analysis. By means of a spatial function G(t) added to the Fourier integral, it permits the time localization. The STFT principle consists of a prefixed window that translates over the whole spatial domain of the analyzed signal and measures around a point x, the amplitude of the sinusoidal component of the frequency. The STFT function can be defined as in II.2 [109]

$$STFT(f,\tau) = \int_{-\infty}^{+\infty} f(t)e^{-j2\pi t}G(t-\tau)dt \tag{II.2}$$

Where; G(t) is the window function and $\tau$ is the shifting parameter.

The employed window is defined as a regular function, that makes the Fourier transform slowly variable and well localized, i.e. it has good properties of decrease to infinity, which means that it is null outside of a particular zone, which represents its support. When multiplying the studied signal by such window, we get a local version, of which we can establish the frequency content by a classical Fourier analysis [109]. In STFT–based analysis, the choice of a narrow window offers a good temporal resolution while a wide window leads to a good frequency resolution. Once the window is chosen, its size is fixed and therefore the temporal and frequency resolution are also fixed, which represents an issue because the researched and the most interesting in signal processing domain, is how to be able to use a sliding window that adapts with the signal irregularities, which is not the case with the STFT that employed an invariable window. In order to surmounts this well known Short–Time Fourier Transform (STFT) limitation. A new theory namely; wavelet transform has been developed [108].

The first come out of wavelet term was in 19th century in a thesis by Haar [110], while Grossman and Morlet [111] introduced the basic concept of this theory in the course of hydrocarbon research improvement and processing of oil exploitation signals, aiming to reconstruct multidimensional seismic signals and to allow the representation of high frequencies employing a time–frequency representation [112]. The Wavelet transform,is a very interesting analytical approach, it facilitates the processing of the studied EEG signal through the application of a multiresolution analysis [113–115]. This type of analysis offers several temporal and frequency resolutions at variance of STFT, in which the resolution is the same from the beginning till the end of the studied signal [109]. The development of the wavelet transform opened up a broad field of applications and leaded to new and more significant results. Currently, it would be hard to list all the fields of application of wavelets theory due to their extensive diversity.

The following sections will present a description of wavelet analysis principle and its application in the detection and prediction of epileptic seizures within the studied electroencephalogram (EEG) signals.

### II.2.2 Theory of Wavelets

As discussed in the previous section, to overcome the limitation of STFT resolution, J. Morlet [116], proceeded again the approach of Denis Gabor, but he selected a $\psi$ function, instead of G function. This latter (G function) in STFT analysis was built by translation and modulation, while the $\psi$ function is based on translation besides an important property, which is the expansion or contraction. i.e. change of scale.

The $\psi$(t) function, is known as a "mother wavelet", The wavelet denomination comes from the fact that, it is an oscillating function (a small wave), localized, with a finite duration and a nil mean value. These conditions enables this $\psi$(t) function to oscillate as a wave and decrease swiftly when |t|increases. While the term "mother" denotes that, the functions (daughter wavelets) with several support regions, which are used in the transformation process are derived from a main function called mother wavelet and can be defined as in (II.3), [117];

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{II.3}$$

where;

$a$ is the scale parameter. $b$ represents the time–shift parameter. $\psi_{a,b}(t)$ represents the wavelet coefficients obtained by dilatation and translation of the main function $\psi(t)$. $\frac{1}{\sqrt{a}}$ is used to ensure that, the energy is the same for all the processing wavelets (for all a and b values).

The wavelet function $\psi(t)$, must satisfy the admissibility condition defined in II.4 Let $\psi(t) \in L^2(\mathbb{R})$ then;

$$\int_{-\infty}^{+\infty} \frac{|\hat{\psi}(w)|}{|w|}\, dw < \infty \tag{II.4}$$

Which implies that;

$$\hat{\psi}(w)|_{w=0} = 0 \tag{II.5}$$

Where; $\hat{\psi}()$ represents the Fourier transform of $\psi$(t).

Besides that $\psi(t)$ should be of a nil average as shown in II.6

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{II.6}$$

The interest of the admissibility condition is that it enables the analysis of the input signal as well as its reconstruction, without any loss of in information.

### II.2.3 Multiresolution analysis (MRA)

The multiresolution basic idea, consists to decompose a signal $f(t) \in L^2(\mathbb{R})$, in such way that, orthogonal projections of $f(t)$ donate by $f_j$ are in the space $V_j.V_j$[3] and $W_j$ being complementary subspaces with $W_j$ represents the difference between $V_j$ and $V_{j+1}$. The refinement equation for the scaling function $\varphi$ shown in II.7, enables the multiresolution decomposition of the data to be processed [118].

$$V_{j+1} = V_j \oplus W_j \tag{II.7}$$

The multiresolution approximation, as established by Mallat and Meyer, is characterized by the following properties.

- $V_j \subset V_j + 1$ function in subspace $j$, is in all the finer subspaces.

which means that, if we define a signal$f_j(t)$ at subspace $V_j$, we can get its coarse approximation, employing the MRA representation. Let a signal being decomposed, through an iterated chain, of complementary filters (low and high pass filters). At each step of the decomposition process, we get a low pass and high pass versions of the input signal. Nevertheless, the low pass signal in the second step is contained in the signal from the first step.

- $V_j \in V_{j+1}$, $f(t) \in V_0 \Longleftrightarrow f(t-k) \in V_0$.

Represents the shifting (translation) property of the subspace. A signal within a determined subspace, when shifted by $k \in Z$, it retains the scale-invariant characteristic inherent in Multiresolution Analysis (MRA). In frequency domain terms, $f(2t)$ contains $2X$ highest frequency in comparison to that contained in $f(t)$. Through the iterated filter bank example, where the low-pass filter halves the frequencies at each step, it becomes evident that by reversing one step in the chain of filters, the highest frequency content doubles at each iteration.

in Figure II.4, a 3–level multiresolution is illustrated, where;

[3]The notation $V_j.V_j$ refers to the inner product of the space $V_j$ with itself. The inner product of a space with itself is a measure of overlapping or similarity within that space. It is frequently employed to measure the extent to which one function or signal is present or represented within another.

$\cap_{j \to -\infty} V_j = 0$. When moving to lower subspaces, the space occupied by $V_j$ shrinks till it becomes almost zero. In simpler terms, as we move to lower subspaces (smaller j), the common elements in all these subspaces become less and less until they approach zero. This implies that the commonalities between consecutive subspaces decrease as we go to lower levels. In practical terms, this means that the shared information or characteristics common to each level diminishes as we move down the levels.

$\cup_{j \to \infty} V_j = L^2\{R\}$. Subspaces union as $j \to \infty$, include the entire $L^2\{R\}$ space.i.e. as we move to higher subspaces (larger j), the union of all these subspaces includes the entire $L^2\{R\}$ space. This suggests that, at the highest level, we have covered the entire space of square-integrable functions over the real numbers.

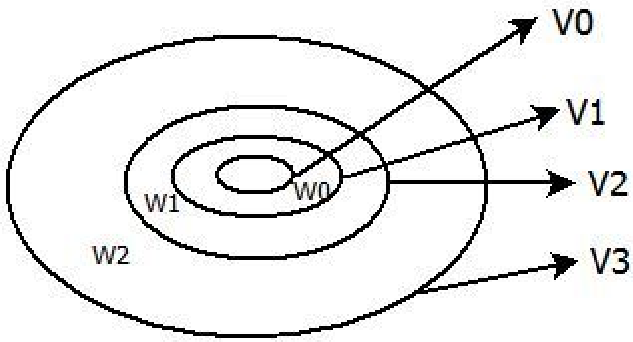



Figure II.4: 3–level multiresolution illustration [119].

To summarise, the method of Gabor, enables an input signal to be decomposed into a judiciously selected linear time–frequency combination. However, it will be preferable to adapt the applied multiresolution analysis with the treated signal,i.e. it is not necessary to to carry out a very high level of resolution, while the signal to be analyzed, consists only the low frequencies, as well as to treat a signal containing high frequencies with too low resolution [120]. Consequently, it is not recommended to choose in advance the resolution level for a given type of signal, but it necessary to carry out an analysis method whose resolution, both in time and in frequency, adapts to the signal according to its characteristics. This solution is enabled in time–scale analysis.

Figure II.5, illustrates the time–frequency resolutions of several signal processing transformations. Where, the the blocks orientation and size refers to the features that can be captured through different time–frequency approaches. First of all, The time–series analysis is typified by high resolution in the time–domain and null resolution in the frequency domain. Which means that, small features can be distinguished in time–domain and none in the frequency domain. In contrary of Fourier Transform, which is characterized by high resolution in the frequency domain and nil resolution in time–domain. The Short Time Fourier Transform (STFT) has medium resolution in both the time and frequency domains. Finally, it can be clearly seen that, in wavelet Transform; low frequencies have a high resolution in the frequency domain and low resolution in the time-domain. While, high frequencies benefit of high resolution in the time domain but low resolution in the frequency domain [121].

In summary, the Wavelet Transforms offers a trade–off, in such way that; time–dependent features are typified by high resolution at a determined scale. while it enables capturing frequency–dependent features at a pre–defined scale [121].

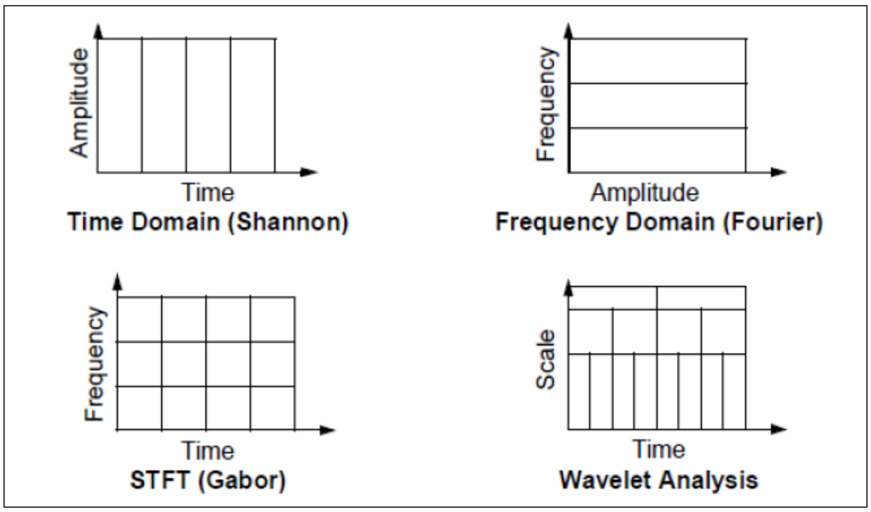



Figure II.5: Time–frequency plane tiling. Source [121]

### II.2.4 Wavelet Families

In the time-scale domain, an infinite number of wavelet functions exists, as any localized and oscillating function can represent a potential mother wavelet. However, not all wavelets exhibit desirable properties. As a result, various specialists in wavelet theory have diligently developed and constructed specific wavelet families with noteworthy characteristics. In this dissertation, we will present three well-known and widely used wavelet families, namely Daubechies, Symlets, and Coiflets.

#### Haar Wavelet

Mathematically, the Haar wavelet is defined as a rescaled square–shaped functions sequence, these latter form a family of wavelet or basis. The Haar wavelet is known as the first and extensively used wavelet basis, besides it represents the first function to introduce as example for wavelet analysis teaching .

In 1909, Alfred Haar proposed for the first time, a sequence of functions, that carry his own name [110]. Haar employed these functions to offer for the space of square–integrable functions, an orthonormal system. Where, the unit interval is $[0, 1]$. Much later, the Haar function, took the denomination of Haar wavelet, since it represents a particular case of the Daubechies wavelet, known as db1.

The Haar function represents the simplest wavelet in time–scale domain. It's discontinuity represents the major disadvantage of this wavelet, which makes it non differentiable. Nevertheless, this discontinuity can be an advantage, when processing signals with abrupt transitions [122].

The Haar mother wavelet function $\psi(t)$ can be represented as in II.2.4 and shown in Figure II.6 (a).

$$\psi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2} \\ -1 & \frac{1}{2} \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$

Besides, its scaling function $\varphi(t)$, which is described in II.2.4 and shown in Figure II.6 (a).

$$\varphi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$

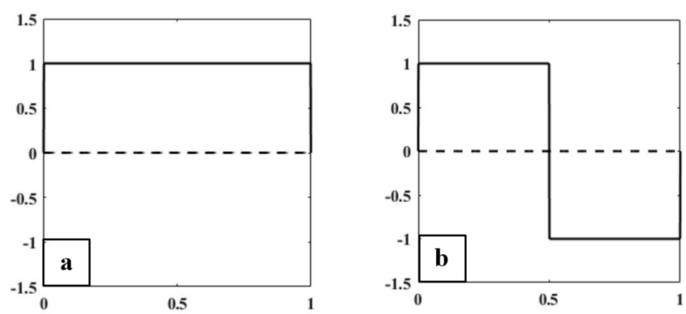



Figure II.6: Haar Scaling Function (a) and Wavelet (b). Source [1]

### Daubechies Wavelets

In the early 80s, Ingrid Daubechies proposed a family of orthogonal wavelets, which establishes the discrete wavelet transform (DWT). These wavelets are characterized by a compact support and a maximal number of vanishing moments. for each wavelet of this family, there is a father wavelet known as the scaling function. this latter serves to generate an orthogonal multiresolution analysis [123].

Basically, the daubechies wavelets were introduced and developed to have an elevated number of vanishing moments (VM). Where, for a determined support width we have $2VM$. Note that, this property does not imply the ideal smoothness [123].

The Daubechies wavelets are named with two schemes, Dn; when considering the length or taps number, dbVM referring to the vanishing moments. Example: D6 and db3 represents to denominations of the same wavelet transform. Note that D2, which is db1 represents the wavelet of Haar [123].

Daubechies wavelets are extensively and widely utilized in solving a several issues, such as; signals self–similarities or discontinuities and fractal problems. These wavelets have no determined expressions, nevertheless, Ingrid Daubechie proposed an explicit and simple filter synthesis algorithm. As shown in Figure II.7, Daubechies orthogonal wavelets from db1—db10 are commonly used. Each wavelet is characterized by a number of zero moments, known as vanishing moments, this number equal to half of the coefficients number. Example, D2 has one vanishing moment, while D4 has two, etc [123].

**Vanishing Moments**. The nth moment of a given function x can be presented as in II.8

$$M_n(x) = \int t^n x(t) dt \tag{II.8}$$

x(t) is orthogonal to $t^n$, if and only if, this moment vanishes. Consequently, if a function has VM vanishing moments, then $M_n$ for $n = 0, 1, ..., N-1$. And due to integration operation linearity, the function x, is orthogonal to all polynomials up to N-1 degree.

When, the wavelet function $\psi$ has a determined number of vanishing moments (VM), then the discretely shifted versions of the scale $\varphi$ enables the reconstruction of all the polynomials that $\psi$ remains orthogonal too.

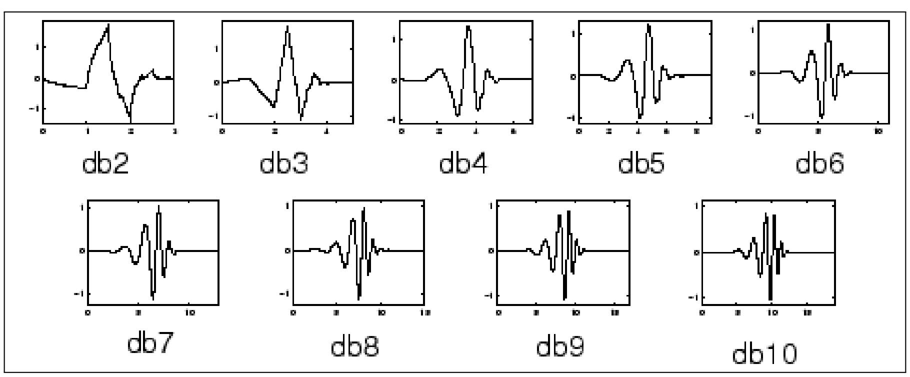



Figure II.7: Daubechies wavelets.

### Symlets Wavelets

Symlets are almost symmetrical wavelets, constructed by Ingrid Daubechies to improve the symmetry of the Daubechies wavelets family. The properties of the symlets wavelets are similar to those of the Daubechies [124].

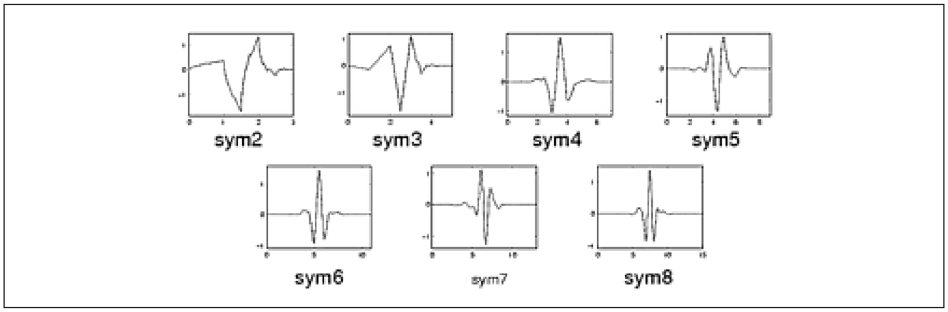



Figure II.8: Symlets wavelets.

**Coiflets Wavelets**

Coiflets are a discrete family of wavelets, designed by Ingrid Daubechies and Ronald Coifman [125], in order to build wavelets characterized by scaling functions with vanishing moments. These latter (coiflets wavelets) are almost symmetric. Where, their wavelet functions contain N/3 of vanishing moments and scaling functions $N/3-1$. The coiflets wavelets family, represents a special case of Daubechies wavelets and they have been employed in several applications.

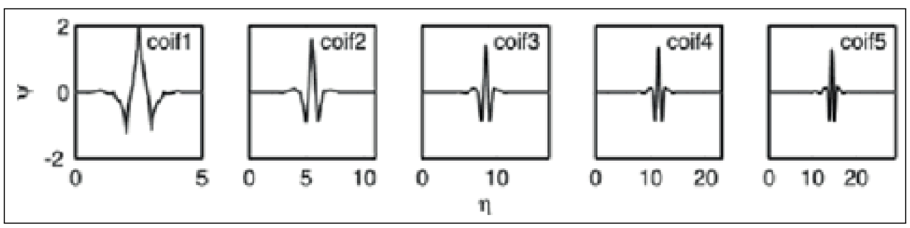



Figure II.9: Coiflets Wavelets.

## II.2.5 Wavelet Transform Principle

### Scale and Shifting Concepts

In time–scale analysis, the concept of frequency is replaced by the notion of scale. The scale parameter ($a$) plays a crucial role in defining the processing window width. This parameter determines how the mother wavelet process contracts or stretches. Consequently, it enables the consideration of both high and low frequencies in the analysis. If $a > 1$ then the mother wavelet is dilated, while if $a < 1$ then the mother wavelet is contracted. The $\psi_{a,b}(t)$ oscillates at a frequency value of $f = 1/a$, which implies that $a = 1/f$ [117].

The shifting parameter ($b$) provides the capability to either delay or advance the position of the wavelet (translation), at a given scale value. The Figure II.10 shows a Haar wavelet at several scale and shifting values; The haar wavelet with blue color, represents the main function or the mother wavelet, while the orange daughter wavelets represents a **dilated** and shifted version of the main function, where; ($a = 5/2, b = -3/2$). Besides the red daughter wavelet, which represents a **contracted** and shifted version of the Haar mother wavelet, where; ($a = 1/2, b = 3/2$).

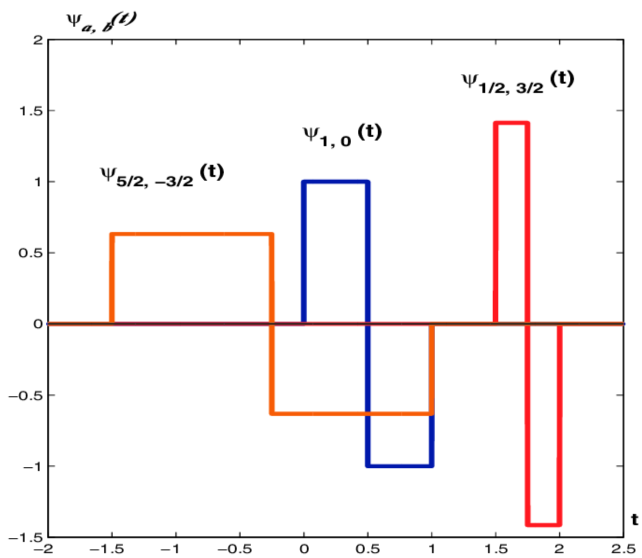



Figure II.10: The Haar mother wavelet at different scale and translation values. Source [126]

### Processing Concept

To illustrate and facilitate the comprehension of wavelet transform–based analysis, we consider an example of a short length time signal shown in Figure II.11. This input and main signal is composed of a sequence of signals with several frequencies, which emerges consecutively. From the example proposed, we can clearly notice that, the signal to be studied, consists of four frequencies, where f1< f2< f3< f4. The hole analysis operation with wavelets consists to represent the signal in a two–dimensional; time–frequency illustration. This two–dimensional space box shown in Figure II.11 is orderly fulfilled with the daughter wavelets[4]. Where the vertical axis is related to the scale parameter (a) and refers to the change of the frequency and the horizontal one is connected to the shifting parameter (b) and represents the change of the time [127].

[4]Daughter wavelets: the functions derived from the mother wavelet by contraction and dilatation process [127].

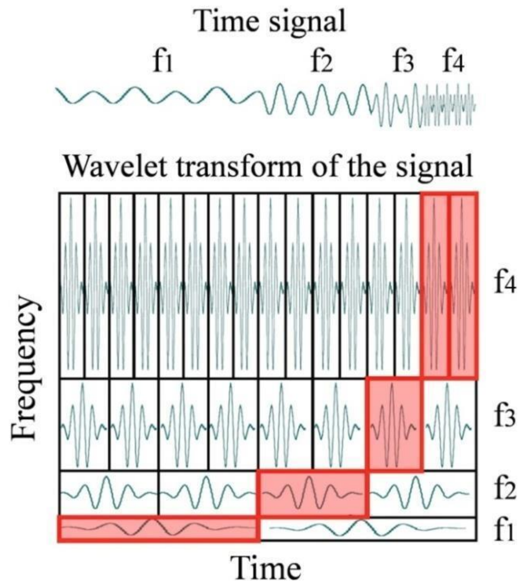



Figure II.11: Wavelet transform multi–resolution representation: Analysis principle. Source [127]

The wavelet based–transformation the signal presented in this example, is performed in the following way: each daughter wavelet from the two–dimensional plane is compared with a determined part of the signal, starting from its beginning, The magnitude of the correlation and similarity between the processed part of the signal and the corresponding daughter wavelet, yields the wavelet coefficient value, encoded in the time–frequency domain. Then this daughter wavelet will be shifted by (b) value along the signal to obtain the corresponding coefficients each time we shift. After that the scale parameter (a) changes to get a dilated daughter wavelet and we repeat the process of calculating the wavelet coefficients [127].

The regions showing the highest correlation between the daughter wavelets and the parts of the studied signal are highlighted with red color in Figure II.11. The representation obtained by [127], confirms that, the wavelet transform–based analysis can extract precisely, the frequency content of the processed signal at any given moment.

### Mother Wavelet Selection Criteria

In wavelet–based analysis, there are several types of mother wavelets, which can be carried out for signals processing in time–scale domain. Nevertheless, employing different mother wavelets to process the same input signal, will yield to different results. Consequently, The main challenge when employing the wavelet transform, is to select the most appropriate mother wavelet for the required application, since the adequate choice of the mother wavelet, plays a significant role in identification and localization of signal changes.

Basically, mother wavelets are typified by certain properties such as; compact support, vanishing moment, orthogonality and symmetry. Taking into consideration, the smoothness and wideness of the mother wavelet. According to previous studies, these properties can be used to select the mother wavelet. However, more than one mother wavelet can have the same properties. To overcome this issue, several studies in the literature, presented a variety of mother wavelet selection approaches, that fall into three categories, namely; qualitative, quantitative, and machine learning based selection.

Qualitative methods [113], are based on similarities between the signal and the mother wavelet as shown in figure II.12. While quantitative methods proposed more accurate mother wavelet selection such as the Minimum Description Length estimation or Energy to Shannon entropy ratio criterion [128].

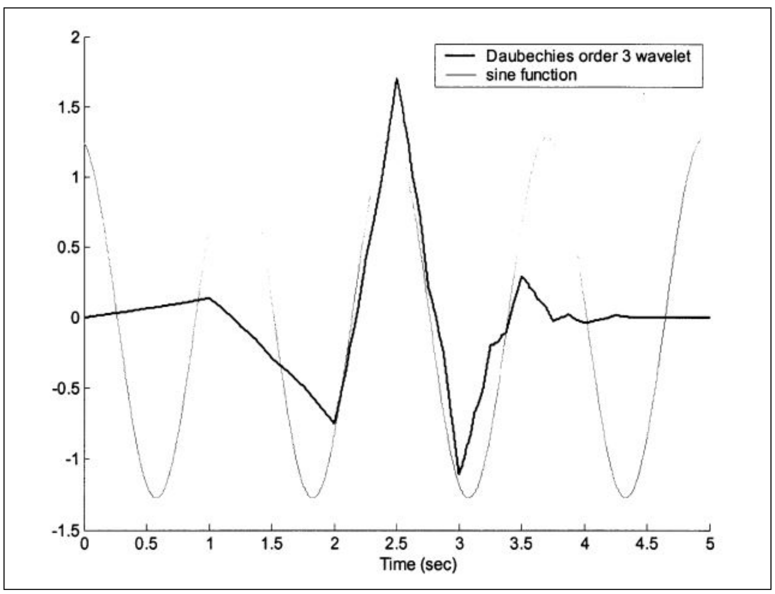


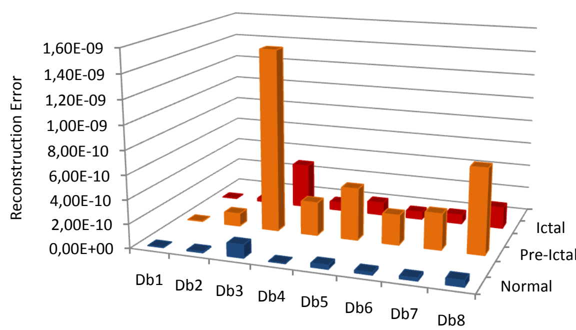

Figure II.12: db3 mother wavelet and a sine function,[same frequency as the center frequency of the wavelet, center F= 0.8Hz; center P= 1.25s]. Source [113]

Chen *et al.* used an accuracy–based mother wavelet selection approach [114], in which they developed an algorithm for automatically identifying the mother wavelet providing the highest accuracy, when detecting ictal periods in EEG signals.

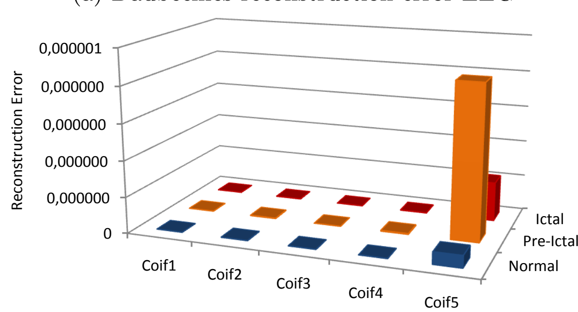
Besides all the cited approaches, studying the error between the original signal and the synthetic signal (signal after reconstruction), can be also used as a criterion to select the mother wavelet that provides the minimum reconstruction error. This latter can be calculated as clarified in II.9

$$R_error = \sum |X_{original} - X_{reconstructed}| \tag{II.9}$$

we achieved a comparative study between several wavelets as an initiating step to explore the degree of similarity between our input signal (normal, pre–ictal and ictal periods) and several orthogonal mother wavelets from both Daubechies and coiflets families using the previously mentioned reconstruction error equation. We processed EEG signal of the CHB–MIT database, recorded from the FP1–F7 differential derivation. We considered a processing duration of 40–seconds for the overall analyzed signals. These segments were decomposed into a 5–level DWT coefficients employing 13 orthogonal mother wavelets from both Daubechies and coiflets families. The reconstruction error between original and reconstructed sub–bands are shown in Figure II.13. From the presented results we can observe that all used mother wavelets are providing closer reconstruction error values excluding coif5, db3, and db8.




(a) Daubechies reconstruction error EEG




(b) Coiflets reconstruction error EEG

Figure II.13: Example of Daubechies and coiflets mother wavelets reconstruction error for normal, pre–ictal and ictal EEGs of CHB-MIT database.

### II.2.6 Continuous Wavelet Transform

The continuous wavelet transform (CWT) roots, can be traced back to Goupillaud *et al* [129]. The signal to be processed with CWT is correlated and convoluted with the wavelet basis function to get high resolution at continuous time and frequency increments. Consequently a set of coefficients $\psi_(b, a)$ are obtained as shown in (II.10)

$$\psi_(b, a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} \psi \left( \frac{t-b}{a} \right) s(t) \mathrm{d}t \tag{II.10}$$

The first step to carry out a CWT–based analysis, is the mother wavelet selection, this latter will serve as a prototype for all the dilated or compressed windows (daughter wavelets) used in the time–scale transformation process. Once this selection is adequately done, the process of CWT coefficients calculation starts; the scale parameter value is a=1, which corresponds to the most compressed wavelet. This latter will be placed at the beginning of the input signal, precisely at the time t= 0. The wavelet frequency at a=1 is multiplied by the signal and then integrated over the time. The integration result is then multiplied by $\frac{1}{\sqrt{a}}$ to obtain the corresponding coefficients of $\psi_{1,0}(t)$, as mentioned in the CWT equation II.10. After that the wavelet is shifted to the right by b, to obtain the CWT coefficients at $a = 1$ and $t = b$, the shifting at the scale $a = 1$ will continue until the wavelet reaches the end of the signal and consequently a row on the time–scale plane for the scale $a = 1$ will be fulfilled. Next, both a and b values will be incremented by a small value continuously, since we are analysing with continuous wavelet transform (CWT) [130].

The CWT coefficients calculation process will continue for all values of $a > 1$ and $a < 1$. The low scale value (a) correlates with high frequencies (compressed wavelet) while high scale value (a) correlates with low frequencies (dilated wavelet). Consequently, several features, that reflects the the resemblance and similarity between the analyzed signal and the wavelets can be captured. Nevertheless, and for practical aims, the signals to be processed are of limited bandwidth, thus performing a complete transformation is not usually requisite and a transformation of a restricted scale values interval will be sufficient [130].

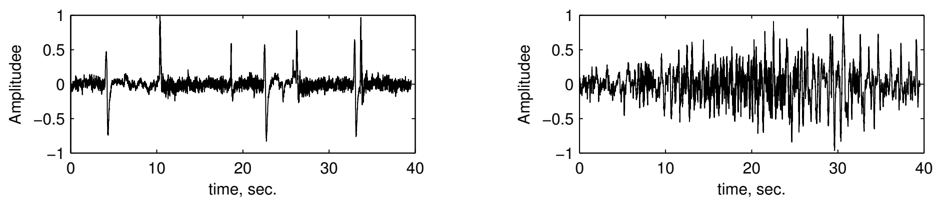
When the input signal has a spectral component that corresponds to the current value of the scale a, then, the product of the employed mother wavelet with the analyzed signal at this point, provides a large coefficients value. Differently, this product will provide a small or a nil value [130].

**Scalogram**. The squares of the resulting CWT coefficients, which forms the scalogram. similarly to the spectrogram, the scalogram can be defined as the visual representation of the wavelet transform coefficients. In real–world signals analysis, the scalogram can be more efficient than the spectrogram, precisely in case of pattern–matching applications and the detection of signals discontinuities [130]. The scalogram can be defined as in II.11

$$\int \int_{-\infty}^{+\infty} |CWT_x(t, a, \psi)|^2 dt \frac{da}{a^2} = E_x \tag{II.11}$$

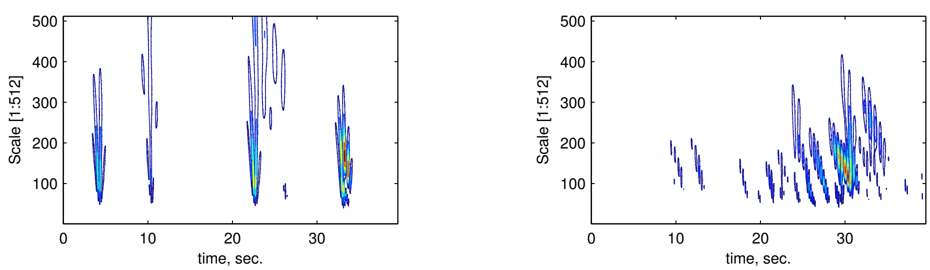
**EEG–scalogram**. We explored the high–frequency content within seizure EEG signal through the CWT scalogram. Indeed, we calculated CWT scalograms of both normal and abnormal EEG signals of the CHBMIT Scalp EEG database with an 8th order Daubechies mother wavelet over a scale going up to 512. As illustrated in Figure II.15b, we can observe that the time–scale plane is blurred by a wide–bandwidth power in comparison to the scalogram of the seizure scalogram in Figure II.15a.

The obtained scalograms in Figure II.15 show spikes' contour within the time–scale plane. High–energy regions can be easily localized for seizure and non-seizure EEG signals. Therefore, the scalogram can be considered as an additional discrimination tool in the time–scale domain between normal and abnormal EEG signals.




(a) Non–seizure EEG (b) Seizure EEG

Figure II.14: CHBMIT Scalp EEG database (CHBMIT): Normal and abnormal EEGs datafiles, FP1–F7




(a) Scalogram of the non–seizure EEG (b) Scalogram of the seizure EEG

Figure II.15: Scalograms of normal (Fig.II.14a) and abnormal (Fig.II.14b) EEG signals

### II.2.7 Discrete Wavelet Transform (DWT)

From the theoretical view, the continuous nature of the CWT offers the finest detail of the processed signal, which enables better illustration of the time–scale transformation. Nevertheless, the CWT–based processing, requires markedly more computations, since the signal will be analysed at continuous scale (a) and translation (b) values, which represents the major disadvantage of this function. In order to overcome this constraint, the discrete values of scale and translation parameters (a) and (b), were introduced to form a new time–scale methodology, that guarantees sufficiently of information for both analysis and reconstruction of the input signal in a significantly reduced processing time. This latter is known as the discrete wavelet transform (DWT) [131].

### Definition

Y. Meyer demonstrates the possibility to increase the efficiency of the wavelet decomposition, by limiting the number of the employed scaling factors, while maintaining the same precision of the decomposition and this can be achieved when the scale parameter $a = 2^j$ and the shifting parameter $b = k2^j$ [131]. Thus, The DWT is in fact a fully discrete version of CWT, in which, the inner product of the signal to be analyzed with the basis wavelet is computed as defined in (II.12)

$$\psi_{jk}(t) = 2^{\frac{j}{2}}\psi(2^j t - k), k \in \mathbb{Z} \tag{II.12}$$

Where, $j$ represents the level of decomposition, and $\psi_{jk}(t)$ forms an orthonormal basis of $L^2(\mathbb{R})$.

### Quadrature Mirror Filters (QMFs) [132]

The two–channel QMF bank is widely and extensively employed in several signal processing applications and fields, such as; wavelet bases conception, image processing, speech signal sub–band encryption, biomedical engineering...etc.

The concept of quadrature mirror filter (QMF) roots can be traced back to Croisier [133], in 1976. Then it has been used by Esteban and Galand [134], in speech encryption scheme. Quadrature Mirror Filters (QMFs) are widely recognized tools in time–frequency analysis. They facilitate the division of an input signal into two or more sub-bands, allowing each resulting sub-band to be separately analyzed. This process enables effective compression. As the decomposition progresses, the resulting sub-band signals can be recombined through an inverse operation, ensuring the accurate reconstruction of the original signal [135]. Thus, QMFs represents the principle idea in the design of wavelet bases in the time–scale domain.

The two–channel QMF bank exemplary, shown in Figure II.16, decomposes the discrete signal to be processed into two sub–band of equal bandwidth, through a low–pass filter denoted $H_0$ and a high–pass filter $H_1$. In order to reduce the signal processing complexity or to achieve its compression, these QMFs resulting sub–band signals will be decimated by a factor of two (2). Then, the two sub-band signals will be interpolated by the same factor of two (2) and passed through the low–pass and high–pass synthesis filters. The QMFs outputs are combined to obtain the reconstructed signal [131].

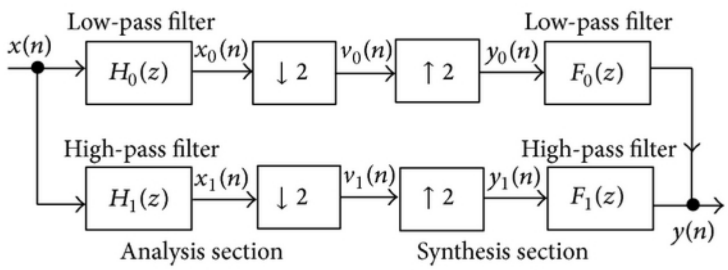



Figure II.16: Two–channel Quadrature Mirror filters (QMF) bank [132]

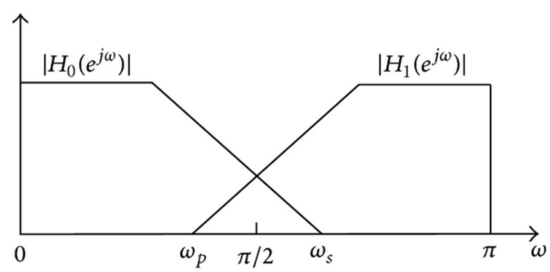



Figure II.17: Frequency response of two–channel QMF. Source [132]

**DWT Decomposition Principle**

The DWT decomposes the signal to be analyzed into two components; the approximation (A) and detail (D) at each decomposition level, through Quadrature Mirror Filters (QMFs), denoted as $H_0$ and $H_1$, as illustrated in Figure II.16. At the first level, the spectral–bandwidth of the input signal is halved through the low–pass filter $H_0$. Consequently, the first approximation is obtained. The other half of the spectral–bandwidth represents the detail, which is covered by the quadrature mirror conjugate filter of $H_0$, denoted as $H_1$. In next levels, each approximation is further decomposed into approximation and detail until reaching the required level $j$ [131].

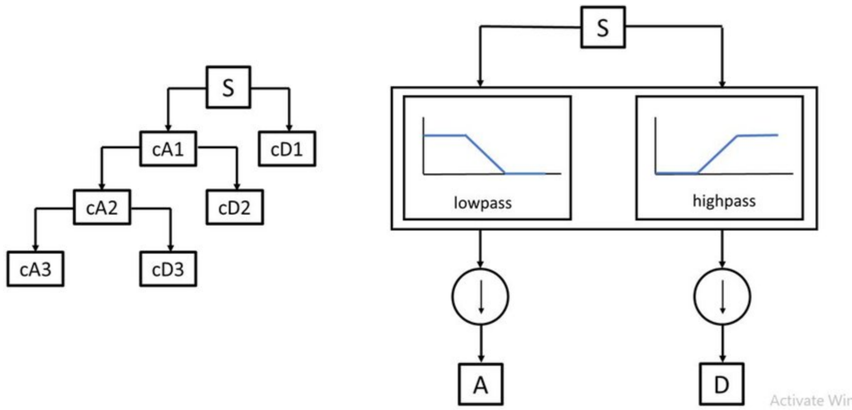



Figure II.18: DWT decomposition principle.

Consequently, as illustrated in Figure II.18, The DWT decomposes the signal into two components; the approximation (A) and detail (D). These components are obtained by complementary filters (low–pass and high–pass filters). The approximation (A) of the signal represents its low frequencies, while the detail(D) is its high frequencies. Every approximation is decomposed again into approximation and detail, thus, several frequency bands of the analyzed signal are obtained depending on the decomposition level.

Analysis with the discrete wavelet transform offers better resolution in time for high frequencies while frequency resolution is better and more precise for low frequencies, this means that at high frequencies the components are better localized in time than at low frequencies. Inversely, a low frequency component is better localized in frequency than a high frequency component [136].

The original signal can be efficiently reconstructed from the obtained wavelet coefficients, with absence of any loss of information, and with the same data points number of the analyzed signal. Thus, it casts all redundant information in CWT and leads to a significant decreasing in computing time due to the orthogonality of the basis function used.

**Decomposition Levels.** The DWT decomposition process is iterative, in theory this latter can be indefinitely continuous. While in reality, this decomposition can proceed until that the detail (D) consists of a single sample or a pixel in case of 2–Dimension–DWT (image processing). In practice, an appropriate number of levels should be determined, according to the input signal nature and the intended application.

**Under Sampling Process.** When performing a filtering operation on a real digital signal, we multiply its amount of information by 2. Indeed, if the analyzed signal has N points at the beginning, it will be of 2*N length. Thus its approximation and its detail will also each have N points.

In order to avoid or remedy the signal length duplication, a down–sampling process is carried out for each signal by factor of 2, as shown in Figure II.19 i.e.

remain only one of the two components in each of the two samples, we obtain two signals of N/2 length, where N represents the initial length of the processed signal).

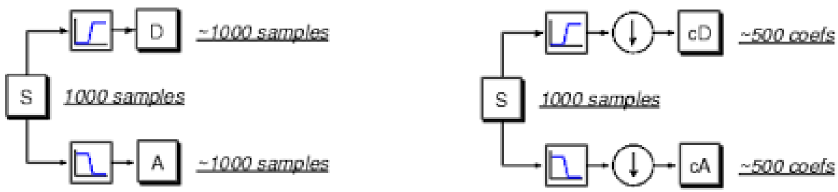



Figure II.19: Signal decomposition by a low–pass and high–pass filters with down–sampling process.

### Reconstruction Principle

As illustrated in Figure II.20, after DWT–based decomposition process, the original signal can be easily reconstructed, by means of its approximation and detail obtained during the splitting process.

The reconstruction of the original signal, can be obtained through the following equation II.13

$$X(t) = \frac{1}{k} \int \int_{-\infty}^{+\infty} W_x(a,b) \psi \left( \frac{t-b}{a} \right) \frac{1}{a^2} dbda \tag{II.13}$$

where; $K$ represents a constant, which depends on the wavelet choice, this latter is given in II.14

$$k = \int_{-\infty}^{+\infty} \frac{|\psi_{a,b}()|^2}{d} < \infty \tag{II.14}$$

The reconstruction operation is similar to that of the decomposition; by inverting the processing direction and employing the interpolation instead of the decimation, which permits to the the approximation and detail lengths to be doubled at each step by introducing a zero between each sample.

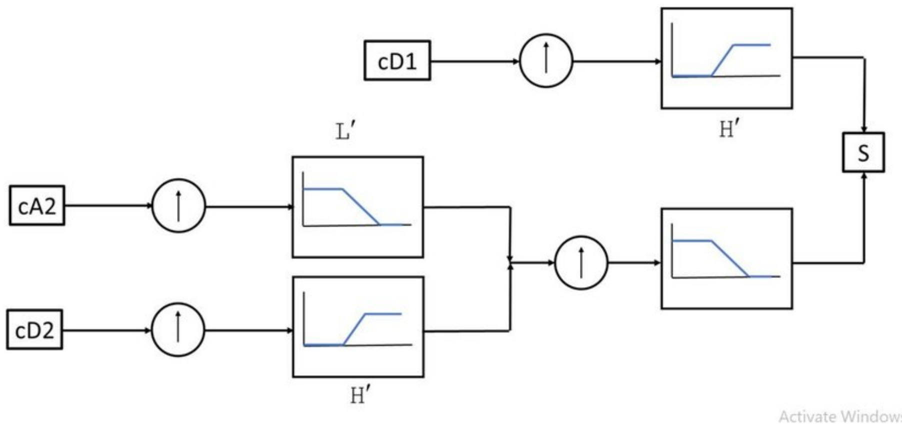



Figure II.20: Signal reconstruction process

**Sub–bands reconstruction.** The resulting approximation coefficient vector (cA1), will be proceeded through the same process employed for original signal reconstruction. However, instead of combining it with the first level of detail (cD1), it will be combined with a vector of zeros, consequently, a reconstructed approximation (A1) is obtained. This latter, is of same length as the original signal and represents a true approximation of it. Similarly, we can proceed the detail of the first level (cD1) to obtain the reconstructed version (D1)

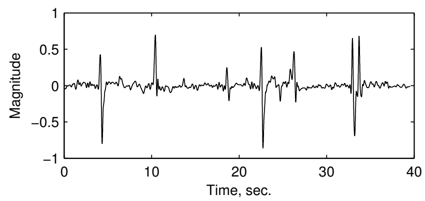
The reconstructed details and approximations represents the true constituents of the original signal. Thus, their combination enables the reconstruction of the input signal. It is fundamental and necessary to reconstruct the approximations and details before their combination.

### II.2.8 DWT–based decomposition of EEG signals

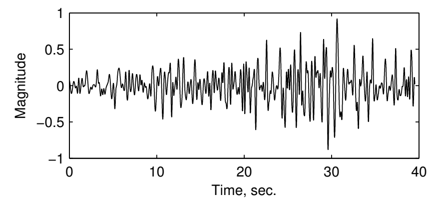
The Discrete Wavelet Transform (DWT) was employed to decompose the CHB–MIT EEG signals As well as Bonn EEGs, into Delta [0–4]Hz, Theta [4–8]Hz, Alpha [8–16]Hz, Beta [16–32]Hz and Gamma [32–64]Hz, the well–known brainwaves of clinical interest as shown in Figure II.21, II.22. We achieved this decomposition according to the Tables II.1 and II.2, at 5 and 4 DWT decomposition levels, respectively.

Table II.1: *Link between frequency bands and decomposition levels for the CHB–MIT signals, Sampling frequency:* $Fs = 256\ Hz$

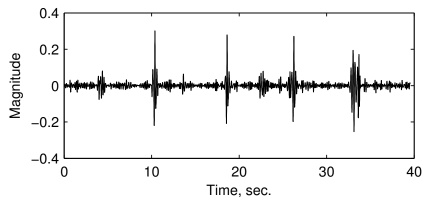
| EEG signal | Delta | theta | alpha | Beta | Gamma |
|---|---|---|---|---|---|
| [0:128]HZ | [0 :4]Hz | [4 :8]Hz | [8 :16]Hz | [16 :32]Hz | [32 :64]Hz |
| rhythm level | A5 | D5 | D4 | D3 | D2 |



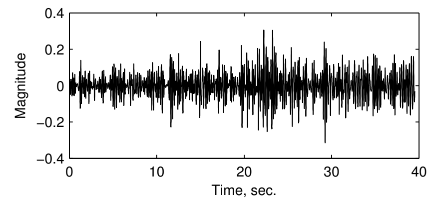

(a) Normal Delta brain wave



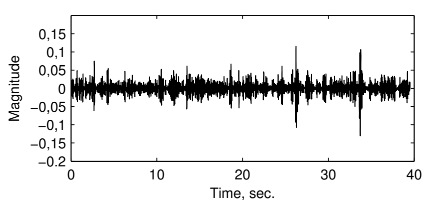

(b) Ictal Delta brain wave



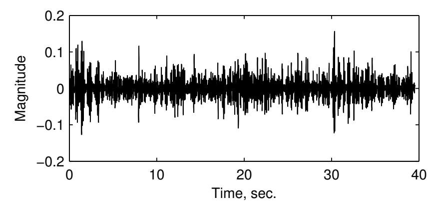

(c) Normal Theta brain wave



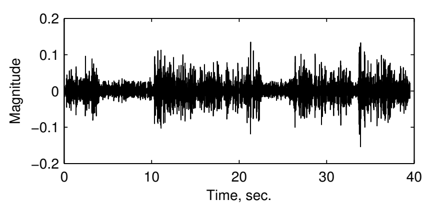

(d) Ictal Theta brain wave



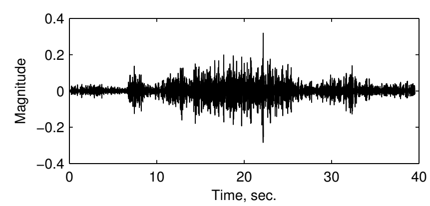

(e) Normal Alpha brain wave



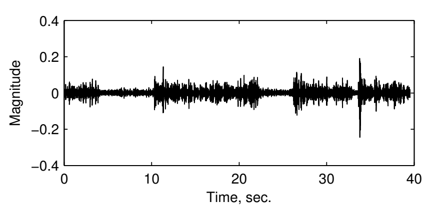

(f) Ictal Alpha brain wave



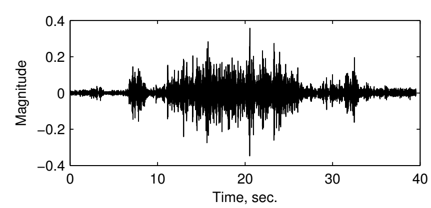

(g) Normal Beta brain wave




(h) Ictal Beta brain wave




(i) Normal Gamma brain wave

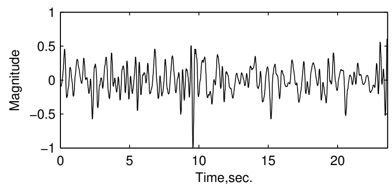



(j) Ictal Gamma brain wave

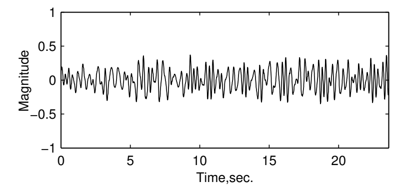
Figure II.21: DWT–Based CHB–MIT EEG signal decomposition into elementary brainwaves during and out of seizure.

Table II.2: *Frequency bandwidths and decomposition levels for Bonn EEGs, Sampling frequency:* $Fs = 128$ *Hz*

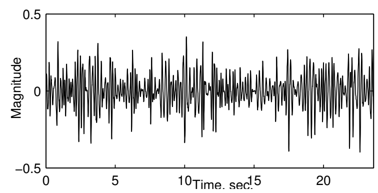
| EEG signal | Delta | Theta | Alpha | Beta | Gamma |
|---|---|---|---|---|---|
| [0:64] Hz | [0:4] Hz | [4:8] Hz | [8:16] Hz | [16:32] Hz | [32:64] Hz |
| rhythm level | A4 | D4 | D3 | D2 | D1 |



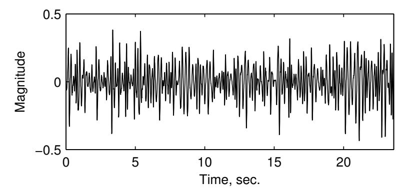

(a) Normal Delta brain wave



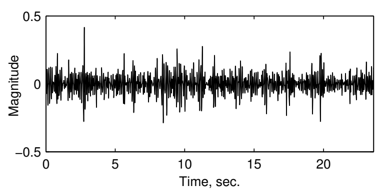

(b) Ictal Delta brain wave



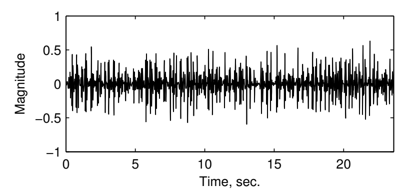

(c) Normal Theta brain wave



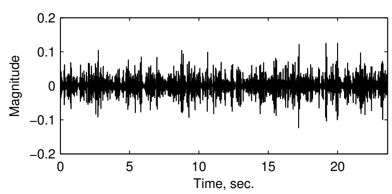

(d) Ictal Theta brain wave



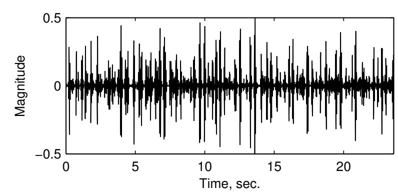

(e) Normal Alpha brain wave



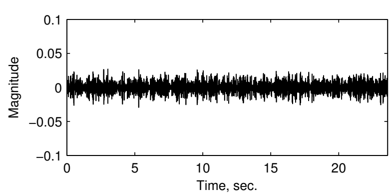

(f) Ictal Alpha brain wave



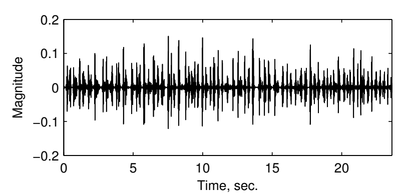

(g) Normal Beta brain wave




(h) Ictal Beta brain wave




(i) Normal Gamma brain wave




(j) Ictal Gamma brain wave

Figure II.22: DWT–Based Bonn EEG signal decomposition into elementary brainwaves during and out of seizure.

### II.2.9 Wavelet Packet Analysis (WPT)

The decomposition employing wavelet packets (WPT), represents a multiresolution analysis generalization. It decomposes the original signal into basic functions tree, these function are derived from a main mother wavelet. Similarly to the discrete wavelet transform (DWT) analysis, it is based on the quadrature mirror filters (QMFs). The signal to be analyzed will be splitted through a low pass filter and a complementary high pass filter. The difference between these two methods as illustrated in Figure II.23, is in the fact that, the various detail sub–bands will also be decomposed at each iteration according to the same principle. Consequently, the decomposition into wavelet packets can therefore be represented in binary tree form [131].

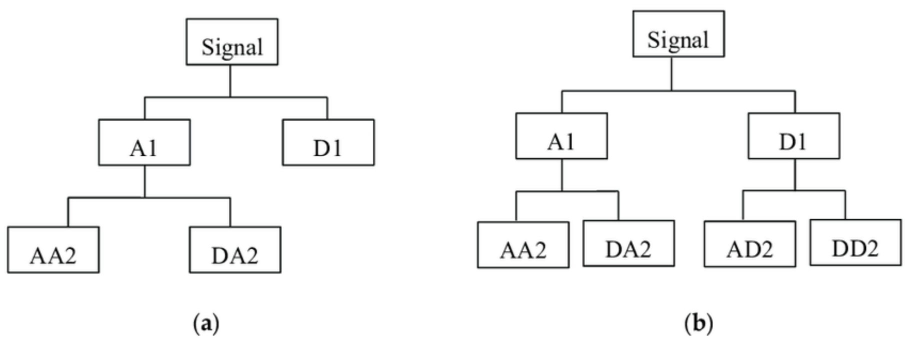



Figure II.23: level–2 Discrete Wavelet decomposition tree(a) ; level–2 Wavelet packet decomposition tree(b)

As shown in Figure II.24, for each intermediate node of the Wavelet Packet (WP) tree, known as the parent node [0,0], an approximation [1,0] and detail signal[1,1] signals are calculated. These two signals are called child nodes. Each child node represents then a father node and in turn generates its two children. The decomposition process continue until reaching the required tree at a determined j–level.

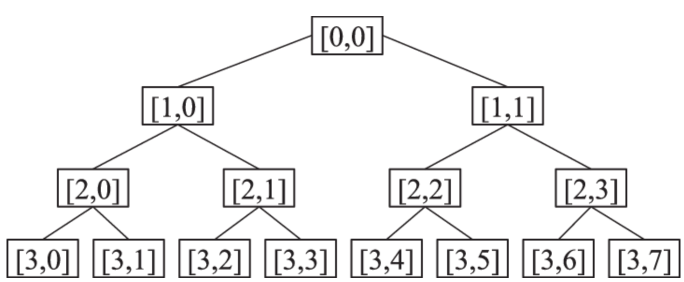



Figure II.24: A 3–level Wavelet packet decomposition tree.

Thus, at j–level of decomposition, we get $2^j$ signals of $N/2^j$ length each. Where, the total points number remains constant all over the decomposition levels. Thus, considering all the obtained signals, creates an information redundancy issue. Therefore, it is necessary to select in this resulting binary tree, the nodes or the sub–bands that satisfy certain criteria for a specific analysis application. For this purpose, several methods were introduced and developed such as; the entropy cost function, in which, the signal cost of each node of the tree, will be calculated and the combination of signals which gives the minimum total cost will be selected [137]. This entropy cost function represents an example from several cost functions. Note that, the signal cost in most of times is called entropy by abuse of language, even if the employed function is not based on entropy. Besides the entropy cost function, we can find also, the optimum node combination selection through the best level or the best–basis methods.

**Best–level–tree**. As shown in Figure II.25, the total cost of each level of decomposition is calculated, through a summation of the nodes costs at each level and the one of the lowest cost will be considered [79].

**Best–basis–tree**. As shown in Figure II.26, each node of the binary tree will be considered individually, until getting the combination of signals or the sub–bands, whose total entropy cost the smallest [138].

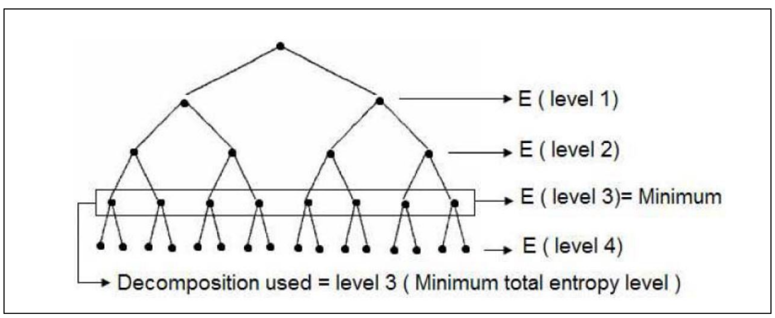



Figure II.25: the best–level tree approach. Source [139]

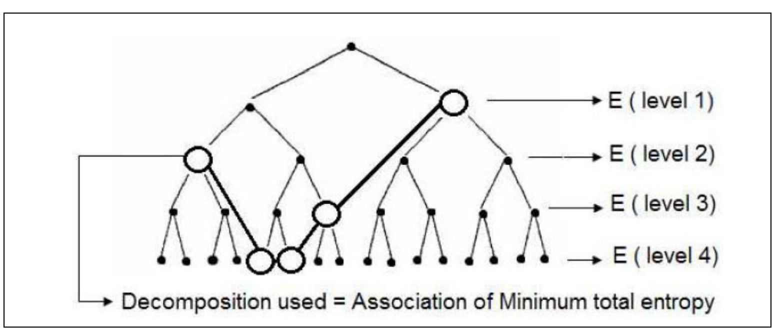


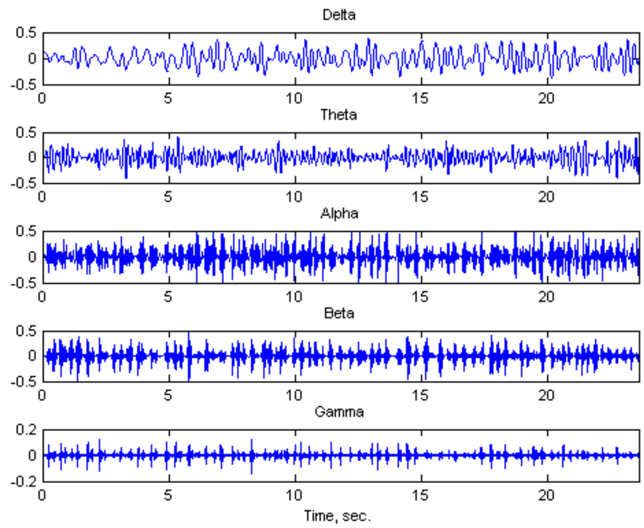

Figure II.26: the best basis tree approach. Source [139]

**Brainwave-Guided Wavelet Packet Tree Selection**.

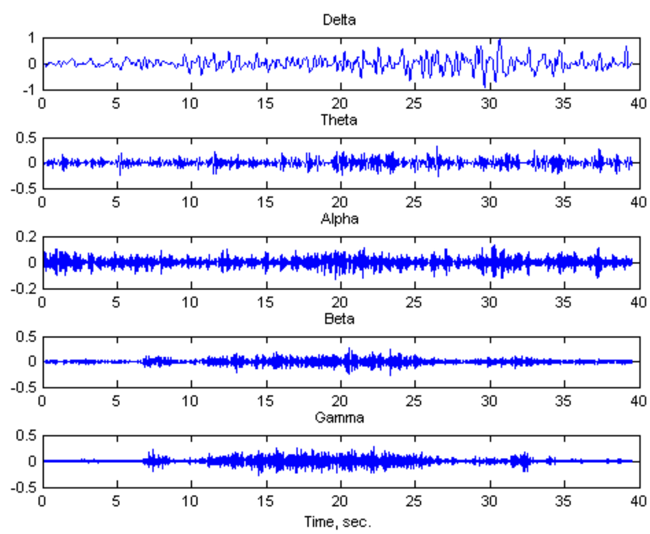
In the pragmatic realm of application, the imperative task of determining an optimal number of decomposition levels assumes paramount significance. This determination is contingent upon both the inherent characteristics of the input signal and the specific objectives integral to the intended application. In this particular context, we applied the Wavelet Packet Decomposition (WPD) methodology to electroencephalogram (EEG) signals procured from the CHB-MIT and Bonn databases. The primary objective of this application was to systematically extract clinically relevant brainwave components, encompassing Delta, Theta, Alpha, Beta, and Gamma frequencies, through a meticulously orchestrated decomposition process.

This systematic decomposition process, marked by precision and methodological rigor, aimed to distill essential brainwave patterns from the complex EEG signals. Noteworthy in this pursuit were the meticulously chosen decomposition levels, denoted as $j = 4$ for the Bonn database and $j = 5$ for the CHB-MIT database. These specific choices were carefully calibrated to achieve optimal WP decomposition outcomes aligned with the nuanced characteristics of each dataset.

The tangible outcomes of this intricate decomposition process are illustrated in Figure II.27, providing a visual representation of the obtained decomposition results. This representation serves as a comprehensive elucidation of the successful extraction and isolation of distinct brainwave frequencies, showcasing the efficacy and precision of the employed WPD methodology in the time scale analysis of EEG signals from diverse databases.




(a) 4-levels WPD, (Fs=128Hz)




(b) 5-levels WPD, (Fs=256Hz)

Figure II.27: db6–WPD–based EEG brain waves generation within seizure EEGs of Bonn (a) and CHB-MIT (b).

## II.3 Conclusion

In this chapter, a popular time–scale approach known as wavelet transform was presented. This latter, has been applied in various fields to process a wide range of signals covering biological and biomedical signals, with the ability to offer both time and frequency localisation, which overcomes Fourier transform limitations and Short–Time Fourier Transform (STFT) resolution trade–off. Indeed, wavelets carry out a multiresolution analysis towards information within biomedical signals, over the hole time–scale domain.

The continuous wavelet transform (CWT), appears to be an appropriate approach, that serves to properly represent temporal and frequency components of the electroencephalogram (EEG) signal, through an analyzing window that dilates and translates in time, Besides the scalogram, in which the high–energy regions can be easily localized for seizure and non–seizure EEG signals. Therefore, this latter, can be considered as an additional discrimination tool in the time–scale domain between normal and abnormal EEG signals. The discrete wavelet transform (DWT) serves as a filtering element, besides, its character of multi–resolution analysis. For the EEG signal, it provides at the appropriate decomposition level a direct detection of the well known brainwaves of interest namely; Delta[0–4]Hz, Theta[4–8]Hz, Alpha[8–16]Hz, Beta[16–32]Hz and Gamma[32–64]. The Wavelet Packet Transform (WPT) offers a more complex and more flexible analysis. Thus, it enables and guaranties capturing more EEG components and transient features, depending on their location at different levels of decomposition.

# Chapter III

# Characterisation and Classification of Electroencephalogram Signals

In signal processing, pattern identification, and machine learning based classification, the characteristics extraction process initiates from a given set of measured data and provides derived values, commonly known as features. These latter, are planned and intended to be highly instructive, precisely informative, and non-redundant, making the learning subsequent and generalization steps more easy and efficient. The features extraction phase, reduces the data dimensionality through the elimination of redundant data. Consequently, it improves training process, inference speed, leads to a minimized error rate of learned models and could certainly minimize the over–fitting risk.

The commonly extracted features for EEG processing studies on seizure and seizure–free epochs detection fall into three principal categories; *time domain attributes*, *frequency domain attributes*, and *time-frequency domain attributes* [140].

**Time domain attributes.** represents those estimated on EEG signal raw or on pre-treated signals, such as; *local gradient pattern*, *local binary pattern*, *local neighbor descriptive pattern*, *magnitude*–based features extraction from the studied EEGs, *line length* known also as *curve length*, which represents the signal's total vertical length and *the magnitude-integrated EEG (mEEG)*, which represents a visual examination that is usually utilized for ictal detection in hospitals, this latter, is obtained through a simple maximum and minimum values difference estimation (peak-to-peak rectification) [140].

**Frequency-domain features.** are derived from discrete–Fourier transform presentation of EEG signals raw. The Frequency domain–based EEG analysis is as well pivotal, since it provides more valuable information about patterns reflected in the signal's frequency components. The Power Spectral Density as well as its normalized version (by the total power) are usually utilized for extraction process of characteristics that represent the frequencies partition power. *The energy* of specific frequency ranges, *mean frequency* called also *intensity weighted mean frequency*, *spectral edge frequency*, *Peak frequency* or *the dominant frequency*, *spectral entropy* and *the intensity weighted bandwidth*, these are the main frequency domain features. Besides, *the power ratio* of background epochs as well the current one at an identical frequency range, which is usually extracted to detect the epilepsy since the power of a ictal epoch is relatively higher in comparison of that of the background one [140].

**Time-frequency-domain features.** are originated from a transformed presentation of EEG signals that comprise both time and frequency characteristics, such as short–time Fourier transform (STFT) and wavelets–based time–scale . A mixture of features can be extracted from specific sub–bands at a desired decomposition level, such as; statistical attributes which are commonly computed to distinguish normal and seizure periods through a statistical study of EEG signals. The entropies such as: *approximate entropy*, *sample entropy*, *permutation entropy*...etc, are also used to explore the irregularity and uncertainty of electroencephalogram signal. Additionally, *Hurst Exponent*, *Auto–regressive* and *auto–regressive moving mean* can be extracted to evaluate the randomness and dynamics of seizure and normal EEG patterns [140].

## III.1 Extracted Features for Epilepsy Detection

Generally, The objective behind the feature extraction process is to elicit a distinguishing characteristics from the processed EEG data, to typify the ictal activity pattern. A variety of features have been developed and proposed in the literature, as cited previously. However, the effectiveness of an automatic EEG classification algorithm for seizure detection relies completely on the fineness of the extracted attributes. Thus, in our thesis work, several basic statistical features were derived from specified approximation and detail sub-bands of WT coefficients corresponding to the well known EEG brainwaves generated at a fixed resolution level. These features are listed as basic features in section III.1.1. Besides three developed features from a combination of existing statistical characteristics, these new features are listed as developed features in section III.1.2

### III.1.1 Basic Features

**Feature 1: Median Absolute Deviation of WPs coefficients (MAD)**

The Median Absolute Deviation (MAD) serves as a statistical metric employed to quantify the dispersion or variability inherent in a given set of quantitative data. Representing a variant of absolute deviation, MAD is notably robust in the presence of outliers positioned at the extremes of the data distribution. This robustness emanates from the reduced influence of data extremes on the calculation of the median, distinguishing it from the mean. Specifically, the impact of data points in the tails of the distribution is less pronounced in the MAD calculation compared to their influence on the arithmetic mean. Mathematically, this characteristic can be precisely expressed as outlined in Equation (III.1).

$$\text{MAD} = median(\mid Cj_i - median(Cj_i) \mid), \tag{III.1}$$

where $Cj_i$ represents WP coefficients at scale $j$ for $i^{\text{th}}$ subband.

The Median Absolute Deviation (MAD) holds significance in the state-of-the-art techniques for epilepsy detection, contributing notably to robust statistical measures in the analysis of quantitative data derived from electroencephalogram (EEG) signals. In the context of epilepsy detection, where accurate characterization of signal variability is paramount, MAD serves as a valuable metric to assess the dispersion of EEG data. By virtue of its resistance to the influence of outliers, MAD aids in mitigating the impact of sporadic, extreme events in the EEG recordings, which are common in the context of epileptic seizures. This robustness enhances the reliability of statistical analyses, particularly in scenarios where the conventional mean-based measures may be distorted by outliers [141].

**Feature 2: Root Mean Square of WPs coefficients**

In the realm of EEG classification, a contemporary approach has garnered attention for its noteworthy efficacy. This methodology distinguishes itself by integrating statistical measures, specifically the Root Mean Square (RMS) and Standard Deviation (STD) of Wavelet Packet (WP) coefficients, as discriminative features. This innovative approach has demonstrated an exceptional accuracy rate of 99.64% [142]. In alignment with the pursuit of heightened classification precision within the scope of our current study objectives, we extend the methodology by incorporating the RMS as a pivotal feature. This augmentation aims to further enhance the discriminative capacity of the classifier, acknowledging the robust contributions of RMS in capturing essential characteristics of EEG signals [142]. The integration of RMS, along with previously employed statistical feature, represents a nuanced refinement that aligns with the evolving landscape of EEG classification methodologies, contributing to the ongoing pursuit of heightened accuracy and reliability in neurological signal analysis.

The Root Mean Square (RMS) of WPs coefficients, given in (III.2), is the square root of the mean square of WPs coefficients.

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} \mid Cj_i(n) \mid^2}. \tag{III.2}$$

where $Cj_i(n)$ represents WP coefficients at scale $j$ for $i^{\text{th}}$ subband.

**Feature 3: kurtosis of WPT coefficients**

The introduction of kurtosis into our analytical framework serves the purpose of assessing the distribution characteristics of the analyzed dataset. As elucidated by Alickovic et al [143], kurtosis plays a key role in discerning the presence or absence of outliers within the data. Higher kurtosis values indicate a distribution with pronounced tails, signifying a greater propensity for outlier occurrences. Conversely, lower kurtosis values suggest a more uniform distribution with reduced tail extremities, indicative of a lower likelihood of outliers. The formal expression of kurtosis, as utilized in our analysis, is precisely articulated in Equation III.3. This inclusion underscores a methodologically rigorous approach to understanding the statistical properties of the dataset, thereby contributing to the robustness of our analytical methodology.

$$K = \frac{E(Cj_i - \mu)^4}{\sigma^4}, \tag{III.3}$$

where $\mu$ represents the mean of $Cj_i$, $\sigma$ is the standard deviation of $Cj_i$, and $E(\cdot)$ is the expected value.

**Feature 4: Variance of WPs coefficients**

The inclusion of the variance feature in our analytical framework serves as a fundamental aspect of characterizing the variability within the analyzed dataset. Variance represents a classical measure of statistical dispersion, quantifies the extent to which individual data points deviate from the dataset's mean. By considering the spread of values, variance provides crucial insights into the distributional characteristics of the EEG data. It is calculated as the average of the squared differences between each data point and the mea as given in Equation (III.4). The utilization of variance as a feature enables a nuanced exploration of the dataset's intrinsic variability, facilitating a comprehensive understanding of the signal dynamics. This statistical measure is particularly relevant in our analytical context, where a thorough examination of the EEG data variability is essential for informed decision-making. The formal definition of variance and its role within our analytical framework are succinctly outlined, contributing to the methodological precision of our investigation.

$$\mathrm{Var} = \frac{1}{N}\sum_{n=1}^{N}(Cj_i(n) - \mu)^2, \tag{III.4}$$

where $Cj_i(n)$ represents WP coefficients at scale $j$ for $i^{\mathrm{th}}$ subband.

### III.1.2 Engineered Features

To enhance the precision of constructing pertinent EEG channels, three supplementary features have been introduced to address the core considerations delineated in Section III.1.1. These features, denoted as Feature 5: Geometric-Harmonic Average Difference of Wavelet Packet (WP) coefficients (GHADWP), Feature 6: Normalized Range of WP coefficients (NRWP), Feature 7: Standard Deviation (STD) of absolute values of WP coefficients ($\sigma_{|WP|}$), and Feature 8: Energy-to-Shannon Entropy Ratio, are all derived from the WP coefficients of EEG signals. This nuanced approach aims to comprehensively capture essential aspects of the EEG signal dynamics. The integration of these features is pivotal in formulating a robust seizure detection algorithm, as the identification of epilepsy hinges on discerning subtle alterations in the processed EEG signal. This strategic combination of primary and advanced features underscores the methodological sophistication employed in devising an effective algorithm for seizure detection.

**Feature 5: Geometric–Harmonic Average Difference of WP coefficients**

The arithmetic mean stands as a prevalent tool in EEG signal processing for epilepsy detection, as highlighted by Chen (2017). Notably, comparative studies [144] have indicated that the geometric mean values are consistently higher over the values of harmonic mean. Consequently, we adopt the Geometric-Harmonic Average Difference (GHADWP) as a feature for seizure detection within EEG signals, a measure defined in Equation (III.5) based on the means inequality principle. This strategic selection emphasizes our methodological decision to capture crucial elements in epilepsy identification by discerning subtle alterations in EEG signals.

$$\text{GHADWP} = G_{mean} - H_{mean}, \tag{III.5}$$

where $G_{mean}$ and $H_{mean}$ represent geometric and harmonic mean values of WPs coefficients.

The geometric mean offers a more precise depiction of central tendency within a dataset when compared to the arithmetic mean. This enhanced accuracy stems from the geometric mean's increased robustness to outliers in terms of their magnitude. The calculation of the geometric mean is delineated in Equation (III.8). Serving as a valuable statistical measure, the geometric mean efficiently summarizes a set of values and yields insights into the inherent distribution of the data.

$$G_{mean} = \left( \prod_{n=1}^{N} \mid Cj_i(n) \mid \right)^{1/N}, \tag{III.6}$$

where $Cj_i(n)$ represents WP coefficients at scale $j$ for $i^{\text{th}}$ subband.

The harmonic mean constitutes a robust measure of central tendency, notably advantageous in scenarios where outliers exert a considerable influence on outcomes. In contrast to the arithmetic mean, which is susceptible to the impact of larger observations, the harmonic mean assigns greater weight to smaller values within a dataset. The formula for calculating the harmonic mean is articulated in Equation (III.7). This statistical measure proves especially valuable in situations where maintaining sensitivity to smaller values is essential, enhancing the harmonic mean's utility in contexts where the presence of outliers can significantly affect the overall results.

$$H_{mean} = \frac{N}{\sum_{n=1}^{N} \left( \frac{1}{|Cj_i(n)|} \right)}. \tag{III.7}$$

where $Cj_i(n)$ represents WP coefficients at scale $j$ for $i^{\text{th}}$ subband

**Feature 6: Normalized range of WP coefficients**

The assessment of the magnitude distribution of EEG signals holds paramount importance in the comprehensive analysis and classification of such signals. To quantitatively capture this distribution, a key feature is introduced, denoting the normalized range of the wavelet packet (WP) coefficients. Computed as the disparity between the maximum and minimum values of the WP coefficients, this feature is precisely defined in Equation (III.8). By employing this feature, we aim to systematically quantify the spread of magnitudes within the wavelet packet coefficients, offering a quantitative measure that contributes to a more nuanced understanding of the signal characteristics in the broader context of EEG signal analysis and classification.

$$\mathrm{NRWP} = \frac{max(\mathrm{Cj}_i) - min(\mathrm{Cj}_i)}{max(\mid \mathrm{Cj}_i \mid)}, \tag{III.8}$$

where $Cj_i$ represents WP coefficients at scale $j$ for $i^{\text{th}}$ subband.

**Feature 7: STD of absolute value of WP coefficients**

In an earlier investigation conducted by Masoum *et al.* [145], power disturbance deviations were categorized through the application of the mean and standard deviation of the absolute values of Discrete Wavelet Transform (DWT) coefficients. Expanding upon this methodology, our present study advances the approach by incorporating the standard deviation (STD) of the absolute values of Wavelet Packet (WP) coefficients, as defined in EquationIII.9. This refinement allows us to precisely quantify the dispersion and alterations induced by seizure epochs within EEG signals. The adoption of WP coefficients in our methodology marks a noteworthy improvement over the previous DWT-based approach, reflecting a more nuanced and effective means of characterizing changes associated with seizure activity in EEG signals.

$$aSTD = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(\mid Cj_i \mid - \mu)^2}, \tag{III.9}$$

where $Cj_i$ represents WP coefficients at scale $j$ for $i^{\text{th}}$ subband.

**Feature 08: Energy–to–Shannon Entropy Ratio**

Navigating the intricate path of seizure progression within the brain presents a substantial challenge, requiring a robust model equipped with specific types of features capable of capturing the general and habitual behavior of each brain region in both normal and seizing states. Numerous studies have underscored that during the ictal period, entropy values of the EEG signal diminish, accompanied by a more regularized aspect [146, 147]. Furthermore, it is established that the energy values of an EEG signal elevate during seizures in comparison to normal behavior [148]. Consequently, both features offer quasi-constant information about the EEG signal's behavior during and outside seizure episodes. In light of this, we have embraced the Energy-to-Shannon Entropy Ratio (ESER), a ratio between these two features. The rationale behind this choice lies in the anticipation that ESER values will be higher during seizures and lower in normal epochs. This strategic adoption facilitates the identification of seizure-affected EEG channels amidst the entirety of channels in the EEG recording, enhancing our ability to detect and characterize seizure events.

The defined ratio between the normalized energy and the Shannon Entropy, denoted as the Energy-to-Shannon Entropy Ratio (ESER), is precisely articulated in Equation (III.10). This ratio, derived from the coefficients of wavelet packets, serves as a critical metric in our analysis, providing valuable insights into the dynamics of the underlying signal.

$$\text{ESER} = \frac{\text{NE}}{\text{SE}}, \tag{III.10}$$

where NE represents the normalized energy of wavelet packets.

The WPs energy is defined as given in (III.11)

$$E_j = \int_{-\infty}^{+\infty} \text{C}_j(t)\text{dt}, \tag{III.11}$$

where $C_j(t)$ represents WPs coefficients at scale $j$.

The normalized energy (NE) of wavelet packets (WPs) is given in (III.12).

$$\text{NE} = \frac{Ej_i}{E_{Total}}, \tag{III.12}$$

where $Ej_i$ represents the energy of the $i^{\text{th}}$ subband at scale $j$, and $E_{Total}$ is the total energy of the analyzed signal.

The Shannon Entropy of Wavelet Packets (WPs) serves as an estimator for the degree of irregularity present in the analyzed signal [149]. The unnormalized Shannon entropy is precisely defined in Equation (III.13). This metric is instrumental in quantifying the information content and unpredictability inherent in the wavelet packet coefficients, offering valuable insights into the signal's complexity and irregularities.

$$\text{SE} = -2\sum_{n=1}^{N} \text{Cj}_i^2(n) \log \text{Cj}_i(n), \tag{III.13}$$

where $Cj_i(n)$ represents WP coefficients at scale $j$ for $i^{\text{th}}$ sub-band.

In the present section, we meticulously examined various techniques for feature extraction from EEG signals, aiming to distill essential information and patterns indicative of neurological phenomena. These extracted features serve as the informative building blocks that pave the way for the subsequent phase of our analysis: classification techniques. As we delve into the realm of classification, the nuanced characteristics captured during the feature extraction process become the bedrock upon which our classification models will be intricately designed. This strategic linkage between feature extraction and classification is fundamental, as the discrimination ability of our classification algorithms hinges upon the richness and relevance of the features obtained. In the upcoming section, we explore diverse classification methodologies that harness the extracted features, propelling us towards a comprehensive understanding and accurate identification of normal and epileptic EEG signal patterns.

## III.2 Features Selection Methods

Feature selection is a requisite stage in data processing and its preparation for the classification process, this stage, ameliorates the model effectiveness and minimizes the analyzing computational complexity through the projection of the extracted features from a higher onto a more lower dimensional space. Feature selection techniques, allow the input dimensionality lowering via an excluding operation of unnecessary and superfluous characteristics from the given attributes set [150–155]. In machine learning written works, feature selection approaches are usually organized in three categories namely; filter techniques, wrapper strategies as well as the embedded approaches [152, 154–156].

***Filter–based feature selection techniques***, utilize the statistical characteristics of evaluative variables known as predictor values and their link to the response variable (the outcomes). These techniques are advantageous in term of computational time. There are numerous filter methods, citing and not limiting; Principal Component Analysis; which is a well known unsupervised feature's dimensionality lowering tool, which does not deem dependent features. Linear Discriminant Analysis and Partial Least Squares. The mutual idea behind this three approaches, is the research of a linear separation between the features, in order to identify and distinguish binary or multi–classes. Nevertheless, in spite of their linearity, simplicity, and relatively minimized cost while reducing the the input data dimensionality, the ranking process of relevant features remains unclear, in other words, there is not an obvious interpretation of the attributes rating operation [157–159].

***The Wrapper–based pertinent features selection strategies*** are employed to come up with a foretell model based on a mixture of features combinations to select further, the set of characteristics that provides the best valuation performance. These approaches are disadvantageous in term of processing time (consumer and slower). Accordingly, they are unsuitable to be used for features subset selection for large–scale issues. The Support Vector Machine–based Recursive Feature Elimination, abbreviated as SVM–RFE, represents one of the prevalent wrapper techniques, that uses the backward features elimination [160, 161]. This latter, constructs a model using the total features set. Then, it calculates the pertinence score of each one. Finally, it eliminates the least considerable attributes at each iteration, consequently, it ameliorates the model performance efficiency. In other words, the features ranked at the top are the last excluded [160–162].

***Embedded techniques*** are entirely different in comparison of the two previously cited approaches. In this technique, the classifier is implemented to perform automatically a relevant features selection while fitting; which means that both attributes selection jointly with model training [152, 161].

The embedded approach represents an optimized establishment of the Gradient Boosting framework. The term Boosting, refers to the implantation of a robust learner, with a hopeful precision rate, where the classifiers are built based on gradient descent to ameliorate the loss function. As an example of embedded approaches, we cite the Extreme Gradient Boosting, which has been widely employed in many fields, due to its significant scalability, simultaneous processing and flexibility [163–167].

In our thesis study, we carried out a feature selection process using the well known relief–F algorithm. This latter, belongs to the filter methods. Its key idea is based on a distance measure technique, generally, the familiar Manhattan distance. The reason behind the selection of relief–F algorithm for relevant attributes recognition and optimal classification performance, is its efficiency when handling with noisy data. Besides that, this latter, was recently utilized for epileptic seizures identification and accomplished meaningful sensitivity results of 99.80% using long short term memory classifier [168]

### Relief–F Algorithm

The first come out of Relief algorithm was in 1992, by Kira and Rendell [169]. They proposed a suitable automatic tool for optimal features selection, and devoted only for binary classification. its principle consists of characteristics weighting operation, where, it attributes several weights depending on the similarity between features and the given classes, to remove further the characteristics whom weights are fewer than a pre–determined threshold. Although the suggested algorithm is uncomplicated, efficacious and provides satisfactory results. Nevertheless, it can not handle with more than two classes, which represents a constraint. As a consequence, Kononenko [170] developed an upgraded version of the present algorithm, called Relief–F, which selects the needed features that distinguishes not only binary classes, but also can deal efficiently with multi–classification issue.

**Relief–F Principle.** At the start, the reliefF algorithm sort out randomly an instances called $R_i$, where R refers to random instance. After that, it searches its k–nearest neighbor in the given differentiated and undifferentiated classes, and assigned H and M as a denomination of the nearest instances from the same and different class respectively. Often, the well known Manhattan distance is utilized for M and H instances identification. Therefore, this Manhattan tool, will keep only restricted attributes to represent and reduce the whole high dimension data. Which is required for an accurate epileptic seizure identification.

The weights $W[F]$ of the attributes to be ranked are regulated in accordance of their values. If $R_i$ and $H$ instances are of distinct values of the given feature $F$, then this latter (feature F) discerns two instances that represents an identical class, which is unrequested and disadvantageous. Necessarily, the quality estimation $W[F]$ value will be decreased. Dissimilarly, if the $R_i$ and $M$ instances of the feature $F$ are of uneven values, then this latter (feature F), differentiates between two instances of dissimilar categories, which is needed to perform a correct classification, hence the quality estimation $W[F]$ will be increased. The complete operation will be repeated $n$ times, where $n$ is represents a user–defined parameter.

$$W[F] = W[F] + (H + M)/n \tag{III.14}$$

Where;

$$H = -\sum_{j=1}^{k} D(F, R_i, H)/k \tag{III.15}$$

$$M = -\sum_{c \neq cl_{(R_i)}} \left[ \left( \frac{Pc}{1 - P(cl_{(R_i)})} \sum_{j=1}^{k} D(F, R_i, M(c)) \right) \right] / k \tag{III.16}$$

Where;

$W[A]$ represents the quality estimation. $R_i$ represents the randomly chosen instance. $F$ refers to Feature. $H$ and $M$ represents the nearest hit as well as the nearest miss values, respectively. $D$ refers to the term Distance. $C$ indicates the classes, $cl_{(R_i)}$: the class of ith sample.

## III.3 EEG Classification Techniques

The electroencephalogram classification plays a primordial role in biomedical field, particularly in neurology, since classifying EEG signals contributes in enhancing the diagnosis of several brain diseases and provides better perception of cognitive processes. A powerful classification technique reliefs to distinguish EEG segments, and therefore, in a person's health decision making. However, the EEG recordings comprise a considerable amount of data and the key issue resides in the pre–processing, processing and preparation of the EEG signals for further classification phase. Thus, it is, necessary to carefully extract the distinguishing features from the EEG signals raw, as discussed in previous section and then use only relevant characteristics for a successful classification. The following sections offers detailed outlines about the EEG signal classification for epilepsy detection and prediction.

The research on epileptic activity detection has been introduced in the 1970s, where, appreciable efforts have been devoted for that within EEG recordings. Efficacious automated ictal detection poses challenges, because of various reasons. Such as, the variation of seizure EEG pattern from patient to another, while the great difficulty appears when, ictal activity arises from several brain areas. In contrary of early studies, which provides suboptimal findings, such as latencies elevation and false alarm ratio. Recent studies addressing the detection problem, demonstrate that, machine learning models can rival proficiency level in electroencephalogram interpretation [171].

In the literature, several classifiers were combined with various processing approach to implement epileptiform detection systems, modified particle swarm optimization (MPSO)–RBFNN [172], support vector machine (SVM) [173–176], due to its hopeful performance results it has been also used in [177–181], the cosine signal measurement, known as CSM–SVM [182], universum twin support vector machine (USVM) [183], RBFNN [180], Artificial Neural Network (ANN) [184, 185], multi–layer perceptron neural network (MLPNN) [179, 186], least square SVM [187, 188], random forest (RF) [187, 189, 190], Artificial Bee Colony Algorithm (ABC) tune Radial Basis Function Neural Network (RBFNN) [191] and K–nearest neighbor provided efficient and economical classification of epileptic seizure

Moreover, the machine learning techniques have been investigated as well in the **epileptogenic area detection**, Dian et al. utilized intracranial EEGs recorded from 6 patients, undergoing ictal–free surgery, to apprenticeship a classification model for identification of epileptogenic area. The proposed system leverages SVM–based Machine learning method, extracted attributes (high and low frequency oscillations) for both seizure detection and precisely locate zones to be resected from the patient brain [192]. Elahian et al. applied a logistic regression learning approach, on the basis of phase locking value between gamma's high activity (up to 150 Hz) and the lower frequency rhythms that spans [4—30] Hz, aiming to efficiently identify the epileptogenic focus from ECoG [193]. A recent approach proposed by Ahmedt Aristizabal *et al.* studied the relationship between anatomo–electroclinical and the epileptogenic network's anatomical localization by a combination of deep learning, brain electrical activity, and anatomical characteristics [194]. Unsupervised learning was also investigated to study the inter–ictal epileptiform discharges and detect the ictal area in the brain, the model represents a powerful tool towards automated epileptogenic focus identification [195, 196].

**Seizure prediction** can be defined as the automatic identification of upcoming ictal activity. Where, the pre–ictal window to be processed can be as long as a couple of minutes [14]. Success in predicting epileptic seizures provide myriad benefits namely; injuries avoidance, sedative effect on anxiety, emergency aid and premature intervention, that leads to early therapy (medicines, vagus nerve's electric stimulation, profound brain stimulation). The K–nearest neighbors classifier has been utilized for abnormal activity prediction in a study by Wang, resulting a prediction performance with 73% and 67% for sensitivity and specificity respectively [197]. Cho *et al.*, computed the phase locking values, to be used as features to train an SVM model for short inter–ictal and pre–ictal EEG segments [198, 199]. Multivariate EEG features and SVM with a successful prediction results (71/83 seizures were correctly predicted) [200]. Mirowski *et al.* used a mixture of machine learning techniques; SVM, logistic regression and CNN, their proposed study outperformed several previous ictal activity prediction methods, where the best pattern recognition was obtained after using the CNN combined with wavelet [201]. SVM classifier and twenty–two linear uni–variate attributes were combined to build a model that discriminates the pre–ictal from normal cases, in which 34/46 of seizures were predicted [202].

In Chiang's research paper, the super SVM found to be more accurate for the mode of online learning, with a hopeful sensitivity values of 74.2% and 52.2% on ECoG and CHB–MIT scalp EEG databases respectively, in comparison to the neural network classifiers, which could be gradually incapable to classify pre–ictal patterns after training with long interictal patterns series. Multi–class SVM combining multiple channels and a large observations sets, were implemented by Direito *et al.* [203], the study accomplished prospective processing of a large diversified, multi–centric databases, with acceptable sensitivity value as well as a hopeful false positive rate. Usman *et al.* pre–processed the EEG signal and then evaluated the performance of seizure activity prediction via three classifiers, namely; k–NN, SVM and Naive Bayes. According to their findings, SVM and Naive Bayes provides more accurate results in terms of sensitivity [181]. Jacobs *et al.*, used the random forest models for ictal state prediction from the CHB–MIT scalp EEG. The developed system exhibited 87.9%, 82.4%, 93.4 for sensitivity, specificity, and area–under–the–ROC

(AUC) [204]. Advanced seizure prediction via ANN along with 72 attributes, was carried out for the prediction of epileptic seizures in a study by Sharma provided a promising accuracy of 92.3%, 100% in sensitivity and a specificity of 83.3% [205]. A 5–layer CNN together with bivariate attributes that qualified intracranial EEG synchronization, the model showed its good generalization, with nill false alarms in 15/21 patients [201].

The long short–term memory networks were investigated for ictal activity prediction within EEG signals [206], the utilization of deep learning algorithms with CNN offers higher sensitivity rates and lower false prediction rates per hour. Most lately, Wei et al. built their epileptic seizures prediction model on the basis of long–term recurrent CNN, providing a slight improvement in sensitivity and specificity in comparison to the deep learning and traditional machine learning techniques [207], since the convolutional network block extracts automatically the distinguishing deep features from the processed EEG data.

### III.3.1 Machine Learning: an Overview

Smart and automatic predictive modeling known under the denomination of machine learning, represents an entire offshoot of computing knowledge, which aims to develop, produce and simulate human superb learning abilities in computer algorithms. Since the early 50s, Samuel introduced for the first time, the machine learning expression, and aims to inspire from the varied intelligent and brilliant human activities and conveyed it to the host. The term host does not refer to the physical meaning of a machine, however, it indicates the development of a computer science system to be further accomplished as a computer software or a smart phone application. Therefore, the key purpose of the machine learning field is to come up with intelligent systems based on relationships between the human apprenticeship capabilities and the possibility to realized by means of computer science programs. Machine learning is investigated in a large diversity of application frameworks, starting from engineering applications such as; robotics or pattern identification and characterisation (speech processing, handwriting analysis, face discrimination), arriving to Internet implementations (text arrangement) as well as the medical field applications namely; diagnosis, expectations, medications discovery...etc.

The classification task took place throughout quotidian life, and simply means, making a decision on the basis of disposable and current information. Daily life classification tasks are uncountable, starting from simple examples known by every one such as; modes of transport classification, animals types (herbivores,carnivores, omnivores), genders classification and food items classification as well. Arriving to more complex examples such as; Email Spam classification, recognition of handwritten Digit, speech, DNA sequence classification...etc, and in our research area, the classification provides a prior diagnosis of a patient's pathology in order to start an immediate treatment, while proceeding definitive test to confirm or not the classification result [208].

The classification process attributes a class or a category to a set of characteristics (features) extracted from the processed signals. For EEG signal classification, this class represents an identified mental state type (normal, ictal, pre–ictal...etc). This step is known also as features translation operation.

Basically, there are three principle types of classification: supervised, semi–supervised and unsupervised classification. In supervised classification, the set of features to be classified are associated with determined class labels. Unlike, the unsupervised classification, in which the observations are unlabelled, consequently the classes are unknown a priory. Whilst, in the semi–supervised learning, a few portion of observations are labeled, while a considerable number of these latters (observations) are unlabeled [209]. Descriptions of aforementioned are illustrated in Figure III.1

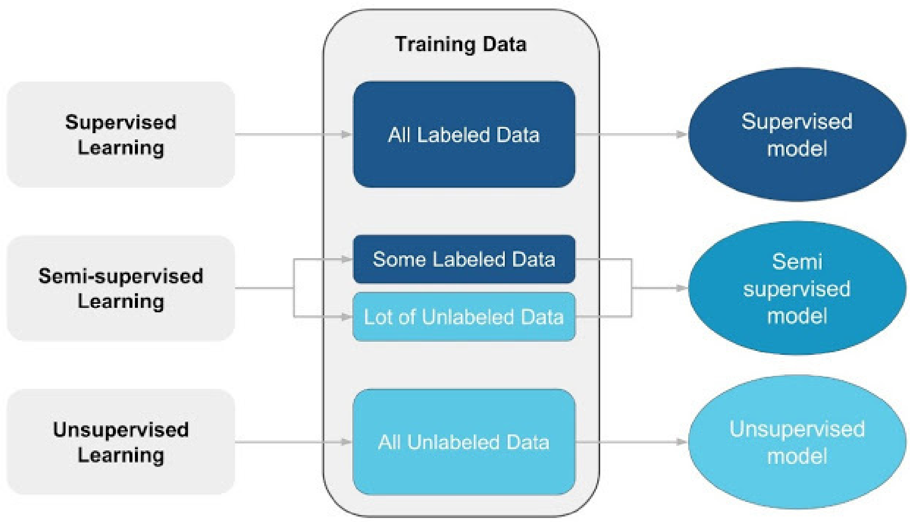



Figure III.1: Machine learning methods. Source [2]

### III.3.2 Supervised Classification

Mostly, the supervised classification is frequently applied in biomedical research area, the majority of classification models, treat a group of observations assigned to specific classes. Therefore, the class label information is provided within the training phase of the implemented model. This type of classification is known as supervised learning, since the construction of the affectation model is instructed by a supervisor. In summery, the supervised approach supposes that, the given set of training data comprises a set of observations that have been manually and carefully labelled by the correct output [208, 210].

The supervised classification procedure, requires to divide the database to be classified into training set and testing set. The training set serves in the classification function construction. Then, the performance of the implemented model will be evaluated by means of the testing set As shown in Figure III.2. This evaluation needs sometimes to be repeated using several parameters of the constructed classifier.

By such procedure the classifier parameters will be optimized. afterwards, this latter (optimized classifier), will be able to assign the right labels to the features of unknown classes. Therefore, the purpose of the apprenticeship procedure is to increase at maximum the test accuracy result, while minimizing the error rate.

Given a size of observations, samples or data points, detained to be used in the **training** phase. Each apprenticeship data point is labeled with an identification outcome, where the principle role of the training phase in machine learning operation, consists of using both observation and their outcomes (labels), to come up with a relationship to be used as a rule to predict unknown data samples detained to be used as **test** examples. In machine learning field, The execution on test observations is named a **generalization**. To achieve this latter (the generalization), a robust predictive model should be build based on the training examples, in other words, the predictive model represents a function with optimum parameters, that have been adjusted while training to achieve the best performance.

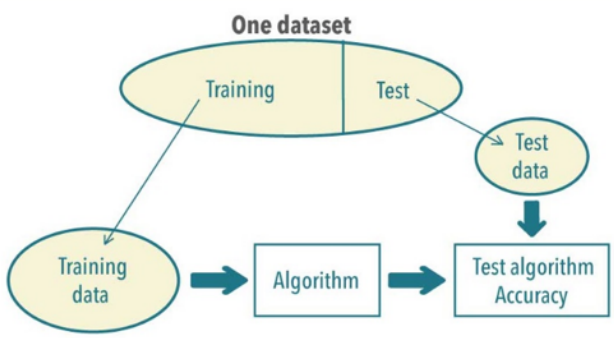



Figure III.2: An illustration of data splitting into training and test groups to be use in the classification process. Source [3]

The common supervised learning based classifiers are several, namely; support vector machine (SVM), K–nearest–neighbor (knn), linear discriminant analysis (LDA), naive Bayes classifier, artificial neural networks (ANN), Decision trees, logistic and linear regressions, Kalman filters, Gaussian process regression...etc.

In general, the term classification refers to a supervised approach. In our thesis research, we have applied several supervised classifiers for various aims, namely; relevant EEG channel selection, epilepsy detection and prediction within EEG signals. During the experiment, we have used several approach to divide the data into training and test sets. The training set is employed in the apprenticeship phase of the used classifiers, while the testing set were reserved for the evaluation of the implemented models performance.

### K–Nearest Neighbors (knn)

The k–nearst neighbors, is a popular and widespread supervised learning classifier, that falls in the non–parametric classification techniques[1]. The knn algorithm roots can be traced back to the statisticians Evelyn Fix and Joseph Hodges in 1951 [211] and improved later by the information theorist Thomas Cover [212]. It is developed to be employed for regression and classification. Where, the input is formed by the k–nearby apprenticeship observations in the employed data set, while the output depends on the objective behind using the knn, whether, for classification or regression; for the first one (classification), the outlet represents a class adhesion, where the test observation will be classified on the basis of a plurality vote of its closest neighbors, in other words, the object will be attributed commonly to the class amongst its k nearby neighbors. In case of k=1, the observation will be labeled merely, to the class of that one closest neighbor. In knn–based regression process, the outlet represents the observation property value. This latter (value) represents the mean of the k nearest neighbors values. The function used for the classification process using the knn model, is only estimated locally and all calculation is deferred till the evaluation function, for the reason that, this algorithm classifies on the basis of distance computation. in case of features with various physical units or variant scales, then a normalization process of the training data, will be needed to improve its performance (accuracy) spectacularly [213]. For both classification or regression, an efficient technique can be utilized, to enhance the performance, known as weighted K nearest neighbor, this latter consists of assigning weights, depending on the effect of the neighbors (their distance from the observation to be labeled), therefore, the nearby neighbors contribute more in the final affectation decision in comparison to the more remote ones. As an example of a common weighting process, which consists of allocating a weight of $1/d$, for each neighbor, where $d$ represents the distance from the test sample. In contrary to other classifiers, no explicit apprenticeship phase is required when applying the knn model, which represents a gain in terms of computational time.

**Principle of the Algorithm**

The apprenticeship observations represent the input feature vectors of multidimensional spaces, each one represents a specific class known through the class label. The algorithm **training phase**, consists of a storing operation of these feature vectors and their corresponding class labels.

In the **prediction phase (classification)**, an unlabeled test point or the vectors kept for the test phase are classified according to the label of the closest training point, depending on the number of neighbors $K$ which is a fundamental user–defined parameter, as shown in Figure III.3. For binary classification, $K$ is usually an odd number.

For the continuous attributes, the commonly applied distance metric for the classification decision is the Euclidean distance. Whilst, the Hamming distance,

[1]The non–parametric classifiers: the algorithms that do not make intense presumption about the mapping function form are known as non–parametric machine learning models. Therefore, they can learn any functional form from the apprenticeship data.

known also as the overlap metric, is widely used for the text classification. Where, the correct rate of the knn can be ameliorated dramatically, if the distance metric is expanded with particular algorithms namely; neighbourhood components analysis or the large margin nearest neighbor [211, 212].

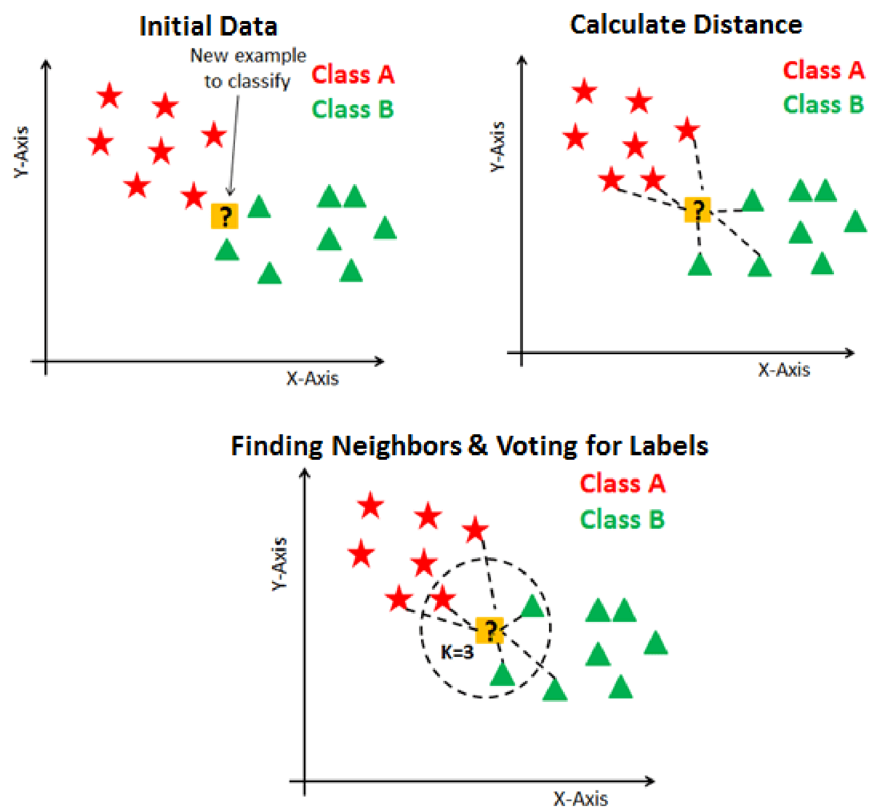



Figure III.3: Knn classification principle (example with three neighbors, k=3. Source [4]

**The K–Parameter Value**

The appropriate choice of the k value, relies on the employed data; in most cases, choosing a large value, helps in reducing the noise effect on the classification performance, however, it creates less distinct boundaries between classes. The right k value can be achieved through various techniques such as the hyper parameter optimization [2]. Besides that, the knn algorithm can be executed several times with various K values and select the one that, minimises the error rate, while keeping

[2]Hyper parameter; represents those machine learning algorithm parameters, that regularise the learning operation while training and we can quantify their effect on the performance through test samples classification [211, 212].

the model's ability to correctly predict unseen data. In the two class (binary) classification problems, it is required to define an odd number as a k value, and that to avoids tied votes [211, 212].

### Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA), was developed by Ronald Fisher in 1936 [214]. Unlike both ANOVA and MANOVA, which are applied to predict one (ANOVA) or multiple (MANOVA) dependent and continuous features, through one or additional categorical and independent variables, the discriminant function analysis is beneficial to reach a decision, whether a features set is qualified to predict correctly a given category membership. This function known also as normal discriminant analysis, was developed to come up with a linear combination of characteristics that typifies or distinguishes two or more objects categories. The outcoming combination, can be commonly employed for dimensionality reduction before launching the classification process or directly applied for a linear classification.

As mentioned previously the LDA is narrowly linked to the variance and regression based analysis, which endeavor also to express a dependent feature as a linear combination of other variables or measurements [215]. Nevertheless, the ANOVA works with categorical independent attributes together with continuous dependent features, whilst discriminant analysis uses continuous independent variables as well as the classes labels (categorical dependent variable). Logistic and probit regressions principles are more comparable to the LDA than ANOVA, since they also express a categorical characteristics through the continuous independent variables values.

Moreover, the LDA is also related to the well known principal component analysis (PCA), since the objective behind applying both of them is to come out with the optimal linear combination that explains obviously the processed data. Where the difference between the two techniques lies in considering or not the difference between the data classes. In other words, the linear discriminant analysis attempts mainly to model the dissimilarity between the classes of input data, unlike the PCA, which does not consider any difference in class. Therefore, the LDA is applied, when the classes labels are already known (dissimilar to the cluster analysis). A score on one or additional quantitative predictor measures must be assigned to each case, besides the group measure score. More explicitly, the discriminant function used for classification, divides the data into classes or the groups that describes the same patterns.

In summery, The linear discriminant analysis (LDA), is merely a Bayes theorem–based classifier. Its key idea consists to employ the input attributes of apprenticeship group to come out with an affectation function. This latter, serves in the prediction of the samples used in the test phase and ensures that the ratio of between–class scatter to within–class scatter is maximum, which guarantees the highest possible separability [216].

Similarly to the Principle Component Analysis (PCA), the LDA can be as well applied for dimensionality reduction by mapping $M$ data into $(M--1)$ dimensional subspace [217].

When using the LDA as a classifier, it creates in the training phase and through a discriminant function, a decision region between the input classes, this discriminant function is defined in III.17.

$$\beta^T \left( x - \left( \frac{\mu_1 + \mu_2}{2} \right) \right) > log \frac{P(c_1)}{P(c_2)} \tag{III.17}$$

Where;

$\beta$ represents the linear model coefficients as shown in equationIII.18, $x$ represents the samples to be affected, $\mu_1$ and $\mu_2$ is the mean of normal and epileptic classes respectively. $P(c)$ represents the class probability.

$$\beta = C^{-1}(\mu_1 - \mu_2). \tag{III.18}$$

where $C$ is the pooled covariance as shown in III.19

$$C = \frac{1}{n_1 + n_2}(n_1 C_1 + n_2 C_2) \tag{III.19}$$

Where;

$n$ represents the length of each class instances.

### III.3.3 Unsupervised Classification

The unsupervised classification approach consists of grouping the input data into classes, on the basis of specific inherent ability measures, such as; distance between instances. This unsupervised approach presupposes that the training data has not been hand–labelled. Therefore, it endeavors to find inherent patterns in the given data, by which it determines the appropriate outlet value for unseen data instance [208,210]. In summery, in the unsupervised learning, no information about the class labels of the observations is available, even for a few set of data.

The common supervised learning based classifiers are several, namely; principal component analysis (PCA), K–means or hierarchical based clustering, Kernel principal component analysis, independent component Analysis (ICA), Hidden Markov Models, categorical mixture model...etc.

#### K-means

K-means clustering is a popular unsupervised machine learning algorithm that excels in partitioning a dataset into distinct, non-overlapping groups, or clusters. At its core, the algorithm strives to minimize the within-cluster variance, seeking to create clusters where the data points share similarities while being distinct from points in other clusters [218].

The iterative process of k-means unfolds through the following equations III.20

$$J(c, \mu) = \sum_{i=1}^{k} \sum_{j=1}^{n} |x_j^{(i)} - \mu_i|_2^2 \tag{III.20}$$

where

$$J(c, \mu)$$

represents the objective function,

$c$ is the cluster assignment matrix,

$\mu$ denotes the cluster centroids,

$k$ is the number of clusters, and

$n$ is the number of data points.

The algorithm iteratively optimizes this objective function by updating cluster assignments and centroid positions. The cluster assignment is determined by III.21

$$c_j = \arg\min_i |x_j - \mu_i|_2^2 \tag{III.21}$$

followed by the centroid update as in III.22

$$\mu_i = \frac{1}{|c_i|} \sum_{j \in c_i} x_j \tag{III.22}$$

This iterative process continues until convergence, typically measured by the stability of cluster assignments or a predefined number of iterations.

While k-means is known for its simplicity and computational efficiency, it is sensitive to initial centroid placement. To address this, multiple runs with different initializations are often performed.

In our study, the k-means unsupervised learning method has been applied to partition each ictal multi-channel EEG recording into distinct clusters. The utilization of the k-means algorithm serves the purpose of unveiling latent patterns and inherent variability within the ictal multi-channel EEG data. By grouping similar channels together, this approach offers valuable insights into distinguishing seizure-affected EEG channels from those unaffected. The overarching objective is to delineate the source of epileptic seizures through a rigorous analysis of the clustering results facilitated by the k-means algorithm. This methodology not only enhances our understanding of the intricate dynamics present in ictal EEG recordings but also provides a refined framework for identifying and isolating channels implicated in epileptic seizure activity.

**k-means Clusters Evaluation Approaches**

Clustering evaluation methodologies are broadly categorized into three distinct approaches: Internal cluster validation, External cluster validation, and Relative cluster validation, as outlined by Charrad et al. [219]. Internal cluster validation, exemplified by metrics like the Silhouette coefficient, gauges the quality of a clustering structure by utilizing internal data intrinsic to the clustering process, without relying on external information.

External cluster validation, on the other hand, involves comparing the results of a cluster analysis with externally known outcomes, often provided in the form of predefined class labels. This external validation is particularly valuable when selecting the most suitable clustering algorithm for a given dataset, as the "actual" cluster number is known in advance.

The third category, Relative cluster validation, exemplified by techniques like the Elbow Curve, assesses the clustering structure by varying the number of clusters ($k$) to ascertain the optimal k. This method involves exploring different cluster configurations to identify the most appropriate number of clusters.

In the context of this dissertation, these three validation approaches—Internal, External, and Relative—are employed to rigorously validate our subsystem for circumscribing epileptogenic. This comprehensive validation strategy ensures the robustness and efficacy of our epileptogenic focus circumscription subsystem, offering a thorough evaluation of its performance under diverse criteria.

### III.3.4 Semi–Supervised Classification

Semi–supervised learning approach is a recent and fast–moving field of research. This latter is, a halfway between supervised (labelled data) and unsupervised (unlabelled data) learning. It incorporates a inconsiderable amount of labeled data with a huge amount of unlabeled data during the apprenticeship phase.

the unlabeled observations, when utilized in conjunction with a few amount of labeled ones, can serves dramatically in the improvement of learning accuracy. The procurement of hand–labelled data for a machine learning purpose, necessitates a competent human agent or an expensive physical materials for experimentation. Therefore, the cost required for such labeling process may render the fully labelling operation impracticable. For this reason, the semi-supervised learning is appreciated and considered of a great practical value [220].

Despite the considerable application of machine learning in the medical domain, multiple challenges need to be notified involving apprenticeship data size, clinical variables, as well as the variability in data collection and its interpretation. Additionally, data dimensionality reduction to avoid the risk of over–fitting. For this end, in our thesis work, we investigated three supervised learning classifiers namely; k–nearest neighbors, Naive Bayes and the linear discriminant analysis, for relevant EEG channel selection, epileptogenic area detection as well as the seizure activity detection and prediction, within the well known CHB–MIT and Bonn databases.

### III.3.5 Cross Validation Techniques

The cross validation approach, has been recently introduced and applied in machine learning as a statistical technique to evaluate, the skill of the built algorithms, compare and finally select a trustworthy model for a given predictive operation. The cross validation is principally applied where the purpose is prediction, and the developer aims to quantify how appropriately, the implemented model will accomplish in practice. Usually, a model is built on the basis of a given training dataset (seen data), and will be tested using the unseen data known as test dataset. The idea behind calling the cross validation approaches, is to test the potentiality of the built model, in predicting a data that has not been employed while estimating it, aiming to flag machine learning issues such as; over–fitting or selection bias [221] and provides an insight about the generalization of the model. In summary, the cross–validation joins fitness measures in the operation of prediction to obtain a more correct estimate of the prediction model performance.

There mainly two types of cross validation, namely; exhaustive cross–validation and non–exhaustive cross–validation. Details of aforementioned types are provided in the following sections.

### Exhaustive cross–validation

Exhaustive cross–validation approaches attempt to learn and evaluate all available manners to split the original database into training and examination set. For such purpose, it offers two techniques namely; Leave–p–out cross–validation and Leave-one-out cross-validation.

- ***Leave–p–out cross–validation (Lpo)*** [222]

When applying this exhaustive procedure, we take p number of observations out from the entire database size (e.g. n data points) for the model validation. Whilst, the apprenticeship phase will be accomplished using the remaining $n - p$ observations. The process will be repeated over all achievable combinations of p from the given database; the number of iterations is $C_p^n$, where C is computed as in (III.23);

$$\mathrm{C} = \frac{n!}{p!(n-p)!} \tag{III.23}$$

Where;
**n**: represents the number of data points and **p** is the number of test observations.

Then, to obtain the final correct rate value, the average of all resulting accuracies from the total iterations is computed. Since, the model is trained on all possible combination of the database samples, this method is classified as exhaustive. With the fact that, choosing a high value for p (e.g. p=35 with n=150), means that the process will be computationally impracticable (repeated approximately $2 * 10^34$ times.

Moreover, An Lpo cross–validation with p=2 called also as leave-pair-out cross-validation, has been found to be approximately unbiased approach, for computing the area under the receiver operating characteristics (AUROC) of binary classification.

- ***Leave-one-out cross-validation (LOOCV)*** [5]

Leave-one-out cross-validation (LOOCV) represents a particular and a simple case of leave–p–out cross–validation. Where, the value of test observation **p** is fixed as one $p = 1$. As a consequence the approach become less exhaustive, since there are only $C_1^n = n$ iterations instead of $C_p^n$, which means that we will have n combinations number and less computation time in comparison of that required when applying the leave–p–out cross–validation. Even if, but n iterations require as well a large computation time, therefore, other techniques like k–fold cross validation may be more suitable.

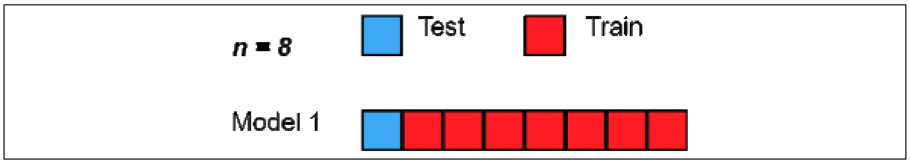



Figure III.4: An illustration of Loocv approach [5].

#### Non exhaustive cross–validation

The non–exhaustive cross validation methods, as the name indicates do not search all possible splittings of the original data. Those techniques represent an approximations of the leave–p–out cross–validation approaches.

- ***Holdout*** [223]

Holdout is simple and completely basic non exhaustive cross validation approach. It serves in splitting the entire input database into two portions; training and testing datasets. Therefore, the model will learn using the training portion, then the examination of the learning rate will be done on the basis of the test dataset. In most cases, the two thirds of the original database is reserved for the training process, while the remaining third is used for the validation. In simple words, the common Holdout–based database division is (70–30)% or (80–20)%, where the 70% and 80% represents the training portions, and the rest; 30% and 20% are the test datasets.

The holdout splitting procedure consists firstly, to shuffle randomly the input database. This method is found to be more efficient to apply in case of extremely large databases. Whilst, in case of small databases, using the holdout splitting approach may leads to an information loss, since the test dataset is not used in other combination in training phase of the model. In summery, the selected train dataset can not be representative of the whole dataset, which is the major disadvantageous point of this approach.

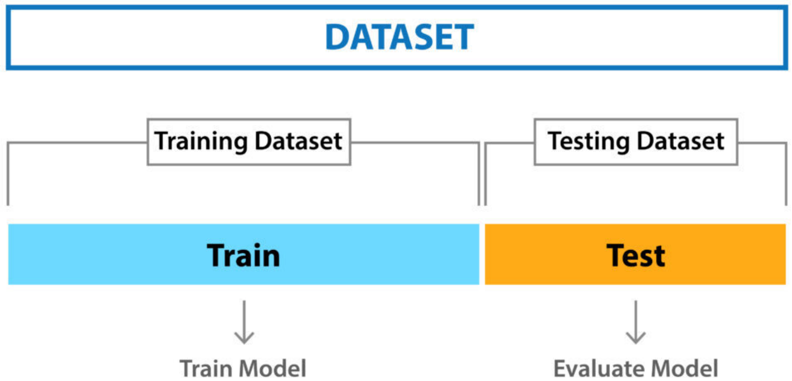



Figure III.5: Holdout approach based data splitting.

- ***k–Fold Cross Validation*** [224]

Aiming to ameliorate the holdout approach, the K–fold cross validation was introduced. This latter, ensures that the performance of the implemented model is independent to the train and test datasets selection. The k–cross validation approach consists of randomly splitting the whole database into **k** subsets, where the holdout approach is repeated **k** times. At each iteration, the fold is divided into k-1 data called training folds and one test fold. At the end of each iteration an accuracy value is obtained. The process will be repeated until each fold served as test and training. Finally, The average of k resulting accuracies known as cross–validation accuracy, will be computed, to find out the performance metric of the built model. Figure III.6, illustrates an example of 10–fold cross validation process.

Since it guarantees that every sample from the given database has the chance to contribute in the algorithm's training and testing, this approach basically ensures less biased models in comparison to other approaches. Moreover, it is considered as the appropriate one in case of limited input data.

The complication of this technique resides in the computational time required, due to the fact that the apprenticeship algorithm has to be re–run for k times to make an evaluation.


Figure III.6: An example of 10–fold cross validation. Source [5]

### III.3.6 Classification Performance Metrics

Whilst data processing and instructing a machine learning model is a substantial step in the machine learning field, it is evenly essential to quantify the performance of this implemented model. In order to come out with a precised decision on whether, the model generalizes on the new and unseen data points. In other words, evaluate the built model adaptation ratio. Without proceeding an appropriate evaluation of the machine learning model employing various metrics, and relying only on the accuracy value, can lead to an issue when this latter (the model) is re–tested via unseen data and may provides poor prediction performance. This weak efficiency can be explained by the fact that the model memorizes instead of learning, and therefore it can not generalize correctly on new data points [225].

Applying different metrics for models efficiency evaluation, provides a decision about the overall predictive power of the implemented model, before it can be re–tested on real unseen data [225].

In the literature, it is seen that there are various metrics, which can be applied for machine learning performance evaluation, namely; confusion matrix, accuracy, recall parameter known commonly as sensitivity, specificity, F1–score and AU–ROC...etc. In the following section a detailed description of the metrics used in this thesis work is provided.

#### Confusion Matrix

In predictive analytics, the confusion matrix, known as well as an error matrix, represents a tabular illustration that summarizes and describes the performance of the built model. This two columns and two rows matrix, reports information about the false positives, false negatives, true positives and true negatives. Thus, it is used in evaluation of supervised learning algorithms. whilst, in unsupervised learning it is commonly known as the matching matrix. Confusion matrix rows represents the actual class instances. Whilst, the columns represents the predicted class instances, or conversely, since both illustrations are found to be correct in the literature[10]. Its name (confusion matrix), comes from the reason that, it shows explicitly whether, the model is confusing (miss–labeling) between the classes. In summery, the confusion matrix is not a proper performance metric but a tool by which the metrics (accuracy, sensitivity, specificity...etc) are computed [225].

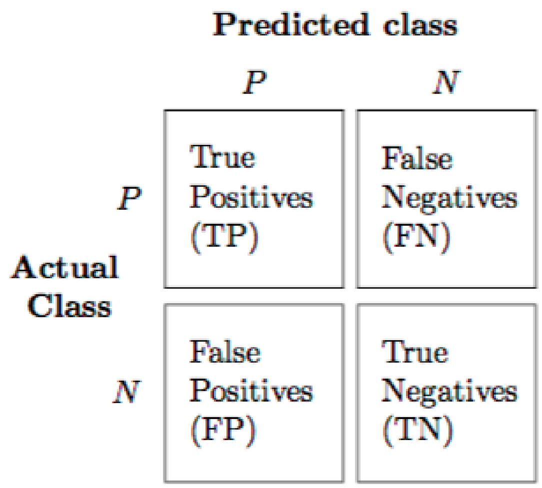



Figure III.7: The confusion matrix.

There are four basic terms containing in the confusion matrix;

- ***True Positive(TP)***

The true positive represents an output where, the employed classifier predicted correctly the positive cases. All observations predicted as positive by the model and were pre–labeled by the professionals as positive. The number of times the classifier succeed this mission is shown in this portion of confusion matrix [225].

- ***True Negative(TN)***

The true negatives represents the number of samples being correctly predicted as negative and therefore classified within the negative class. All the observation that were assigned with negative labels and were in real negative (don't have the disease).The number of times the classifier succeed this mission is shown in th True Negative portion of confusion matrix [225].

- ***False Positive(FP)***

Refers to the number of negative class observations predicted incorrectly by the model. In more precise words, all observations that were predicted and labeled as positive, while in fact they were negative cases (predicted as abnormal while they are in normal health status). Which is called in statistical field as Type–I error [225].

- ***False Negative(FN)***

Refers to the number of positive class observations predicted incorrectly by the model. In more precise words, all observations that were predicted and labeled as negative, whilst in fact they were positive cases (predicted as normal while they are in abnormal health status). Which is called in statistical field as Type–II error [225]. Basically, there are three fundamental metrics, that can be computed on the basis of the confusion matrix results, namely; Accuracy, also called the correct rate, Sensitivity or recall, and Specificity, these metrics are defined in the following sections.

### Accuracy

The accuracy is one of the common metrics used for evaluating classification models. It summarizes the efficiency and performance of the entire prediction process by computing the ratio between the number of correct predictions and the total number of predictions [225]. The accuracy known also as the correct rate is defined in (III.24)

$$\text{Correct rate} = \frac{TN + TP}{FN + TP + TN + FP} \tag{III.24}$$

### Sensitivity

In machine learning–based diagnostic, the sensitivity is a measure that refers to the number of abnormal (positive) cases correctly known by the implemented classification model [225]. this latter known also as the recall is defined in III.25

$$Sensitivity = \frac{TP}{TP + FN} \tag{III.25}$$

### Specificity

Specificity represents the ratio of real negative samples that were labeled as negative; as consequence, it is a measure of the model efficiency in identifying normal cases [225]. This latter is called also the true negative rate as defined in III.26

$$Specificity = \frac{TN}{TN + FP} \tag{III.26}$$

Where $TP$ represents the true positive, $TN$: true negative, $FP$: false positive, and $FN$: false negative.

## III.4 Conclusion

This chapter provides a comprehensive overview of EEG signal characteristics and the methodologies employed in its classification. Initially, it delineates the process of feature extraction, elucidating commonly utilized EEG attributes in the literature. Prior to delving into the classification phase, a crucial step involves dimensionality reduction of the original data. This ensures the retention of pertinent features that effectively represent the entire database. To address this, various feature selection techniques are briefly discussed. Emphasis is placed on the impact of different classifiers on epilepsy detection and prediction within the current state of the art. A synthesis of reported studies reveals certain limitations, particularly in the realm of EEG dimensionality reduction to mitigate the risk of overfitting. Consequently, there is a compelling need for enhancements, necessitating the incorporation of improved classification models tailored to handle a constrained dataset, encompassing relevant channels, essential features, and optimized parameters for classifiers. In conclusion, the quest for a reliable diagnosis, treatment, and prediction of epileptic seizures in all dimensions requires continual improvement. Additionally, exploring the integration of these epilepsy detection models into telemedicine applications holds immense potential. Such applications can significantly contribute to patients' daily life adaptation and aid in their healing process, potentially through seizure-free surgery. The subsequent chapter delves into the realm of telemedicine and its diverse applications.

# Chapter IV

# Telemedicine: a brief Overview

In the few recent years, the telemedicine (TLMD) has been introduced as a new technological domain, which contributes in enhancement and modernization of actual healthcare systems, particularly, in developed countries, unlike Third World countries, wherein a necessity exists in the investment of these new technologies, easily applicable and economical. The Telemedicine (TLMD) represents the modern extension of the early telecommunication system that can be traced back to the 1900s. Investing technology of information and telecommunication in the medical domain allows necessary healthcare delivery, especially when the patient is isolated from the medical staff because of geographical distance issue. Therefore, using telemedical technologies enables the doctors to perform consultations even when they are out of their hospital work shits, or are unable to travel, which, increases doctors accessibility besides all medical staff intervention, in such way the regions which lack specialists residing, benefit nevertheless from high quality of healthcare. In summery, telemedicine platforms and its phone applications, are found to be efficient in terms of increasing medical services and patients access, while reducing monetary cost, traveling time besides eliminating the discomfort related to the waiting for a near or far appointments given by these distant medical services.

In order to highlight the relevance and the dramatic impact of telemedecine and its applications, the present chapter is organized in the following principal sections, The first **Section IV.1**; Definition of Telemedecine; offers a detailed explanation of this expression besides its historic roots presented in **Section IV.2**.

Telemedicine has been applied in various medical fields as described in **Section IV.3**.

In addition, each new application requires a study to evaluate its benefice and relevance, therefore this **Section IV.4**, summarizes this positive impact of telemedicine in few points. while the emphasis will be on the contribution, effect, besides the issues of telemedicine on health system in general **Section IV.6** and particularly in neurology and epileptology, to enhance the health care accessibility for the patients in isolated and rural regions **Section IV.7**. Finally, some legal and ethical points to ensure the right utilization of telemedicine are discussed in

**Section IV.8**.

## IV.1 Definition of Telemedicine

The prefix –***tele***–, in the term telemedicine is a Greek word that signifies ***remote***, ***distant*** and ***far***. For that reason, the combination between these two words namely; ***tele*** and ***medicine***, resulting in the term telemedicine, denotes: medical services provided remotely. In more precise words, the Medical Institute defined the telemedicine as the application of technologies of information and telecommunication to support and offer the necessary health care when distance precludes the in–person (face–to–face) access [226].

The word telemedicine summarizes the process of medical information exchanging from one site to a remote one through the modern electronic communication technologies, where the main intent is to enhance patient clinical health status. Therefore, it involves the application of modern technology devices such as; audio/video communications, computers, smart phones, and telemetry, to transmit health services to distant patients and to enable information exchange between specialists and physicians of primary care, regardless the distances from each other [227].

Globally, the term telemedicine represents a discursive concept with various interpretations, in which there is no scientific community consensus about what to be affiliated within the telemedicine scope. As a consequence, the word telemedicine owns multiple synonyms (104 expressions) that refers to the sort of services associated to the telemedicine [227].

According to the brief definition given by the World Health Organization (WHO), the telemedicine represents the delivery of necessary health care services using the ICT tools, particularly, to remove distance barrier from the way of health care [228].

In academic literature, some definers [226] declare that the term tele–health is a synonym of the word telemedicine, and therefore, they are similar. While in fact, they are not according to the definition given in a paper by Norris [229], in which he denied the similarity of these terms, and defined each of them with its appropriate signification (see Figure IV.1), keeping the previously cited definition of telemedicine, he added that the ***tele–health*** uses the telecommunication technologies to transmit healthcare information (transmission of clinical, educational and administrative services), thus it includes non–clinical services. Moreover, he defined the ***tele–care*** as a form of distant care provided for physically less able people, to ensure offering all reassurance needed to their own homes, it utilizes wearable devices and sensors for people suffering from dementia or at risk of falling...etc.

## IV.2 History of Telemedicine

After a precise scrutiny of multiple sources, It was found that the telemedicine roots can be traced back to the early pre–electronic era, more precisely to the 1726, were an epistolary exchange process were carried out to prescribe a treatment for

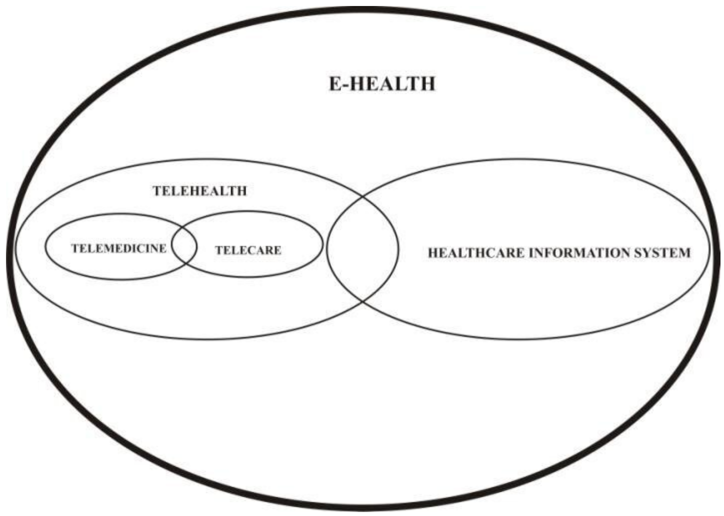



Figure IV.1: illustrative framework of the link between e–Health, Tele–health, Tele–care and Telemedicine. Source [6]

a distant patient and denoted in the history as the birth of a new field, known as telemedicine with modest and ancient telecommunication tools. In 1906, the second telemedicine operation was recorded, when the Dutch psychologist; Willem Einthoven, utilized a telephone for monitoring and long distance transfer of cardiac rhythms, and by that the tele–cardiology was introduced as a new application of telemedicine. Subsequently, in 1959 the interactive television took place in medical use, where it was interestingly applied in a tele–psychiatry consultation between Omaha, Nebraska and the State Psychiatric Hospital (112 mile of distance). The reason behind this time gap (from 1906 till the 1959), estimated to be of 53 years, is that the association between sound and image was not easy to be achieved (invention of television). Followed shortly thereafter by the tele–radiology experiments in the United States and Canada as well. In general, the late 1950s, represents the era of the first organized wave of telemedicine applications in the United States. It lasted approximately two decades. In addition to these cited telemedical operation, two other connotative dates that can be considered as landmarks in the emergence trajectory of telemedicine, where the first one was in 1965 and consists of a video–conference in cardiac surgery that was achieved between the United States and Switzerland. Whilst, in 1973 the first international congress on telemedicine was recorded, this latter was between Michigan and USA as an opportunity to proceed several relevant projects [230].

In summary, a variety of telemedicine projects were planed and implemented. Nevertheless, the experts in the state–of–the–art declare a failure in the majority of these applications, wherein the reason behind this lack of success being in the low technological performances of the computers associated with high costs. Moreover, it is necessary to point out, and above all, the mistaken organization of the established networks. In other words, there haven't been a considerable medico–economic studies on this first wave of telemedical projects. However, several studies have been carried out in terms of technical feasibility [230].

The re–birth of a new telemedicine projects wave, dates back to the late 1980s in Scandinavia, particularly Norway, with the trigger of a telemedical program named *Access to health care services*. Additional advancement in telecommunication technologies associated to highly reduced costs, contributes in success of various telemedicine projects. These projects focal points includes real–time video consultation in several medical services namely; cardiology, radiology, psychiatry, otolaryngology, dermatology...etc [230].

It is basic that the geographic distance was the first and only reason which motivates the investment of telecommunication technologies to control time and space and remove all barriers that prevents health care access for those whom need it. And therefore, it is no longer the patient who travels and suffers to be treated or probably dies while waiting for an appointment, but it is the medical services which regroups to be at his service and ensures necessary procedures to take care of his health while he is comfortably at his home [230].

## IV.3 Applications of Telemedicine

Telemedicine applications represents a potential step forward in enhancing the availability of healthcare opportunity to all patients, especially, those living in regions with restricted local health experts and specialists. Moreover, these applications, provide efficient benefits and minimised cost in comparison to the conventional in–person consultations. Telemedicine can be broken down into numerous areas known also as applications, using a variety of information technology and telecommunications tools. These telemedicine applications involves those that are directly associated to the care production, besides those that assists in enhancing the quality and continuity of health care procedures. The main applications are described in the following sections [231].

### IV.3.1 Tele–Consultation

The tele–consultation known also as remote consultation, represents an a medical act that refers or describes the virtual interactions made between a medical staff (doctor in most cases) and a remote patient (not face–to–face consultation) for the goal of diagnostic or therapeutic counsel by means of electronic tools (see Figure IV.2). The tele–consultations are a safe and efficient means to evaluate suspected cases and orientate the patient's to the appropriate treatment while reducing the risk of disease transmission (very useful in the COVID–19 pandemic) [7].

Figure IV.2: An example of tele–consultation session. Source [7].

### IV.3.2 Tele–Surveillance

The tele–surveillance known mostly as the remote monitoring is a transmission operation of relevant medical parameters to enable the doctors to remotely interpret these submitted data and make decisions relating to the care of this patient (see Figure IV.3). The recording and transmission of data can be done automatically or carried out by the patient himself (auto management of his pathology) or by an assistant (family or healthcare professional) [8].

### IV.3.3 Tele–Surgery

The tele–surgery idea came up about more than 20 years ago, it involves tow aspects, the first one can be carried out by a remotely piloted robot (Lindbergh Operation), whilst the second one is a remote surgical assistance known also as the tele–companionship. Both remote–surgery types necessitate a transmission of patient's images in real time. During the tele–surgical assistance, the expert (the supervisor) and the operator (the assisted doctor) see the same images of the patient, and therefore, the expert instructs the operator step by step along the entire operation (carrying out the gesture), which offers comfort and safety for both patient and the one operating him. Nevertheless, tele–surgery (see Figure IV.4) is yet a highly expensive process to take a place in practical care, besides ethical and legal contours which are still unexplored points [9].

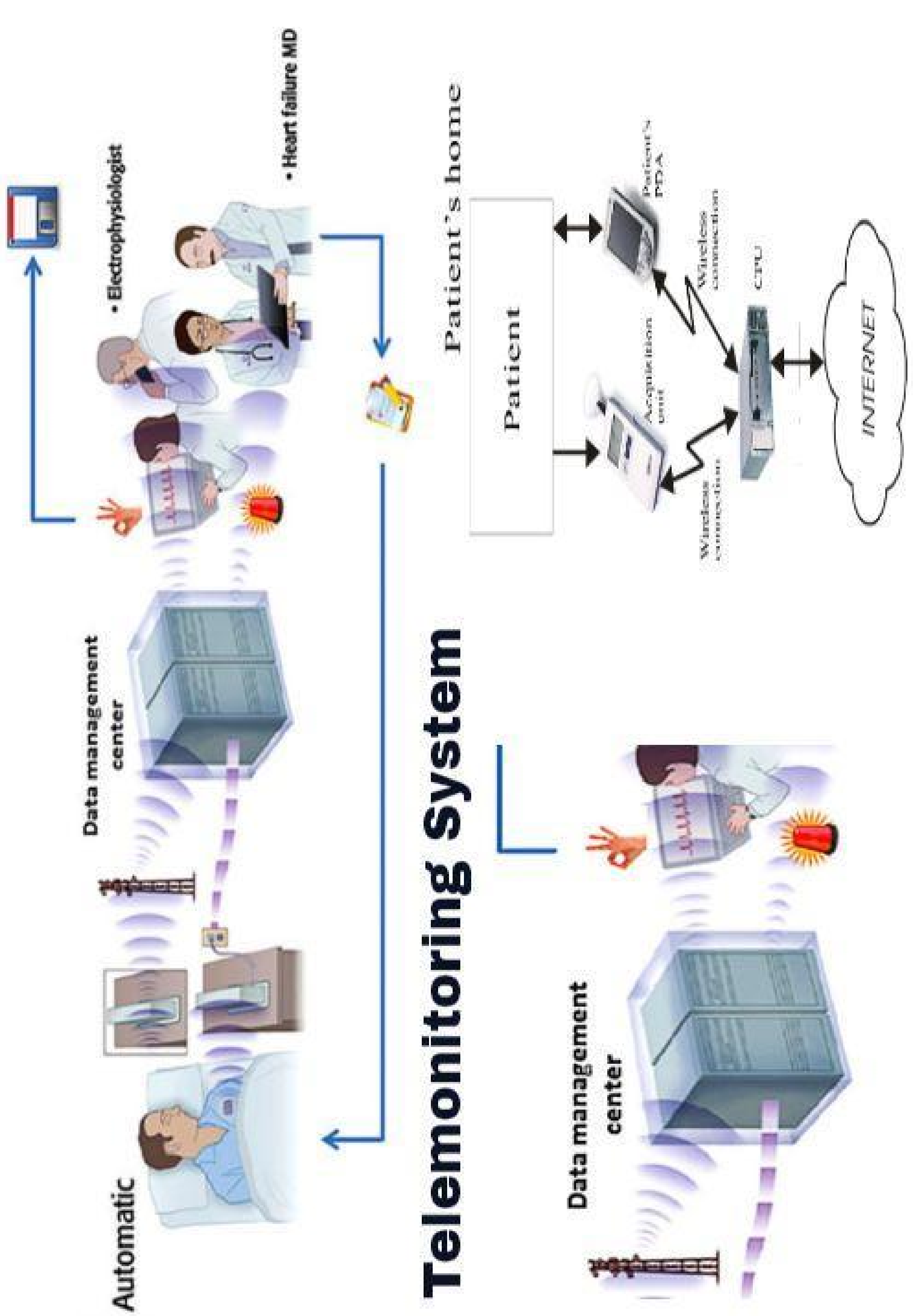



Figure IV.3: An illustration of a tele–surveillance system. Source [8].

Figure IV.4: Tele–surgery equipment. Source [9].

### IV.3.4 Tele–Expertise

As its name indicates, the tele–expertise is a virtual interaction between two or more medical professionals for a remote counsel or additive opinion about a patient's health status (see Figure IV.5). In other words, it allows doctors to benefit from particular skills of each other, and update their medical information, where the first and only purpose is the patient's care [10].

Figure IV.5: A second opinion requirement: tele–expertise. Source [10]

### IV.3.5 Tele–Training

Tele or distant learning (see Figure IV.6), in some cases called e–learning, is a formalized system designed to teach and learn remotely by means of electronic communication. Since the distant learning is less expensive and independent to geographic considerations in comparison to support [12].

### IV.3.6 Tele–Assistance

Tele–assistance or tele–alarm is a telemedicine service that provides remote medical care, through an intelligent device (see Figure IV.7), connected to an operating center that provides the aid and assistance to the elderly, facing a sudden medical problem or loss of autonomy (fall, faintness) [11].

Figure IV.7: Example of an intelligent device for tele–assistance of aged and sick persons. Source [11].

The previously presented titles represent the main applications of telemedicine, however there could be several ones in all fields of medical specialties such as; tele–ophthalmology, tele–cardiology, tele–dermatology...etc.) [232].

## IV.4 Benefits of Telemedicine: Patient–Doctors & Health System

A global survey reported by Cisco declare that around 74% of patients prefer remote healthcare services of easy access in comparison to the face–to–face interactions with medical staff. Therefore, the telemedicine provides the convenience for both patients and doctors besides its contribution in enhancement of health system. Investment of virtual technology tools in medical practice changes dramatically the relationship


Figure IV.6: Tele–training session: a surgery. Source [12] between doctors and their patients. It renders the classic in–person appointments more comfortable, by eliminating the wasted waiting time besides the high cost of these medical visits. Moreover, the patients whom live in rural regions can access to these services without traveling. In particularly the tele–monitoring and tele–assistance serves Efficiently in keeping patients with chronic diseases in maximum safety and ensure emergent intervention when needed. In summary, telemedicine has great positive effects on the patients' in terms of security and health care, whilst it supports and assists the medical professionals in their diagnostic decision and treatment prescription since significant amount of patient health status data will be available. However, these cited points are not seen usually as benefits in some telemedicine applications such as; the tele–radiology, in which the specialists does not have any opportunity to meet the patient in–person (only its radio images results are transmitted). Although this contact was limited even before introducing this tele procedures, but it becomes completely impersonal, which may not be counted as beneficial point. Additionally, in some situations, supplementary clinical information about the patients may be needed, which is not always obtainable and can leads to problems, particularly, in external institutions cases [233].

The health system, as well, benefits from the involvement of medical technologies called telemedicine, these benefits can be summarized in the following points; first of all, it offers better care quality in the situations mentioned above (isolated regions, lack of specialists...etc). Besides, it addresses some issues and constraints in the entire health system such as; accessibility to health care services for every one, medical demography issue, unnecessary and non–emergent hospital visits, organization of health care permanence shits....etc. Telemedicine contributes additionally in the advancement of medical progress completely as the clinical and therapeutic innovations. And the most important point after the geographic distance issue is that the telemedicine enables access to required services while controlling the expenditure, through the appropriate utilization of resources [233].

Particularly, telemedicine has become more appreciated during the coronavirus (COVID–19) pandemic. Fears of diffusion and catching the virus during the face–to–face medical visits have led to a considerable interest in applying these new technologies to offer the necessary health care remotely [7].

## IV.5 Types of Telemedicine

Telemedical applications described previously, can be implemented using two main types of telemedicine namely; synchronous and asynchronous telemedicine. Where, the choice of the appropriate type depends entirely on the application needs, for example a tele–consultation necessitates a real time conversation between doctor and his patient, which refers to a Synchronous Telemedicine type. Whilst tele–radiology can be achieved asynchronously; by transferring these radio images to the specialist and he can later interpret them (excluding emergency cases), consequently it belongs to the Store–and–Forward Telemedicine type known as asynchronous telemedicine ...etc. The following sections offer a detailed definition of these tow main types of telemedicine [234].

### IV.5.1 Synchronous Telemedicine

According to the NCHIT; National Coordinator for Health Information Technology, the synchronous telemedicine covers all types of telemedical applications that uses a two–way audiovisual (live video–conferencing) interaction between clinicians and patients. This definition was also provided by the Veterans Affairs (VA) states Department of The U.S, in which they declare that Synchronous telemedicine is achieved only, when both parties (clinician and patient) were present at the same time and communicate through a real-time interaction link [234].

Moreover, Any kind of medical information transmission in two directions during the same period of time is classified as synchronous telemedicine according to the American Telemedicine Association (ATA) [234].

An explicit definition of the synchronous telemedicine is provided by the University of Miami (UM) Miller School of Medicine states, in which they affirm that each live and interactive tele–health session, that uses video–conferencing technologies, frequently with an assistant that perform a physical examination by means of tele–devices that allows transmission of required information simultaneously, are considered as real–time or synchronous telemedicine [234].

#### Benefits of Synchronous Telemedicine

The main advantageous point of a real time (synchronous) telemedicine is the high diagnosis quality gained because of the opportunity to refine maximum pertinent details during the virtual interactive session, besides the ability of supplying a medical decision or instruction within the session [234].

Synchronous telemedicine enables timely care, particularly in case of emergencies, and keeps the doctor-patient relationship concept by offering virtual face–to–face diagnostic and treatments. By means of synchronous telemedicine the clinician is capable to see, discuss, and examine easily his patient even if they are not in the same place [7].

Real–time audio–video telemedicine helps patients in terms of reduced cost in comparison to distant and expensive care settings [7].

Synchronous tele–psychiatry found no statistical dissimilarity in pharmacotherapy and psychotherapy clinical outcomes delivered through synchronous telepsychiatry session and face–to–face treatment [234].

Small hospitals with restricted resources can profit from immediate, real–time consultation by a neurologist, when a stroke is suspected, and starting simultaneously thrombolysis treatment [234].

Synchronous telemedicine applications enhance access, convenience , and effectiveness of health care services [234].

### IV.5.2 Asynchronous Telemedicine

The National Coordinator for Health Information Technology named the asynchronous telemedicine as store–and–forward video–conferencing operation, signifying by that denomination the submission of a registered health history of a specific patient to a specialist for remote asynchronous interpretation or patient folder accomplishment [234]. The Veterans Affairs states that the store and forward telemedicine type is defined from its name as acquirement and recording of medical data, then transmitting them to a clinician or medical experts at an appropriate time for interpretation offline [234].

The American Telemedicine Association, defines the store and forward process as the submission of medical data (images, signals, biological parameters...etc.), because their transfer process simultaneously requires a considerable time [234].

the University of Miami (UM) Miller School of Medicine states that the store–and–forward telemedicine is a process in which the data are locally acquired and carefully registered, then transferred at a later time, either through a highly secured web server, e-mail–based transmission, or principally–designed store-and-forward application. The health provider then consult the stored data and makes decisions in terms of; diagnosis, treatment...etc, that are later transferred to the referring provider" [234].

#### Benefits of Asynchronous Telemedicine

Asynchronous telemedicine systems separate the interaction components, consequently they can be used at the convenience time of the participating parties. Nevertheless, it often requires episode context refreshing during this process [234].

Asynchronous services are appreciated when the telemedical activity does not require real–time interactions, particularly, when it does not necessitate direct interchange with the patient. Patients benefits from timely health care without travel necessity or waiting times. Particularly, in zones with lack of medical specialists. Consequently, the asynchronous process overcome languages, distances and cultural barriers [234].

A recent study showed that asynchronous hypertension control sessions assist in the regulation of patients blood pressure and minimized in–clinic primary care occupations [234].

Store–and–forward–based platforms are effective for prove–based health care, in which clinicians are able to collect all the necessary information about the patient, treat that gathered data, link it to the prove–based care and make the right diagnosis. It offers an opportunity for clinicians to add some supplementary clinical decisions and eliminates the sometimes–uncomfortable necessary presence of both patient and doctor at the same time. However, the asynchronous telemedicine are not appropriate for emergency cases [234].

## IV.6 Contributions and Issues of Telemedicine

The efficiency of telemedicine can be primarily perceived in the fact that, medical staff (specialists mostly) are not obliged to travel (far distances), as a consequence there will be no loss in term of working time and no supplementary costs, and that lies in the positive impact of information and communication technologies. Besides the time and cost gain, telemedicine has a great and positive effect on person's health care status in terms of; benefit from prevention, speed diagnosis, as well as an appropriate treatment. Telemedicine can be easily used in various medical fields, particularly, in visual diagnostics and tele–monitoring of necessary health parameters. In some cases, it may offers a health service which is identical to the traditional impersonal doctor–patient contact such as; the tele–radiology. Nevertheless the telemedicine was not introduced to replace the in–person healthcare appointments but to support, supplement, facilitate, and improve it. As a complementary procedure, along with the classical healthcare, can presumably offer an optimal quality of healthcare in comparison to its absence (telemedicine). Accordingly, certain services of telemedicine are not yet considered in daily healthcare system and even are not funded, which represents an additional task for the parts whom planning to employ it. Moreover, the modern information and telecommunication tools devoted for better availability of medical professionals (specialists mostly) may in parallel be a reason of their workload increasing, as a consequence it is necessary to manage effectively both virtual and in–person consultations [235].

For practitioners (doctors, nurses, physicians..etc.) side, it is primordial to create an appropriate cooperation between the different medical community networks: city–hospital, general experts–specialists, and public–private sectors. In order to create communication gateways for transmission of information and exchange of knowledge [235].

Aspects of data and knowledge sharing represents an other challenge in establishing telemedicine applications, therefore, systems interoperability, definition of protocols of communication, ontologies, and the involvement of a shared electronic medical record... etc, are required [235].

For patients, applying telemedicine improved the quality of care due to the possible remote expertise and, However, when considering the particular case of tele–monitoring, telemedicine some points should be appropriately explored such as; autonomy, security and social integration of patients aiming to stay at their homes, and it represents therefore a part of the dynamics of alternatives to hospitalization [235].

## IV.7 Contribution of Telemedecine in Neurology

The Tele–neurology is an advanced application area of telemedicine. It includes distant neurological consultation, employing several technologies such as; internet, smart phones applications, and platforms...etc, to enable the connectivity. Tele–neurology, may be exerted also in form of tele–conferencing, tele–monitoring and tele–education, launched by clinician or patient [236].

Neurologists declared that the telemedicine can be applied in particular neurological provisions, covering; dementia, headache, stroke, epileptic seizures, sclerosis...etc [236].

Tele–neurology applications can be basically splitted into two branch, namely; clinician (medical staff)–launched' and patient—launched applications [236].

The application of patient–launched tele–neurology is notably expanding via the prevalent accessibility of the internet and the utilization of various search engines-—resources that may dramatically impact the classical expert-–patient relationship. Whilst, clinician initiatives have been found to be mostly applied in stroke situations, in order to avoid their incidence and take a speed decisions about proceeding thrombolytic treatment [236].

Consequently, the tele–neurology will automatically impact the usual consultations done by the neurologists [236].

### IV.7.1 Tele–neurology: Tele–consultation

According to a statistical study by the World Federation of Neurology, it was found that, globally there is a considerable lack in the number of neurologist per populations, particularly, in developing countries, where, they counted approximately 6240 neurologists over 4 millions of population. Moreover, the medical education required for the neurologist is available only in 54% of these developing countries. As a consequence, it poses issues in terms of patient access to the neurology services outside of most metropolitan medical centres. Applying the tele–neurology may preclude such access hardness. In addition, real–time neurological consultations through interactive platforms or applications is beneficial for both out–metropolitan–patients and inpatients as well. These virtual consultations are managed identically to the in–person (face–to–face) ones, with an on–site medical provider (doctor, nurse or a well selected medical person) proceeding an examination, through a specific secured medical video link. All tele–consultations should be precisely and appropriately noted as for in–person consultations [237].

Using the convenient technical support, allows tele–consultation to perform efficiently in terms of diagnosis accuracy, from a side because telemedicine enabled virtual neurological consultations to be as perfect as in–hospital examination (bedside). In the other hand, it minimizes the rate of hospitalisations [237].

Advantages of tele–neurological consultations (see Figure IV.8) encompass minimized patient transportation requirements, which represents the major difficulty for patients suffering from epileptic seizures, whom may be unqualified to drive because of their health status, besides that reducing traveling helps in reducing the carbon footprint, when considering the climate change issue. Moreover, these tele–neurological consultations, offer an opportunity for family members to attend this virtual session with their patient, therefore, the clinicians can benefit from collateral history leading to a correct and precise diagnosis [237].

Figure IV.8: Tele–neurology: example of a tele–consultation. Source [13].

### IV.7.2 Tele–neurology: Tele–conferencing

The tele–conferencing or videoconferencing cross countries and even continents render it possible to bring remote expertise to regions that are poorly or non–served by neurological services. As an example of these successful application; the one performed in 2001, between the Neurosurgery Department of Apollo Hospitals in Chennai and the same Department of Fujitha Health University in Japan, the tele–conference lasted two hours. Another similar tele–meeting was organized in the same year (December 2001) with Prof. Michael Schulder from the Neurosurgery Department in New Jersey [236].

Multi point intercontinental tele–conferences were held in Chennai,Paris , Geneva, and Tunisia, to address several issues in various neurological troubles namely; trauma, neurosurgery, emergencies, stroke...etc, besides disaster management. Thereafter, about ten (10) tele–conferences were carried out between neurology departments worldwide [236].

Nevertheless, it is yet an expensive operation to interact with neurosurgeons and neurologists around the world.

### IV.7.3 Tele–neurology: Tele–education

Websites and e–learning are a popular tools for education and apprenticeship, they are effectively contributing in spreading of medical knowledge, including continuing medical education through videoconferencing, with patient consent. Google neurology, which represents another e-learning tool assisted with neurologist diagnosis that provides responses to several requests of user's (searchers). In spite of the fact that, its efficiency relies on prior neurological knowledge to ease and guarantee an accurate strategy of searching and to interpret the pertinence of the accessed results [236].

As an example of educational teleconferencing in neurology, 35 virtual sessions was organized between SCB Medical College, Cuttack and Sanjay Gandhi, Post Graduate Institute of Medical Sciences, Lucknow; (1550 km distance), these sessions were conducted using a platform for video conferencing system and a PTZ ((pan–tilt–zoom)) camera. Moreover, Apollo hospitals has performed tele–programs for continuing medical education weekly and for three years, where 144 pediatrics participated besides some neurologists and neurosurgeons. Realising and knowing the pertinence of this speedily advancing field, a full session about the impact of Telemedicine in Neurosciences was discussed during the 13th Congress of the World Federation of Neurosurgical Societies, since the international exposure enables perspectives changing and supports global tele–education, where the geographic issues are totally ignored [236].

### IV.7.4 Tele–Epileptology

Epileptic seizures are not always the well known and appeared tonic–clonic called also grand mal seizures that can be easily identified and conducted by a family or a neighbor physician. The large spectrum resulting from epileptic seizures manifestations and recorded in the EEG signal requires a clinical observation and interpretation by a neuro–specialist. Typically, the electrical activity of the brain, particularly in case of epilepsy should be recorded by means of simultaneous video EEG analysis. Nevertheless, these advanced tools are mostly and exclusively available in metropolitan care centers, and this fact is not because smaller hospitals cannot offer such equipment, but because of the lack in experts. As a consequence, several studies proved that introducing tele–communication tools in epileptology helps in transmitting EEG signals remotely, which allows epileptologists to enlarge their reach dramatically and offer the needed health care for such a complicated pathology, typified by its sudden and dangerous seizures As an example of tele–epileptology; in Finland some neuro–clinicians asked for a second opinion from a centre of excellence, about the interpretation of a digital EEG recordings, by means of an interactive tele–consultations video link [238].

In neuro–emergencies, the status epilepticus (a series of epileptic seizures) and stroke have been found to have the highest potential for enhancement of patient health management by means of telemedicine tools [238].

## IV.8 Telemedecine: Ethical and Legal Issues

Telemedicine has recently establish itself as beneficial tool in under served regions, where, a lack or absence of necessary clinical care is recorded, such as rural areas. For the first time, in both developed and third world countries as well, found, trustworthy and cost–efficient tele–health, particularly; telemedicine services are accessible at scale. And that goes back to the application of sturdy, speedily and enabling technology infrastructure [239].

The purpose behind telemedicine has approximately realised. Instead of patient transportation to benefit from distant services, It becomes easy now to harness the technology power to deliver the knowledge and care of the medical specialist right to the person in need (patient). Consequently, this advanced change in health care procedure can open up new doors in terms of legal, and ethical issues and have a great effect on health authorities decision making. All medical staff who take part in telemedicine applications have an ethical responsibility that can be summarized in few principle points [239];

- Expose any financial or other benefits the clinician has while exerting telemedical application besides eliminating conflicts of interests.

- At each use of telemedicine applications through websites or mobile health applications, clinicians must assure that their provided information or the once attributed to them are objective, correct and accurate.

- The patient–clinician relationship should relies entirely on a personal interrogation that offers all needed details about the patient's medical history.

  Moreover, telemedicine should be exerted only in cases in which a doctor is unable to be physically present within the necessary time period. It should be as well used in chronic conditions management or in daily follow-up subsequently to an initial treatment, to ensure its safety and effectiveness.

- The patient–clinician relationship must be trustful and respectful. As a consequence it is fundamental that the clinician and patient identify obviously each other when launching telemedicine applications.

  Moreover, when the patient is medically followed by more then one professional, the first doctor who launched the telemedical process stay the responsible for the health care delivering and management of the patient's with the delivering medical team.

- Patient confidentiality, privacy and data integrity must be the first priority of the clinician. Loss of medical data is prohibited; unwitting loss of data must be at maximum obviated. Therefore, Data received during the telemedical applications must be highly secured to block unauthenticated attempts to access and contraventions of personal patient data by means of trustworthy and modern security techniques in conformity with local legislation. Electronic transmission must be as well highly secured.

- Consent of patient to be treated using telemedicine should be taken after a detailed explanation of the entire telemedical process, including; how this new technology works, appointments schedule, privacy preoccupations.

  Besides the most important point which is the probability of technological failure including; infringement of personal confidentiality, communication protocols used for virtual consultations, and providing detailed explanation about coordination with health professionals and care policies, while, the patient's choices should not be influenced by the telemedicine users.

## IV.9 Conclusion

In a short amount of time, a quite fertile branch namely; telemedicine has spectacularly revamp the face of healthcare. Enhancing the frequency and broadness of tele–communication and information exchange between patients and medical staff, has dramatically upgraded the levels of healthcare services accessible to the patients around the world. In summary, the telemedicine creates virtual spaces for doctors and other health personals to enable them to diagnose and follow up their patients in such a reliable and unprecedented degree. This chapter, presents an overview about telemedicine in terms of definition, history, domains of application besides legal and ethical issues. While, the important part of this chapter was devoted to evaluate the contribution of this new technology in neurosciences, particularly in epileptology, since it is unfortunately known that in the majority of countries, there is a considerable shortage of neurosciences specialists. In addition, the available ones (neurologists and neurosurgeons) are grouped in the metropolitan regions. Consequently, those living in rural and suburban zones are suffering from limited or no bout to neurological care services. For this reason this chapter describes the impact of telemedicine and ICT practice in neurosciences enhancement, in addition to presenting the authors developed application for remote epileptogenic focus detection, in the next **Chapter**, **Section** V.2.

# Chapter V

# Unveiling Results and Perspectives - An EEG-Independent System for Epilepsy Detection and Epileptogenic Area Circumscription with Remote Accessibility

In the pursuit of advancing epilepsy detection and understanding epileptogenic areas within the brain, Chapter 5 introduces a groundbreaking EEG-type-independent system. This system stands at the forefront of innovation, capable of capturing ictal patterns within EEGs or iEEGs while processing a reduced amount of data, preserving the critical epileptic information. As we delve into the intricacies of this development, the chapter unfolds the pertinent and distinguishing features that, coupled with robust machine learning methods, shape an intelligent model for epilepsy detection within EEG signals. Emphasizing the significance of epileptogenic focus detection in the realm of epilepsy management, our approach, anchored in the study of entropy and EEG signal energy, offers a novel technique for identifying the epileptogenic area. Moreover, recognizing the transformative potential of information and telecommunication technologies in healthcare, especially in rural zones, we highlight the impressive contributions of telemedicine in advancing neurosciences, particularly in epileptology. Despite its dramatic assistance in removing barriers to medical services access, a significant portion of individuals, particularly the 40% in the pharmaco-resistant epilepsy category, has not yet benefited from these telecommunication advancements. To bridge this gap, we present an asynchronous telemedicine application specifically developed for this sensitive category, where traditional medications prove ineffective, and the likelihood of brain surgery becomes a crucial consideration. This application represents a first initiation to fill the gap in current tele-epileptology practices and reflects our commitment to leveraging technology for improved epilepsy care.

This chapter is divided into two main parts, namely;**An EEG-Independent System for Epilepsy Detection and Epileptogenic Area Circumscription** and **Epileptica: An Asynchronous Application For remote access to the Epileptogenic Focus Detection results.**

# Part I: An EEG-Independent System for Epilepsy Detection and Epileptogenic Area Circumscription

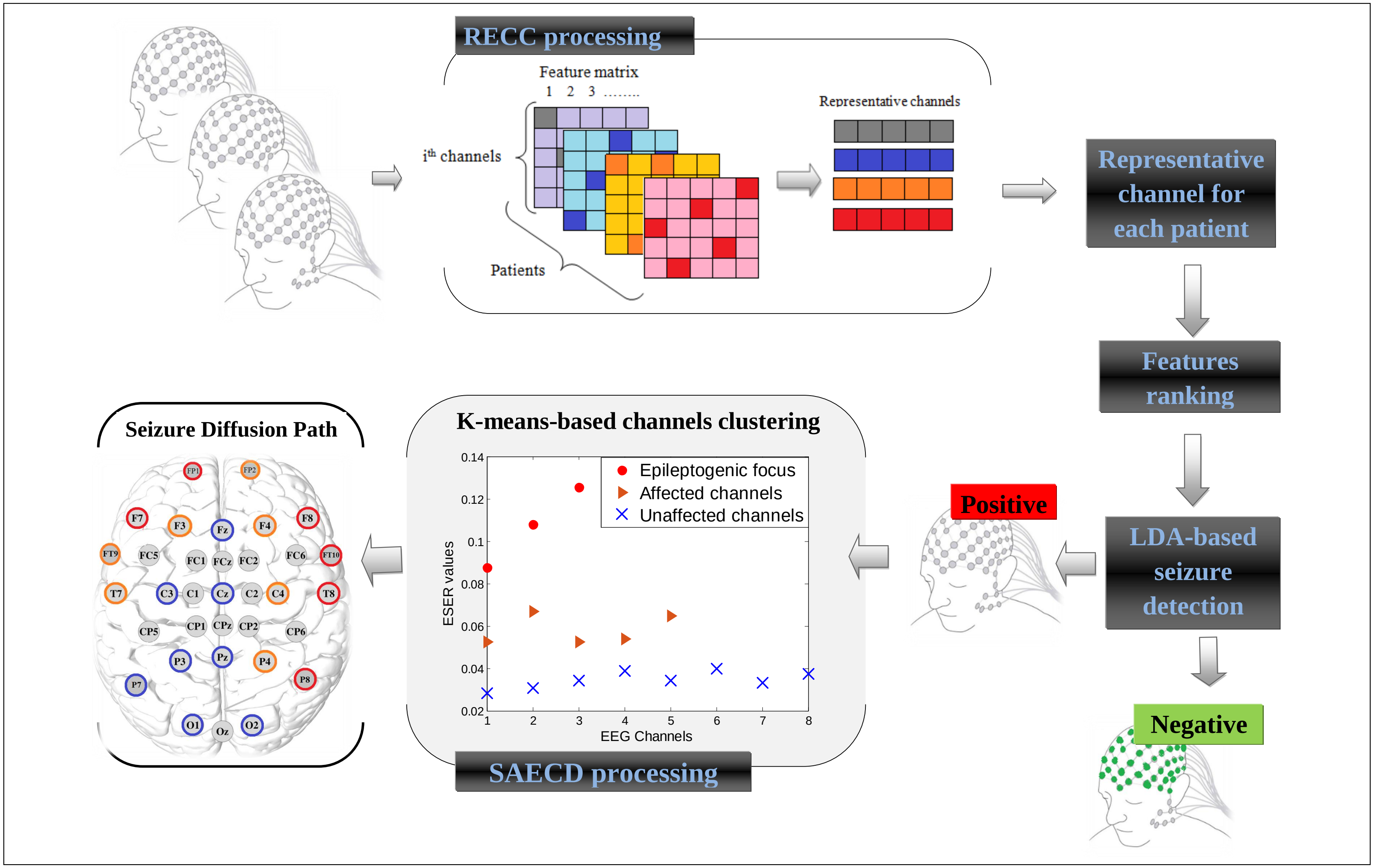



Figure V.1: Graphical abstract of the proposed EEG-type-independent system for EEG dimensionality reduction and epileptogenic focus detection.

## V.1 Developed EEG-type independent system

### V.1.1 Followed Methodology

This system is oriented towards surmounting the constraints inherent in contemporary multi-channel EEG methodologies. The methodology herein is centered on the development of an EEG-type-independent system tailored for the detection of epilepsy, leveraging the wavelet transform alongside supervised and unsupervised machine learning paradigms. A primary objective is to address challenges associated with high dimensionality and precise localization of the epileptogenic focus. The envisaged system comprises two interdependent subsystems, namely, the Representative EEG Channel Creator (RECC) and the Seizure Affected EEG Channel Detector (SAECD). A visual representation of the proposed system's conceptual framework is elucidated in the graphical abstract, as depicted in Figure V.1.

The efficacy of the proposed system is meticulously evaluated and benchmarked against extant studies, thereby substantiating its prowess in addressing the identified inefficiencies and advancing the current state of the art in epilepsy detection methodologies.

#### Representative EEG Channel Creator (RECC)

A depiction of the envisaged RECC subsystem is delineated in Figure V.2. This component engages in the analysis of the complete set of 16 channels present in the CHB-MIT Scalp EEG Database recordings (refer to Figure I.11). Its operational framework involves the application of wavelet packet decomposition techniques to discern and identify the five fundamental EEG brainwaves, namely Delta, Theta, Alpha, Beta, and Gamma (refer to Figure II.27).

From each channel, we derived seven notable features, as elaborated in Section III.1. These features encompass Median (MAD), Root Mean Square (RMS), Kurtosis (k), Variance (var), Normalized Range (NRWP), the Geometric Harmonic Average Difference (GHADWP) of wavelet packet coefficients, and the Standard Deviation (STD) of the absolute values of wavelet packet coefficients (aSTD). Consequently, this extraction process yielded a matrix of dimensions 16x35 for each patient. This matrix comprises 16 channels, each characterized by 7 distinct features, and spans across the delineation of 5 brainwaves.

In the endeavor to formulate a singular representative channel for each patient, we employed an improved methodology. This involved selecting the maximum values among the extracted features for each brainwave and across all 16 channels. The outcome of this process yielded a novel representative vector with dimensions of 1x35 for each patient, as illustrated in Figure V.2.

Our novel methodology extended to the analysis of both normal and ictal Bonn EEG signals, which constituted single-channel EEG recordings. These signals underwent a 4-level wavelet packet decomposition, extracting the aforementioned seven significant features.

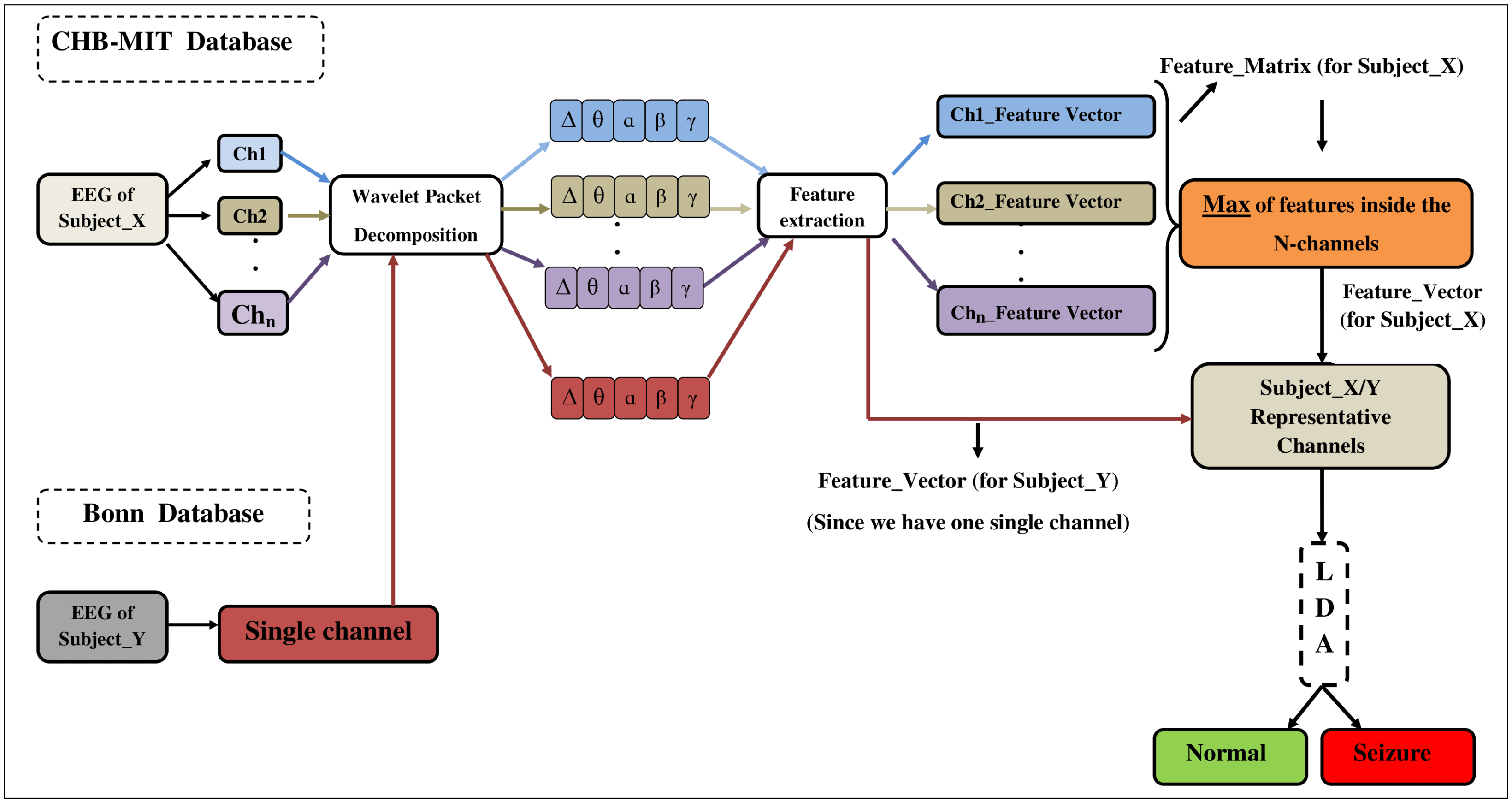



Figure V.2: Detailed diagram of the proposed EEG dimensionality reduction RECC subsystem.

This process yielded individual 1x35 dimensional feature vectors for each patient. The resultant representative channels from the CHB-MIT Scalp EEG Database, along with the feature vectors from the Bonn EEG signals, were amalgamated into a unified 248x36 dimensional feature matrix. This matrix encapsulated 248 final representative channels, each characterized by the 35 features (7 features multiplied by 5 brainwaves) and incorporated the corresponding class label. Subsequently, this feature matrix served as input for our epilepsy detection algorithm, leveraging a linear discriminant analysis (LDA) classifier. Our method evidences a robust enhancement in the analysis of EEG signals for the purpose of epilepsy detection.

**Seizure Affected EEG Channels Detector (SAECD)**

The multi-channel EEGs depicting epileptic activity are annotated solely with seizure start and end times, lacking specific details about the channels affected by ictal events and those that remain unaffected, as annotating individual channels in large clinical datasets is a resource-intensive endeavor. Addressing this challenge and aiming to elucidate aspects of seizure diffusion, we have employed the k-means unsupervised learning method to delineate clusters within each ictal multi-channel EEG recording. The utilization of the k-means algorithm is motivated by the objective of discerning latent patterns and variations within the ictal multi-channel EEG data, facilitating the grouping of similar channels. This clustering approach sheds light on the differentiation between seizure-affected EEG channels and those that remain unaffected.

Hence, we have introduced the Seizure Affected EEG Channels Detector (SAECD), marking the second stage in our EEG-type-independent system designed for epilepsy detection. Following a positive response from the Representative EEG Channel Creator (RECC), the SAECD subsystem comes into play, discerning the epileptogenic focus and the trajectory of seizure diffusion within the ictal multi-channel EEG recording, as illustrated in Figure V.3.

Nonetheless, evaluating and quantifying cluster quality in unsupervised learning poses a greater challenge compared to supervised learning, primarily due to the absence of class labels. Specifically, following the clustering of EEG channels, the difficulty arises in interpreting and distinguishing which cluster encompasses epileptic channels and which one encapsulates unaffected channels. To address this challenge, the utilization of a highly discriminating feature becomes imperative, one that can effectively capture abrupt changes during a seizure. In essence, the values of this feature should either exhibit a marked increase during epileptic seizures and a decrease otherwise, or vice versa. This feature becomes crucial in interpreting samples within each cluster, for instance, identifying a cluster with elevated values as corresponding to epileptic channels, given the prior knowledge that this particular feature exhibits heightened values during seizures. The Energy-to-Shannon Entropy Ratio (ESER) stands as a quintessential feature fulfilling this criterion, as elucidated in Section III.1, Feature 08.

To probe the efficacy of ESER values during and outside of seizures, an investigation was conducted employing 48 CHB-MIT EEG signals (24 normal, 24

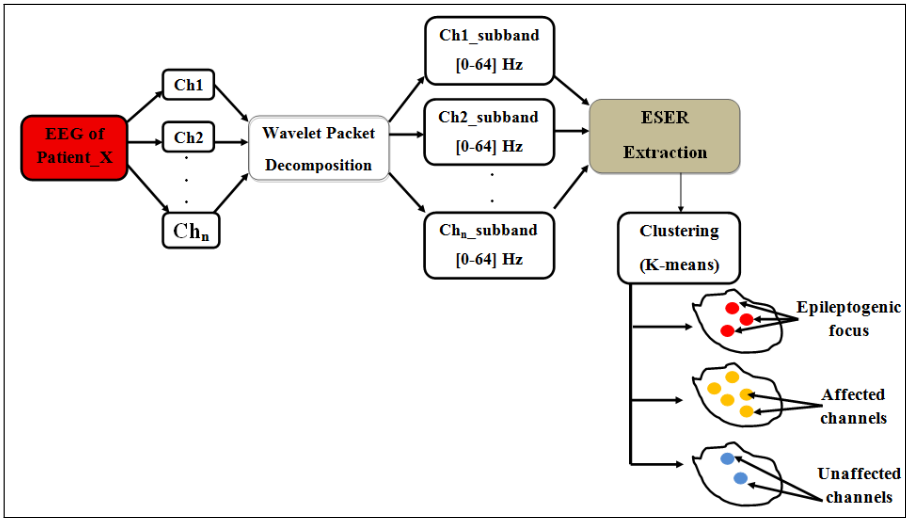



Figure V.3: Diagram of the proposed SAECD subsystem (detection of epileptogenic zone within **Ictal multi-channel-EEGs**).

ictal), each comprising 16 channels. Wavelet packet analysis at a 1-level, retaining the mother wavelet that yielded optimal results in the Representative EEG Channel Creator (RECC) subsystem, was applied to each channel with a sampling frequency of 256Hz. This 1-level decomposition produced an approximation (A) covering the [0:64]Hz bandwidth and a detail (D) covering the [64:128]Hz bandwidth. The Energy-to-Shannon Entropy Ratio (ESER) for the 1-level approximation was computed across all EEG brainwaves and all 16 channels.

The results revealed that ESER values in normal EEGs were substantially lower compared to values observed during seizures, where an unexpected increase was observed. Consequently, within the same ictal EEG recording, the channel exhibiting the maximum ESER value in comparison to other channels is identified as the closest to the epilepsy source, commonly known as the epileptogenic focus. Conversely, channels with low ESER values remain unaffected by the seizure. Building upon this insightful outcome, ESER, in conjunction with k-means clustering, can be employed to derive a cluster with markedly high ESER values indicative of the epileptogenic focus, a cluster with intermediate ESER values housing channels affected by the seizure, and another cluster characterized by very low ESER values, representing channels that remain normal even during seizure activity.

### V.1.2 Obtained Results

The objective of this section of the dissertation is to assess the effectiveness of the developed EEG dimensionality reduction and epileptogenic area detection subsystems. Additionally, it aims to scrutinize the impact of the mother wavelet and decomposition level on seizure detection through the utilization of wavelet packet analysis (WP).

### RECC–based Classification Results

Evaluating a model's efficacy across various metrics is crucial for gauging its performance. However, imbalances in the dataset can introduce bias to individual metrics. To mitigate this, we have employed an equal sampling of data for both normal and ictal EEGs. Furthermore, within the realm of machine learning, sensitivity pertains to a model's capacity to accurately identify abnormal cases. Hence, sensitivity served as the primary metric for assessing the performance of the Linear Discriminant Analysis (LDA) model, allowing for a comparative analysis with other developed systems. The outcomes of the LDA classification, involving 22 mother wavelets and utilizing the Representative EEG Channel Creator (RECC) technique, are delineated in Table V.1.

Table V.1: RECC–LDA-based classification results of 248 signals (CHB–MIT and Bonn datasets as one population) over 22 Mother Wavelets (using 10–fold cross-validation)

| N | M_w | acc (%) | sens (%) | spec (%) | F1-score (%) | MCC (%) | Prec (%) | AUC |
|---|---|---|---|---|---|---|---|---|
| 1 | db2 | 95.48 | 96.97 | 94.91 | 95.33 | 91.45 | 94.29 | 0.98 |
| 2 | db3 | 96.35 | 98.46 | 94.84 | 96.22 | 93.03 | 94.36 | 0.94 |
| 3 | db4 | 96.30 | 98.40 | 94.92 | 96.07 | 92.97 | 94.23 | 0.92 |
| 4 | db5 | 95.53 | 96.85 | 94.72 | 95.42 | 91.33 | 94.29 | 0.99 |
| **5** | **db6** | **96.72** | **98.46** | **95.66** | **96.55** | **93.79** | **95.06** | **0.99** |
| 6 | db7 | 95.13 | 97.80 | 93.70 | 94.91 | 90.94 | 92.82 | 0.97 |
| 7 | db8 | 95.13 | 97.68 | 93.55 | 94.86 | 90.77 | 92.69 | 0.986 |
| 8 | db9 | 95.93 | 98.40 | 94.21 | 95.72 | 92.26 | 93.52 | 1 |
| 9 | db10 | 95.55 | 97.80 | 94.39 | 95.35 | 91.67 | 93.59 | 0.986 |
| 10 | coif2 | 94.68 | 97.02 | 93.60 | 94.42 | 90.02 | 92.63 | 0.94 |
| 11 | coif3 | 95.53 | 98.40 | 93.55 | 95.28 | 91.55 | 92.76 | 0.95 |
| 12 | coif4 | 93.08 | 97.02 | 91.05 | 92.60 | 87.17 | 89.49 | 0.98 |
| 13 | coif5 | 95.11 | 97.56 | 93.32 | 94.87 | 90.57 | 92.63 | 0.94 |
| 14 | sym2 | 95.48 | 96.97 | 94.91 | 95.33 | 91.45 | 94.29 | 0.98 |
| 15 | sym3 | 96.35 | 98.46 | 94.84 | 96.22 | 93.03 | 94.36 | 0.94 |
| 16 | sym4 | 95.11 | 97.03 | 94.26 | 94.93 | 90.80 | 93.52 | 0.99 |
| 17 | sym5 | 95.50 | 97.68 | 94.14 | 95.26 | 91.42 | 93.4 | 0.97 |
| 18 | sym6 | 93.93 | 97.02 | 92.36 | 93.59 | 88.66 | 91.15 | 0.986 |
| 19 | sym7 | 96.33 | 98.46 | 94.89 | 96.19 | 93.05 | 94.4 | 0.99 |
| 20 | sym8 | 95.10 | 97.74 | 93.55 | 94.87 | 90.77 | 92.69 | 0.95 |
| 21 | sym9 | 94.76 | 97.56 | 92.66 | 94.50 | 89.88 | 91.92 | 0.98 |
| 22 | sym10 | 95.53 | 97.80 | 94.27 | 95.39 | 91.61 | 93.59 | 0.97 |

The application of the LDA–RECC approach, incorporating the db6 mother wavelet and 33 pertinent features, demonstrated outstanding performance, achieving an epilepsy detection sensitivity of 98.46%, specificity of 95.66%, and an overall correct rate of 96.72%. Notably, the LDA exhibited remarkable proficiency in accurately identifying abnormal cases and retrieving relevant elements, evidenced by an impressive F1-score of 96.55%. Furthermore, the substantial Matthews correlation coefficient of 93.79% when employing the RECC and db6 mother wavelet affirms that the creation of a representative channel is an effective strategy for EEG dimensionality reduction, concurrently ensuring reliable epilepsy detection within EEG signals. These results underscore the critical importance of selecting an appropriate mother wavelet, particularly in capturing transient features and addressing the non-stationary nature inherent in EEG signals. In light of this thorough assessment of the developed RECC subsystem, this study confidently introduces a notable advancement in EEG dimensionality reduction and seizure detection methodologies.

### The impact of Engineered features on epilepsy Detection

We assessed the efficacy of our proposed features, GHADWP, NRWP, and aSTD, through the utilization of the Relief–F algorithm. This involved ranking the feature vectors, comprising five sub-bands (delta, theta, alpha, beta, and gamma), seven features, and labels (1x36 dimension). The outcomes of the RECC features ranking and their associated weights are presented in Table V.2.

Table V.2: Relief-F–based extracted features ranking, (db6 mother wavelet, RECC subsystem)

| Feature | Ranking | Weight | Feature | Ranking | Weight |
|---|---|---|---|---|---|
| **Gamma_aSTD** | **1** | **0.0995** | Delta_GHADWP | 19 | 0.0071 |
| **Beta_aSTD** | **2** | **0.0950** | Theta_aSTD | 20 | 0.0058 |
| Gamma_RMS | 3 | 0.0761 | Alpha_Variation | 21 | 0.0039 |
| Gamma_Variation | 4 | 0.0661 | Beta_MAD | 22 | 0.0035 |
| **Alpha_aSTD** | **5** | **0.0650** | Alpha_NRWP | 23 | 0.0027 |
| Gamma_MAD | 6 | 0.0624 | Gamma_kurtosis | 24 | 0.0019 |
| **Gamma_GHADWP** | **7** | **0.0604** | Alpha_kurtosis | 25 | 0.0008 |
| Beta_RMS | 8 | 0.0555 | Beta_kurtosis | 26 | 0.0006 |
| Delta_kurtosis | 9 | 0.0401 | Beta_GHADWP | 27 | -0.0001 |
| **Theta_NRWP** | **10** | **0.0361** | Alpha_GHADWP | 28 | -0.0004 |
| Delta_aSTD | 11 | 0.0338 | Theta_RMS | 29 | -0.0019 |
| Delta_Variation | 12 | 0.0333 | Alpha_MAD | 30 | -0.0030 |
| Alpha_RMS | 13 | 0.0315 | Theta_GHADWP | 31 | -0.0065 |
| Delta_RMS | 14 | 0.0245 | Beta_NRWP | 32 | -0.0077 |
| Beta_Variation | 15 | 0.0229 | Theta_MAD | 33 | -0.0101 |
| Theta_kurtosis | 16 | 0.0177 | Theta_Variation | 34 | -0.0210 |
| Delta_MAD | 17 | 0.0170 | Gamma_NRWP | 35 | -0.0329 |
| Delta_NRWP | 18 | 0.0147 | | | |

The specified features are positioned within the top ten relevant parameters. According to the Relief–F algorithm, the Standard Deviation of absolute values of Wavelet Packet coefficients ($\sigma_{|WP|}$) (aSTD), the Geometric–Harmonic Average Difference of Wavelet Packet coefficients (GHADWP), and the Normalized Range of Wavelet Packet coefficients (NRWP) hold the first, seventh, and tenth places, respectively. This outcome affirms the reliability of the proposed features in effectively distinguishing between seizure and seizure-free epochs. It further underscores their significant contribution to maintaining robust epilepsy detection within single-channel EEG signals.

**Evaluation of Kmeans–SAECD Clusters**

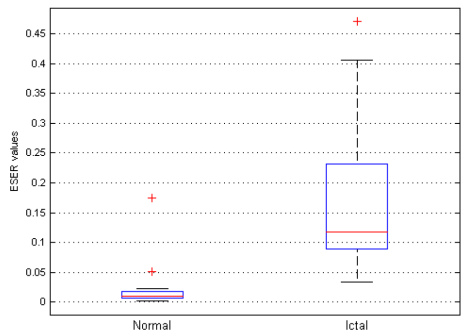
As elucidated in Section V.1.1, the Seizure Affected EEG Channels Detector (SAECD) subsystem was formulated by combining the Energy-to-Shannon Entropy Ratio (ESER) with the k-means clustering algorithm. To assess the efficacy of the derived clusters, three distinct approaches were employed: External cluster validation, Relative cluster validation, and Internal cluster validation.

Observing the results presented in Figure V.4a, it is evident that ESER values for ictal EEGs are notably higher [$0.04 \leq ESER \leq 0.41$] compared to normal EEGs [$0.01 \leq ESER \leq 0.03$], underscoring the efficiency of the ESER feature in distinguishing between normal and ictal EEG behaviors. Notably, the 'ictal-boxplot' exhibits a positive-skewed distribution, with an uneven size and the median line closer to the $1^{st}$ quartile in contrast to the 'normal-boxplot'. This indicates variability among ictal data points, with a majority displaying high ESER values and a smaller subset exhibiting low ESER values. Such variability reinforces the notion that, within the same ictal EEG recording, certain channels maintain their normal characteristics even during a seizure, while channels with elevated ESER values are influenced by ictal activity. Moreover, the extended upper whisker of the 'ictal-boxplot' signifies some channels attaining even higher ESER values, implying their proximity to the epileptic seizure source. Based on these findings, it is deduced that the optimal number of clusters should be $k = 3$ for focal seizures and $k = 2$ for generalized seizures.

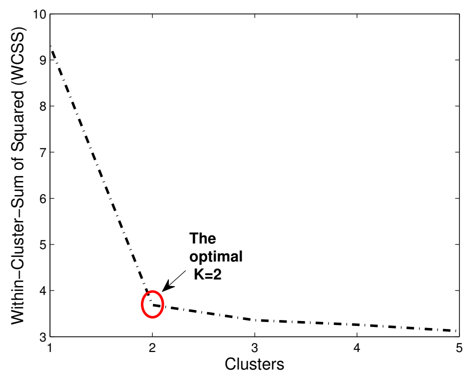
In the context of external cluster validation, involving a comparison to an externally known result, the obtained box plots of normal and ictal ESER values serve as a metric. The k-means clusters are labeled based on ESER values, designating the cluster with lower ESER values as the Unaffected EEG channels cluster, the cluster with high ESER values as the Affected EEG channels cluster, and the cluster with extremely high ESER values as the epileptogenic focus cluster.

Furthermore, the elbow approach (relative cluster validation) was applied to the ictal EEGs to discern whether they form a single cluster (all channels equally affected by the seizure) or multiple clusters (channels categorized as exceedingly affected, affected, and unaffected). As illustrated in Figure V.4b, the processed EEGs exhibit an elbow point at k=2, corroborating the results obtained from the external cluster validation metric.

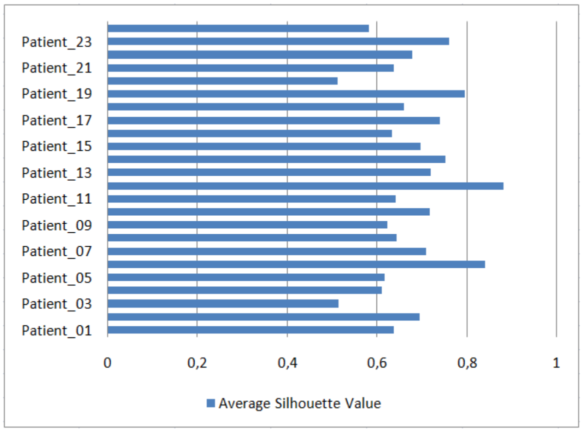
Ultimately, in order to enhance the validation of clustering, we utilized the mean silhouette coefficient method for internal cluster validation. Illustrated in Figure V.4c, the favorable average silhouette values ranging from 0.51 to 0.88 affirm




(a) The ESER values variation




(b) Elbow-based k clusters selection




(c) Average silhouette values

Figure V.4: Results of K-means clusters evaluation approaches the accurate execution of the clustering process.

### SAECD-based Epileptogenic Focus Detection

We successfully conducted the identification of various epileptic seizure types using the advanced Kmeans clustering-based SAECD subsystem developed in our study, as visually represented in Figure V.5. The robustness of our approach is highlighted through the utilization of internal, external, and relative cluster validation methods. Notably, EEG channels with low ESER values [$ESER \leq 0.03$] are distinctly visualized in calming shades of blue, unequivocally denoting unaffected channels within the brain. Conversely, channels with medium ESER values [$ESER \geq 0.04$] are vividly portrayed in warm orange hues, indicating regions of the brain affected by seizures.

The data points characterized by the highest ESER values are of particular interest, representing the most severely affected channels and those positioned closest to the source of the seizure. These critical channels are visually highlighted in a striking red, effectively serving as markers for the epileptogenic focus. This nuanced approach not only enables precise identification of the seizure-affected areas but also provides valuable insights into the severity and proximity of these affected regions within the brain.

Examining the specific outcomes of the Kmeans-SAECD methodology for patients CHB-06 and CHB-15, as presented in Figures (V.5a &V.5b) and Figures(V.5e &V.5f), we observe a distinctive pattern. The seizures in these cases originated from both sides of the brain, aligning with the clinical classification of primary generalized epileptic seizures [240]. Intriguingly, this pattern extends beyond the presented cases, as we identified the same clinical scenario in an additional 13 patients from the CHB-MIT database, namely patients 02, 03, 05, 07, 08, 10, 11, 16, 17, 19, 21, 23, and 24. This consistent observation further underscores the reliability and generalizability of our approach across a diverse patient cohort.

In contrast, the remaining nine patients (patient 01, 04, 09, 12, 13, 14, 18, 20, and 22) exhibited a different seizure pattern—specifically, tonic-clonic seizures. These seizures are characterized by epileptic activity originating from one side of the brain and spreading to its entirety, as outlined in the comprehensive Figures(V.5c & V.5d). The distinct differentiation in seizure types not only demonstrates the sensitivity of our method to various seizure manifestations but also provides crucial information for tailored treatment and intervention strategies.

In summary, our innovative Kmeans clustering-based SAECD subsystem, coupled with meticulous cluster validation techniques, not only allows for precise identification of epileptic seizure types but also provides a comprehensive understanding of the affected brain regions' severity and spatial distribution. This holistic approach enhances the diagnostic capability of our system and contributes valuable insights to the field of epilepsy research and clinical practice.

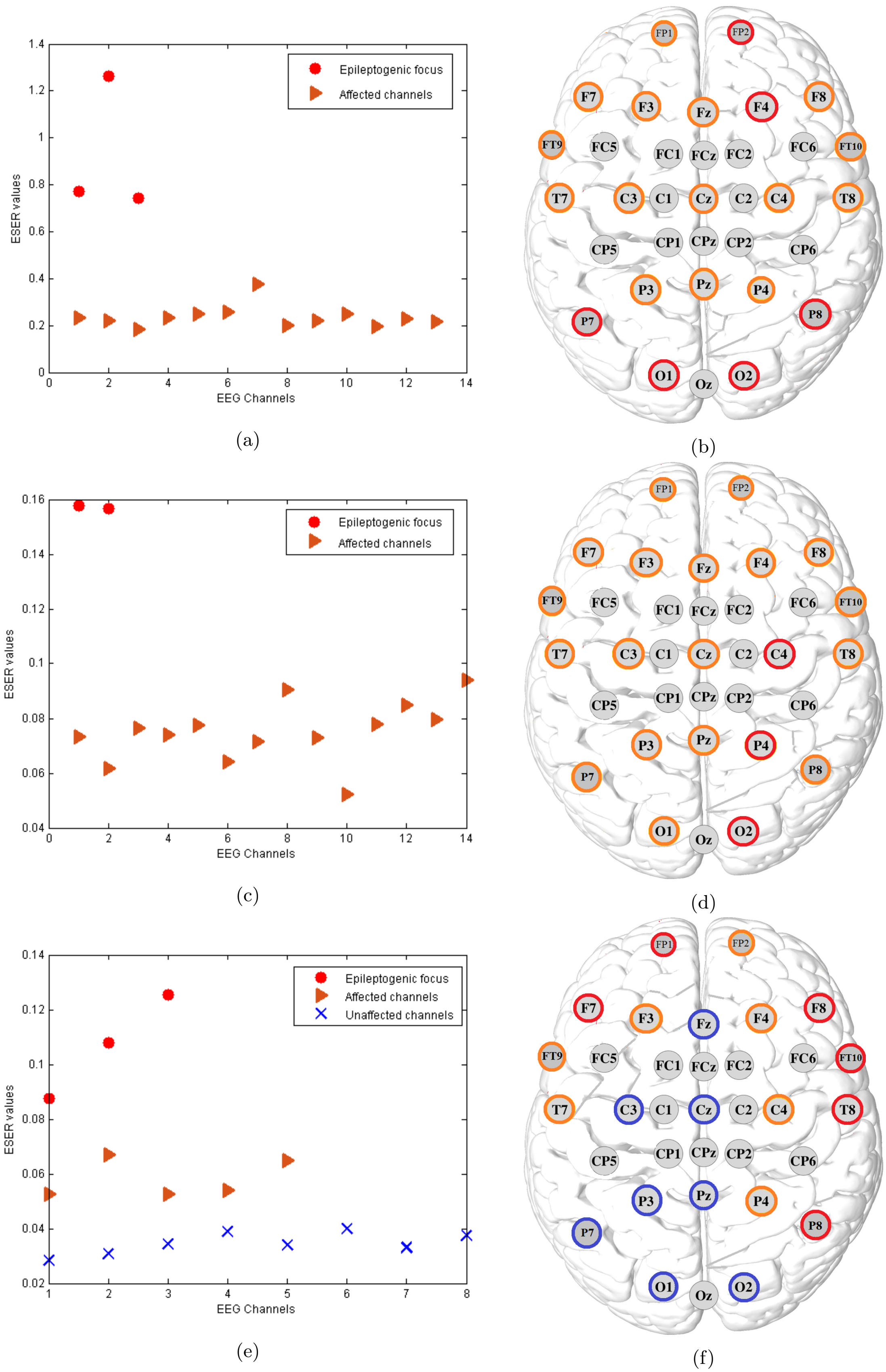



Figure V.5: The developed SAECD results of Patient 6 ((a)&(b))), Patient 12 ((c)&(d))), and Patient15 ((e)&(f))) of the studied CHB-MIT database. Unmarked electrodes refer to those unused during the recording process of the studied database.

### V.1.3 Discussion

In this dissertation section, we discuss the outcomes while considering various objectives, including the efficiency of the RECC and SAECD subsystems (V.1.3), the selection of an appropriate mother wavelet for EEG signals (V.1.3), the anticipated impact of our developed approaches in neurology (V.1.3), and a comparison with previous works (V.1.3). Our method has significantly enhanced epilepsy detection by introducing innovative and robust features.

#### Effectiveness of RECC and SAECD Subsystems

It has been observed that by selecting the maximum value for each feature across all recorded channels, the dimensionality of EEG can be reduced by 93.75%. Instead of utilizing 16 channels per patient, a single representative channel proved to be sufficient, maintaining a high level of epilepsy detection performance (precision value of 95.06% and AUC= 0.99, as indicated in Table V.1). As a result, RECC offers the advantage of reducing EEG dimensionality without compromising epilepsy detection performance, while the Kmeans–SAECD subsystem enables the identification of epileptogenic zones in all CHB-MIT patients. These two subsystems, introduced in this study, complement each other by providing unique benefits. Together, they form a potent tool for the diagnosis and monitoring of epilepsy.

#### EEG signals appropriate mother wavelet

Our results indicate that the choice of the mother wavelet significantly impacts the detection of ictal periods in WP-based approaches. As shown in Table V.1, the db6 wavelet proves to be highly suitable for the analyzed signals, achieving an LDA accuracy of 96.72% and a sensitivity of 98.46% for the RECC approach. The specific characteristics of the wavelet, including symmetry, scaling functions, vanishing moments, and the coefficient of the dyadic filter, strongly influence the EEG signal processing. Consequently, db6 emerges as the optimal mother wavelet for the studied EEG signals. Additionally, the decomposition level is a crucial parameter in wavelet analysis. In this study, 5 and 4 decomposition levels were applied to the CHB-MIT and Bonn databases, respectively, covering all EEG rhythms: Delta [0–4], Theta [4–8], Alpha [8–16], Beta [16–32], and Gamma [32-64] Hz.

#### Comparison with previous works

In our investigation, we employed a thorough methodology to tackle the complexities of epilepsy detection while minimizing dimensionality. To offer a nuanced assessment of the efficacy of our proposed method, we conducted a detailed comparison using three distinct tables. Table V.3 compiles information from studies specifically focused on epilepsy detection with reduced dimensionality, enabling a comparison of our findings with established approaches in the field.

Our system surpasses prior studies through the analysis of a more extensive database, the creation of representative EEG channels, and the detection of the

Table V.3: *Comparative presentation between the proposed work and previous* ***EEG dimensionality reduction approaches*** *published in the literature, for epilepsy detection*

| Authors | Dimensionality reduction Method | Acc (%) | Sens (%) |
|---|---|---|---|
| Faul et al [241] | REACT | 90 | / |
| Faul et al [242] | Classification behaviour | 96.55 | / |
| Duun et al [44] | Variance and Entropy | / | 96 |
| Bhattacharyya et al [243] | Least STD | 99.57 | 97.91 |
| Alani et al [244] | Classification behaviour | 89.96 | / |
| Solaija et al [245] | Common 18 channels | | 87 |
| Aydemir et al [246] | RSS–SFSM | 84.02 | / |
| Moctezuma et al [247] | Energy and fractal features | 93 | / |
| Moctezuma et al [248] | NSGA II and III | 97 | / |
| chen et al [52] | Pairwise one-class SVM | 94 | 97.80 |
| zubair et al [54] | SUBXPCA + Random forest | 98.00 | 96.78 |
| Keyvan et al [55] | Patient-Specific- DRT | / | 100 |
| singh et al [249] | Patient-Independent Approach | 96.43 | 100 |
| amiri et al [56] | sCSP | 98.81 | 98.44 |
| **This study** | **RECC** | **96.72** | **98.64** |

epileptogenic focus. Results are presented in terms of accuracy, sensitivity, and the method employed for EEG dimensionality reduction. The RECC subsystem, demonstrating accuracy that exceeds most previous studies, is comparable to the works of Moctezuma [248] and Amiri [56]. Furthermore, our single-channel system outperforms the five-channel system proposed by Bhattacharyya et al. [243] in terms of sensitivity values, despite the use of five selected channels and a Random Forest classifier. Additionally, a recent study by Razi and Schmid [55] on iEEG signals achieved a perfect sensitivity of 100%, emphasizing the superiority of intracranial EEGs in selecting the closest channels to the epileptogenic area. These results underscore the effectiveness and confidence of our proposed system, marking a significant advancement in EEG-based epileptic seizure detection.

Moreover, our study comprehensively evaluates various mother wavelets for the detection and classification of epileptic seizures within EEG data. As depicted in Table V.4, the Daubechies with order six (db6) mother wavelet exhibits promising results, aligning with outcomes reported in the literature in terms of accuracy and sensitivity of epilepsy detection. While emphasis has been placed on constructing a robust machine-learning model using time-scale domain features extracted from iEEGs and EEG signals during and outside of seizures, our primary goal is to detect ictal activity within EEG signals with reduced computation time and high performance. To this end, we conducted a comparative study of our proposed system (Figure V.6) against several clinical applications for identifying epileptic seizures and seizure-free classes within EEG signals in terms of computational time. As shown in Table V.5, our system demonstrates high performance with minimal computational time.

Table V.4: Comparison with previous studies of mother wavelet selection for epilepsy detection

| Authors | M_wavelet | Acc (%) | Other metrics |
|---|---|---|---|
| Gandhi et al [250] | Coif1 | [63-99] | - |
| Rafiee et al [251] | db44 | - | Shape-similarity |
| Chavan et al [252] | db4 | - | Power-rest=99.99 |
| Chen et al [114] | coif3<br>sym7 | 92.30<br>99.33 | -<br>- |
| Tzimourta et al [253] | db4 | [87-99] | - |
| Ahmadi et al [254] | Bior1.1 | [96-97] | - |
| Salankar et al [255] | dmey/ db4 | 99.71 | - |
| Anila et al [256] | db10 | [88.26-99.21] | Min entropy |
| Sayilgan et al [257] | Haar (db1) | 100 | - |
| Shen et al [258] | db4 | [96.38-97] | - |
| **This study** | **db6** | **96.72** | - |

Table V.5: Comparative presentation in terms of computational time (CT) between the proposed system and other epilepsy detection applications published in the literature

| Authors | seizure detection CT (sec) |
|---|---|
| Qu et al [259] | 9.60 |
| Osorio et al [260] | 2.10 |
| Grewal et al [261] | 17.1 |
| Gardner et al [262] | 7.58 |
| Aarabi et al [263] | 11.0 |
| Zhang et al [264] | 10.8 |
| Hocepied et al [265] | 14.8 |
| Krishnan et al [266] | 0.48 |
| Arunkumar et al [267] | 1.14 |
| Song et al [268] | 0.31 |
| Chen et al [52] | 7.71 |
| zubair et al [54] | 1.02 & 0.71 |
| **Proposed RECC** | **1.37** |
| **Proposed SAECD** | **0.974** |

**Expected Effect of the Developed system in Neurology**

Luders and Comair [99] provided a comprehensive definition of the epileptogenic focus, characterizing it as the specific region within the brain responsible for initiating epileptic seizures before their propagation to localized areas. This fundamental concept serves as the cornerstone of our exploration into epilepsy detection and monitoring.

Figure V.5 visually represents how our developed SAECD subsystem aligns with Luders and Comair's definition, facilitating neurologists in pinpointing points of brain dysfunction. This is particularly crucial in the context of pharmacoresistant epilepsy, where identifying the epileptogenic focus becomes a challenging yet pivotal aspect of effective treatment strategies. Furthermore, our approach introduces a novel dimension to seizure detection through the RECC subsystem, a concept not previously explored or introduced in existing literature. Overcoming the limitations posed by early EEG abnormalities, the RECC subsystem adeptly identifies specific features where the impact of a seizure is most pronounced. This results in the creation of a robust representative channel, providing a valuable foundation for accurate and efficient epilepsy detection. The proposed diagnostic assistance system, as depicted in the structured diagram of Figure V.6, embodies the synergy between the RECC and SAECD subsystems. The combination of these elements, each contributing unique strengths, establishes a powerful tool for the diagnosis and continuous monitoring of epilepsy. Notably, the RECC subsystem boasts an impressive sensitivity of 98.46%, underscoring its efficacy in capturing subtle yet crucial seizure-related features. Complementing this, the SAECD subsystem contributes to the diagnostic arsenal with an average silhouette range of [51.21-88.18%], demonstrating its ability to discern distinct clusters in the data, thus enhancing the precision of epilepsy diagnosis.

Our comprehensive approach integrates established principles from Luders and Comair's work with innovative concepts like RECC and SAECD, resulting in a sophisticated diagnostic system poised to make significant contributions to the field of epilepsy research and clinical practice. The combination of theoretical foundations, novel methodologies, and advanced visualization tools positions our system as a potent and versatile resource for neurologists and researchers working towards improved epilepsy management.

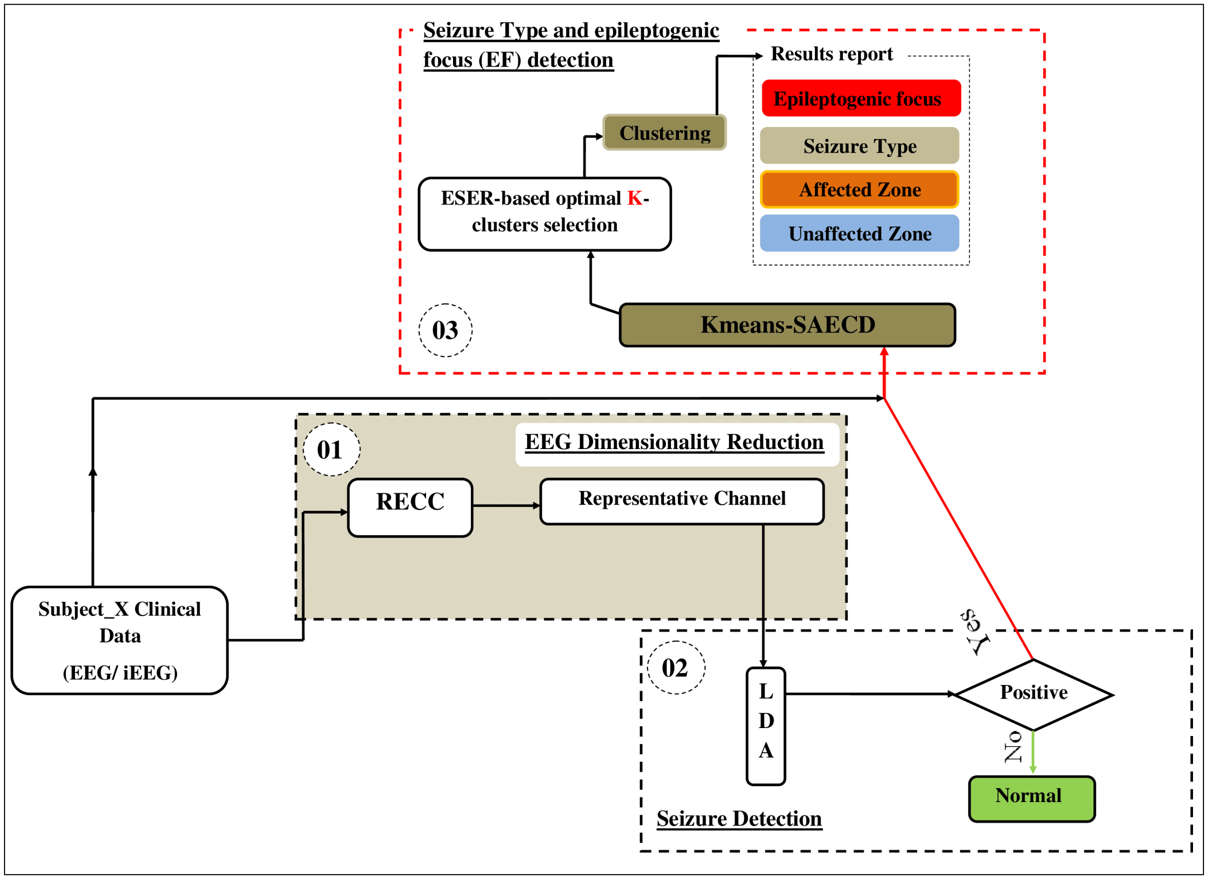



Figure V.6: **Proposed EEG-Type-Independent Seizure Detection System (for Clinical Applications)** The integration of RECC and SAECD provides two options for these purposes. RECC, detailed in section V.1.1, is utilized for EEG dimensionality reduction. The wavelet packets (WP) frequency bands are formed using the db6 mother wavelet and a decomposition level encompassing the five human rhythms. In the Seizure Detection phase (2), the processed EEG is labeled as either seizure or normal by the fitted LDA model. If a patient's EEG is classified as positive, SAECD is then employed to identify the seizure type and epileptogenic focus, as described in section V.1.1.

# Part II: An Asynchronous Application For Epileptogenic Focus Detection: Epileptica.

## V.2 Epileptica

Numerous technologies has been developed and devoted to enhance the accessibility, opportunity and efficiency of Electroencephalogram (EEG) based epileptic seizures diagnosis. However, these tele–technologies are all dedicated to patients with fully controlled seizure (anti–epileptic medicines). While, the pharmacoresistant category, are totally ignored. Patients in this category suffer from uncontrolled seizures that leads to psychosocial debilitation, depression, anxiety, veritable risk of injury or death. Treating this kind of pharmacoresistant epilepsy needs firstly and essentially a precise detection of epileptogenic focus. Thus, the appropriate tool for such complicated operation is the intercranial electroencephalography exam (iEEG). Nevertheless, the iEEG is a multi–channel recording exam, which increases the risk of cerebral infection. Therefore, EEG dimensionality reduction is needful. In this sens we represent our Epileptica application that offers a remote epileptogenic focus detection and reduces the multi–EEG channels into one single EEG channel of interest.

Epileptica is a client–server application for EEG signal analysis, devoted for patients with pharmacoresistant epilepsy. Since, the epileptogenic focus detection (EFD) represents a crucial factor for a successful seizure–free surgery, detecting the epileptogenic zone using a single–intracranial channel (electroencephalography iEEG), is required for cerebral infection risk diminution in comparison with that caused by multi–channel iEEG

Epileptica consists of two sides; the client side represents the neurologist, who will store the recorded EEG signal in a specific and server–shared SQL database, then this EEG signal will be analyzed in the server side (biomedical engineer) for seizure onset area detection. Obtained results will be further stored in the same SQL database, where the neurologist could easily and remotely access to them.

### V.2.1 Main Features of Epileptica

Epileptica is a client–server telemedicale application built using the Visual basic environment that allows the development of high design interfaces. Epileptica is developed to be a two sides application;

#### Epileptica–client side

the Epileptica installed on the client host, as shown in Figure V.7, enables the client (neurologist) to manage **remotely** the server host SQL database. After a successful login process, Figure V.7b, the Epileptica main menu appears as shown in Figure V.8. The first option; Access to Epileptica Database, allows the neurologist to register and store the clinical data of the patient; The patient code which represents a specific identification code (values, letters, both...) and the EEG exam recordings, besides some additional operations such as; Delete patient, Update, Open file path, load and read the EFD report (EEG processing results). These are the main services offered by the developed Epileptica application, Figure V.9


(a) Epileptica Splash screen

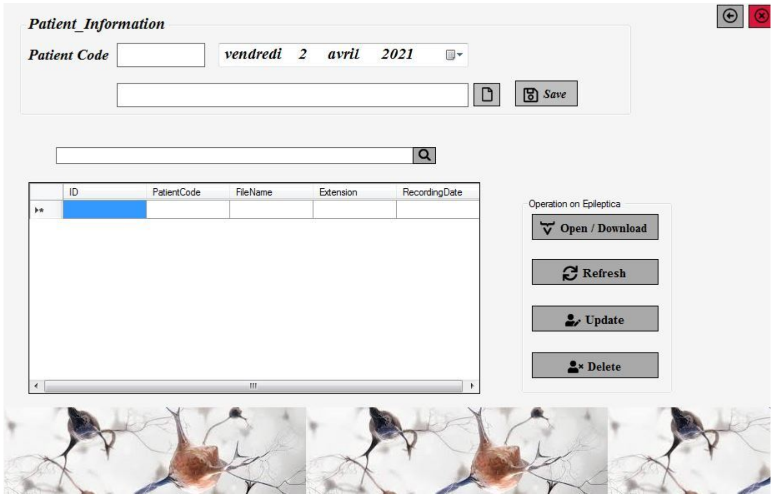
(b) Login screen

Figure V.7: Epileptica application installed on the client host (neurologist)

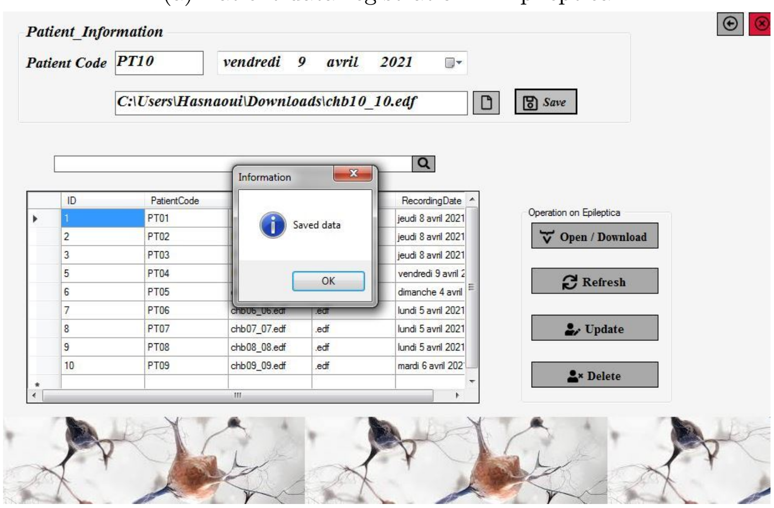

Figure V.8: Epileptica main menu (neurologist side)

**Epileptica–server side**

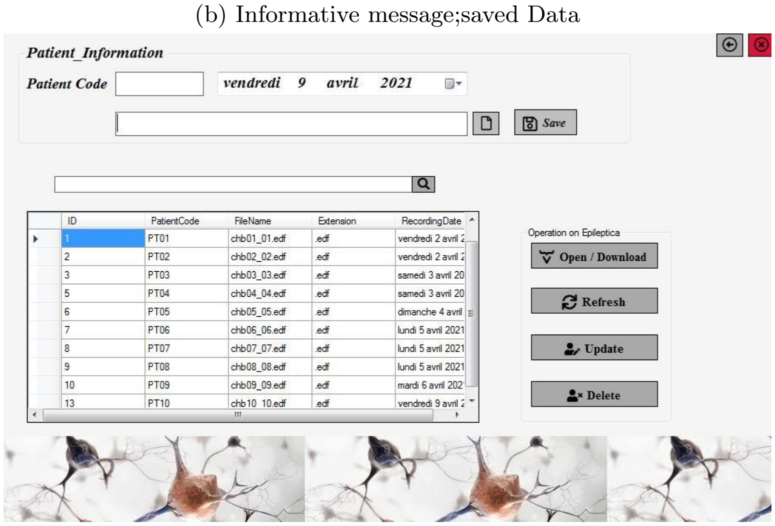
The stored data will be further analyzed by the server, who will retrieve the EEG signal, through the Epileptica application developed for the server host, Figure V.10. Noting that the SQL database (Epileptica database) is created in the server host. Where, the purpose behind the application made for the server, is to facilitate the **local** management of the database. The server (biomedical engineer) can easily download the stored EEG signal for analysis and store the final result (EFD result) corresponding to a specific patient through the propriety of Patient Code.




(a) Patient data registration in Epileptica




(b) Informative message;saved Data




(c) All the added and saved data by the neurologist

Figure V.9: Storing process of patients clinical data by the neurologist

Once the data is added by the neurologist, the server receives a message that a new data has been added, as shown in Figure V.11, by a simple click on OK, only the new added data will appears as shown in Figure V.12 As well as, when the server is still treating the data the client receives a message that the EEGs signals are still in processing,Figure V.13, and an OK click to see which of the data are in processing as shown in Figure V.12.


Figure V.10: Epileptica main menu (server side)

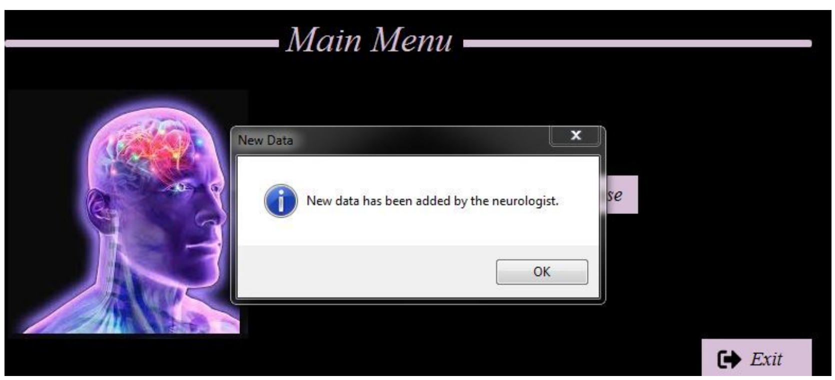



Figure V.11: An informative message for the server (biomedical engineer

### V.2.2 EEG Processing for Epilepsy Detection and Epileptogenic Area Circumscription

Once the neurologist has finished storing the EEG exam, the processing operation starts immediately, using our EEG-Type independent system as explained in previous sections. Finally, this result will be generated in PDF file and it will be stored

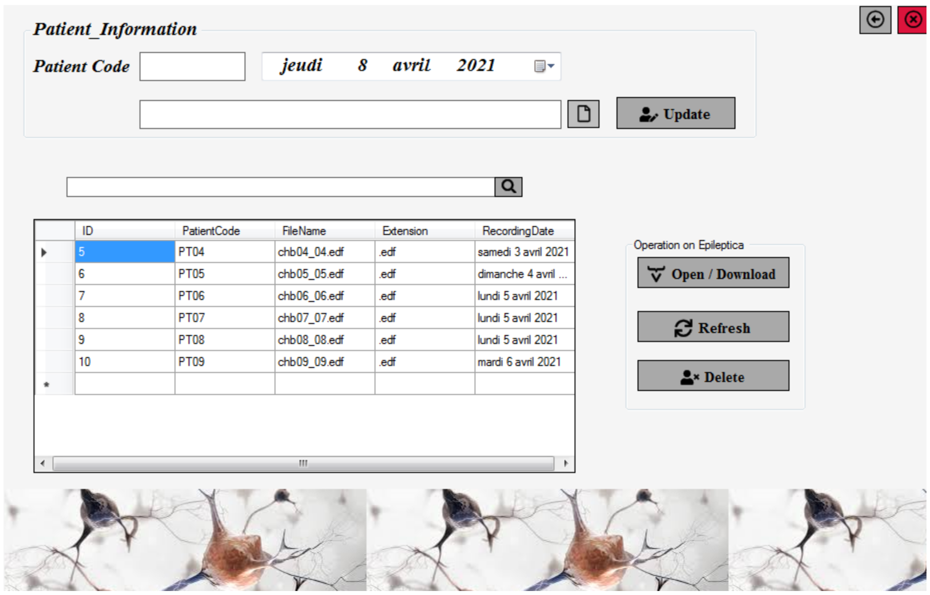



Figure V.12: The new EEGs added by the neurologist

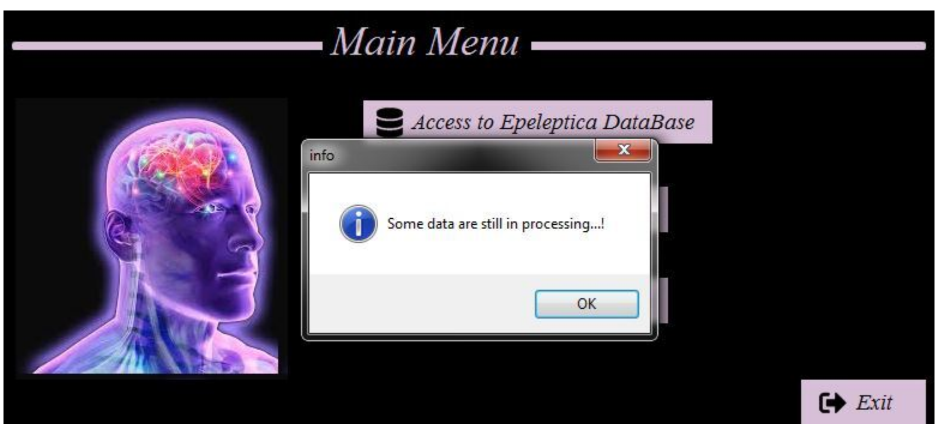



Figure V.13: An informative message for the client (Neurologist

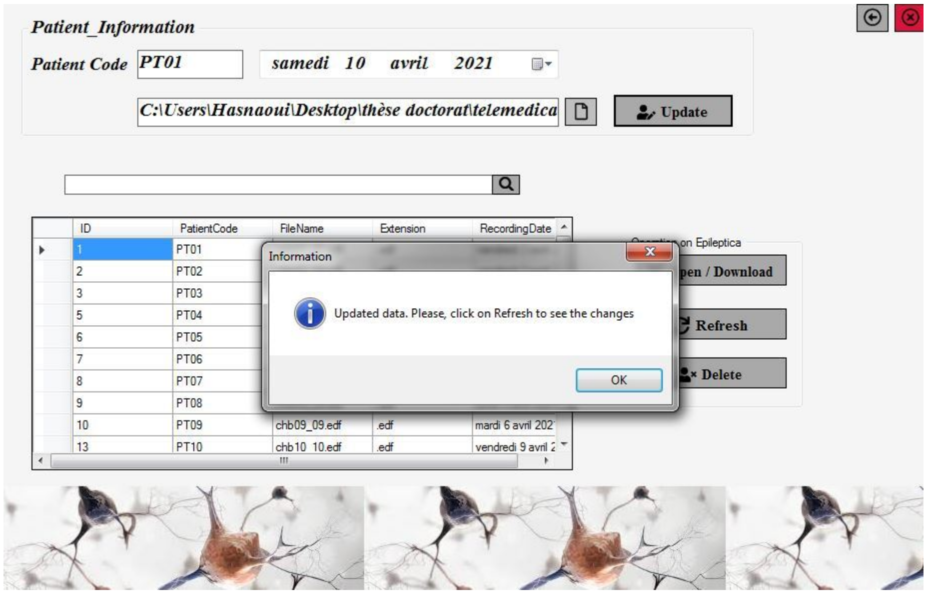



Figure V.14: Updating Data by the server (storing EFD result)

in Epileptica database as shown in Figure V.14. The neurologist can easily access to this stored PDF.

## V.3 Conclusion

In this chapter, we present a robust system designed for the reduction of dimensionality in EEG data, exhibiting the capability to identify pertinent epileptical patterns within ictal electroencephalogram (EEG) data. The devised system comprises various components, including wavelet packet decomposition (WPD), feature extraction (basic and engineered features), feature selection, as well as supervised and unsupervised machine learning algorithms. Our evaluation encompassed 34 subjects from two datasets, namely the CHB–MIT Scalp EEG and Bonn Datasets. A departure from previous studies, we opted for a combined approach, consolidating the two datasets into a singular database consisting of 248 EEG signals. This strategic amalgamation serves the purpose of constructing an EEG-type-independent system proficient in capturing ictal patterns within both EEGs and intracranial EEGs (iEEGs). This integrated approach enhances result credibility by accommodating diverse populations and addresses the high dimensionality challenge associated with EEG signals through the utilization of the RECC subsystem. Our findings indicate a remarkable 93.75% reduction in the dimensionality of the electroencephalogram, maintaining a heightened sensitivity in epilepsy detection through the utilization of just one representative channel. From a mathematical perspective, our results affirm the superior performance of the Daubechies mother wavelet of order six (db6) in comparison to the 22 other mother wavelets examined in this research. This underscores its suitability as an effective tool for identifying ictal epochs within non-stationary EEGs. Furthermore, the inclusion of engineered features demonstrates efficient contributions to the fitting process of Linear Discriminant Analysis (LDA), enabling commendable performance even with a limited amount of data. Clinically, our Kmeans–SAECD subsystem has been tailored to meet authentic requirements in the realm of seizure detection and the delineation of epileptogenic focus. The adaptability and effectiveness of this subsystem offer promising prospects for practical applications in the clinical domain, emphasizing its potential as a valuable tool in epilepsy diagnosis and monitoring. The second part introduces a telemedicine application based on client–server architecture, that allows doctors to remotely access to the results obtained by our system. An overall conclusion that summarizes this dissertation achievements and highlights some pertinent research lines for our future targets will be presented in the following part.

# Conclusion

Analysis and classification of EEG signals contributed saliently in neurosciences improvement by allowing a precise exploration of the interior activity of the brain, and therefore, it assists meaningfully in the diagnosis and treatment of epileptic seizures. Notwithstanding, when processing EEG recordings we often have a huge amounts of data (multiple channels) with various status (normal, ictal, pre–ictal and inter–ictal epochs), especially, if these signals were recorded over a long period of time, which represents an issue, and thus, dimensionality reduction approaches that keep only relevant information carried within these EEG channels are needed, to ensure a correct performance of epileptic activity classification, without disturbing the classifier (resulting in less accuracy values) or over–fitting it (deceptive high accuracies).

As this comprehensive dissertation draws to a close, it is imperative to synthesize the multifaceted contributions and insights garnered throughout the study. The exploration embarked on a journey through the intricate realms of EEG signal analysis, wavelet transform applications, and the fusion of machine learning techniques to enhance the detection and localization of epileptic activities.

In the initial chapters, the foundational understanding of the human brain's structure, electroencephalography (EEG), and the influence of ictal activity on EEG laid the groundwork for a nuanced investigation. The subsequent delve into time scale analysis through wavelet transform in Chapter 02 illuminated the efficiency of this approach in deciphering non-stationary signals, particularly within the context of EEG datasets. Chapter 03 emerged as a pivotal juncture, unraveling the intricacies of significant features in EEG signals and surveying the landscape of contemporary classification methods. The proposed features tailored for enhancing epileptic seizure cessation detection and preventing status epilepticus marked a substantive contribution to the field. The dissertation's focal point expanded in the latter chapters with an exploration of telemedicine, shedding light on its diverse applications and transformative impact in the neurosciences, with a specific focus on epileptology. The creation of a dedicated telemedicine platform, Epileptica, tailored for individuals with pharmacoresistant epilepsy, reflects a forward-looking approach to optimizing patient care.

The culmination of these endeavors materialized in the design of an innovative EEG-type-independent system. This system, integrating wavelet transform, supervised and unsupervised machine learning techniques, presented a promising solution to the challenges associated with high dimensionality and precise localization of epileptogenic focus. The tandem subsystems, Representative EEG Channel Creator (RECC) and Seizure Affected EEG Channel Detector (SAECD), showcased the potential for improved epilepsy pattern detection and precise epileptogenic area localization.

As a broader implication, this dissertation responds to the evolving landscape of EEG signal analysis, presenting a synthesized framework that encompasses technological advancements, methodological innovations, and a visionary approach to patient care through telemedicine. The envisaged impact extends beyond academic discourse, offering tangible contributions to the field of epileptology and providing a foundation for future explorations and advancements in the dynamic intersection of neuroscience, signal processing, and healthcare technology.

Our future work could focus on refining and expanding the proposed system's capabilities. Exploration of additional datasets, including diverse clinical populations, can contribute to the generalization and robustness of the system. Moreover, while our study incorporated feature extraction and selection techniques, future research could delve into optimizing and exploring novel features. Besides investigating the impact of different feature subsets on the performance of the system may provide insights into the most discriminating features for epilepsy detection. Additionally, the development of real-time monitoring capabilities can enhance the practical utility of the system in clinical settings, allowing for prompt intervention and personalized treatment strategies. Overall, the future directions outlined above aim to propel the field towards a more sophisticated and clinically applicable paradigm for EEG-based epileptic seizure detection. By addressing these aspects, we can further refine the accuracy, reliability, and real-world applicability of the proposed system, ultimately contributing to advancements in epilepsy diagnosis and treatment.

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# Appendix A

# Developed Software

To enhance the accessibility and practical utility of the developed EEG-type-independent system tailored for epilepsy detection and the precise delineation of epileptogenic zones, we have leveraged the capabilities of the Matlab graphical user interface (GUI) environment. This strategic integration aims to cultivate a user-friendly application that facilitates seamless interaction and intuitive navigation for biomedical engineering professionals and researchers. By embedding the system within a GUI, we seek to optimize user experience, allowing for efficient utilization of the system's functionalities without necessitating extensive technical expertise. This approach aligns with the broader objective of fostering widespread adoption and utilization of the developed system within clinical settings, thereby contributing to its translational impact and applicability in real-world scenarios.

## A.1 EEG-type-independent system for epilepsy detection and epileptogenic zones circumscription

As depicted in Figure A.1, the epilepsy detector GUI exemplifies a user-friendly application designed for ease of use and efficiency. The operational steps involve loading the EEG signal intended for testing, specifying the number of channels, and entering the sampling frequency value. Following these straightforward inputs, a mere click on the "Detect Epilepsy" button initiates the analysis, culminating in the prompt display of test results, as delineated in Figure A.2. In instances where the result indicates a positive epilepsy detection, a secondary window, namely the SAECD system, promptly emerges, as illustrated in Figure A.3. This secondary window provides a comprehensive array of essential information pertaining to the epilepsy source, its diffusion path, and the identification of normal or unaffected zones. The seamless transition from the initial epilepsy detector GUI to the SAECD system window ensures a coherent and thorough presentation of critical information for enhanced clinical insights and decision-making. The intentional simplicity of the interface, coupled with the integration of detailed visualizations, contributes to an accessible and informative user experience within the realm of epilepsy detection and characterization. As part of ongoing development, user feedback will be instrumental in refining this interface to meet the evolving needs of healthcare professionals and researchers.

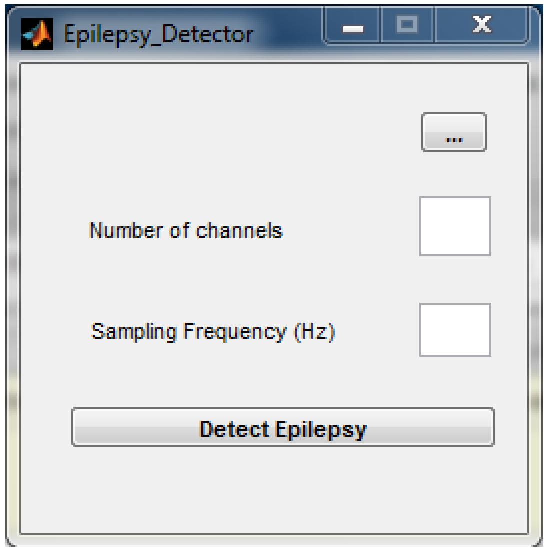


Figure A.1: Epilepsy detector

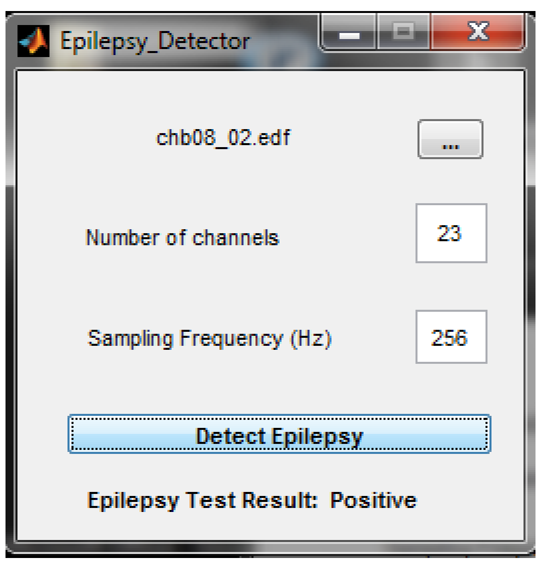


Figure A.2: Epilepsy Detection process; example

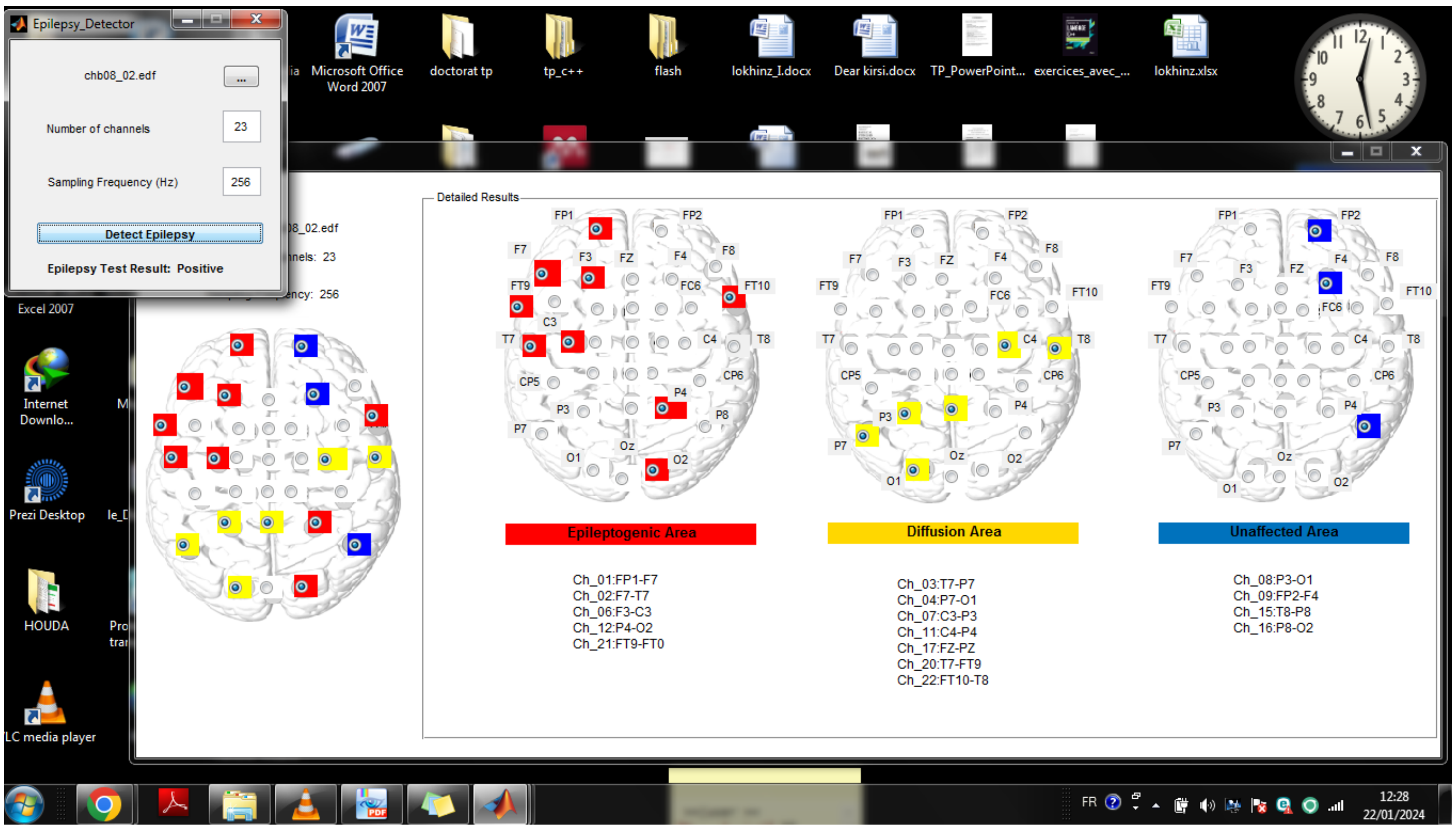


Figure A.3: Final Detection results

# Appendix B

# Epileptica: Programming Language& Communication Protocol

## B.1 Client–Server Architecture

The client—server architecture represents a distributed structure that divides tasks or workloads between two parts; the servers, whom represent the providers of a resource, and the requesters, known as clients.

Frequently, servers and clients communicate through a computer network on detached hardware but in the same system. The server host launches one or more of its services, that share their resources with its clients. In most cases, the client does not share any of its resources, but it merely requests a service or content from the server. Therefore, the client starts communication sessions with the host server, which stays in listening status waiting for incoming requests.

Currently, In the world of computing, client–server model has become so popular and widely used for different applications; World Wide Web, Email and Network printing ...etc.

Generally, the client–server model is made up of server application, database server and a computer, with two main architectures; the 2–tier and 3–tier client–server architectures (see Figure B.1). The 2–tier client–server architecture implies only the server Database and the client computer. The users (Clients) will run on their own computers the applications, which allows them to connect to the server via a network. The client has a direct access to the server database, without involving any intermediary. While the 3–tier client–server architecture involves the client computer, server Database and a server application. This latter, can be extended to N–tier in case of more servers application. Where, the server application is called middle ware [269].

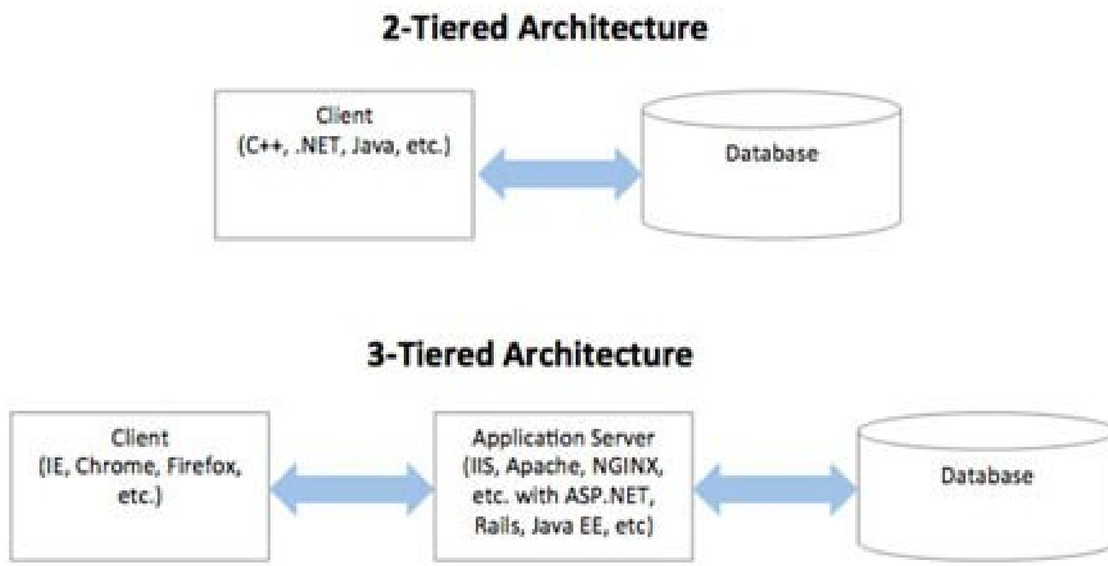


Figure B.1: An illustration of 2–tier and 3–tier architectures

## B.2 The Visual Basic.NET Environment (VB.Net)

VB.NET represents a programming language tool developed by Microsoft. It was launched for the first time in 2002 as a new version that replaces the oldest Visual Basic 6 (VB6) version. The VB.NET was designed to be an object–oriented programming language, easy to understand and manipulate by both beginners and advanced programmers. An object–oriented programming language means that it supports multiple programming features such as; inheritance, polymorphism, abstraction and encapsulation. VB.Net applications run with much scalability and reliability due to the .NET framework. Additionally, the VB.NET, enables programming fully object–oriented applications similarly to the ones created with other languages such as Java, C++ or C# [270].

VB.NET (2015 version) was used in the development of our Epileptica application devoted for remote epileptogenic focus detection.

## B.3 Structured Query Language (SQL) Server [271]

The SQL Server represents a relational system for databases management developed by Microsoft. In 1988, SQL server first version was designed to compete with Oracle and MySQL database. Then, in 1990s Microsoft developed a new version of SQL Server for the NT platform. Due to its language known as Transact–SQL (T–SQL), SQL server offers more capabilities of variables declaring, stored procedure, exception handling...etc.

### B.3.1 SQL Server role in Client–Server Architecture.

The client sends requests to the SQL SERVER installed on a given server host. Then the server processes the input data as requested and responds with the analyzed output data.

### B.3.2 Connection to a remote SQL server database

In order to allow access to a remote SQL Server database, the Transmission Control Protocol/Internet Protocol (TCP/IP) should be enabled. Besides, setting up a firewall rule for the appropriate port. Where, the connection string syntax should contains the server host IP address, the port (1433), the database name, User ID and the pass word.

SQL server was used to create Epileptica database on the server host. where, the right connection string syntax was established to ensure a successful remote access to the database by the client.

### B.3.3 SQL Server Security

SQL Server environments security represents the prime responsibility database administrators. Basically, the SQL Server was developed to be a highly secured platform for database creation and sensitive data storing (such as personal medical data...etc). It provides multiple features for data encryption, authorization and limited access, and that to maintain the data from destruction, theft , or other malicious behavior types.

Securing SQL Server can be summarized in two main steps, namely: authentication, data encryption. First of all the SQL Server consists of two options for authentication :

**Windows Authentication**. This option depends entirely on the Active Directory (AD) to substantiate the correct users in advance of each connection to SQL server. It represents the preferable mode for authentication, since the AD is the efficient technique to manage policies of password besides the accessibility borders to the various data management applications, for users.

**SQL Server Authentication.** represents the second authentication mode, which performs on the basis of saving specific users–defined usernames and passwords (with control options of password complexity) on the SQL server database. This authentication mode can be enabled in case where the AD is not within reach for some reasons.

The user can enable both SQL Server and Windows Authentication modes simultaneously (known as mixed–mode),

For **Data Encryption** the SQL Server offers a variety of encryption options:

- **Secure Sockets Layer (SSL)**

Encrypts traffic as it transports between the client application and the server instance, similarly to the internet traffic security between server and browser. Moreover, the client can confirm the right identity of the server through its certificate.

- **Transparent Data Encryption (TDE)**

Serves in encryption of the complete log files and data within the disk.

- **Backup Encryption**

This mode of encryption is identical to the Transparent Data Encryption option with a slight difference that this latter, encrypts only SQL backups as its name indicates (instead of active data encryption)

- **Column/Cell–Level Encryption**

Encrypts a determined data in the the database and stays encrypted even after its is storage in memory. The data can be easily decrypted through a particular function

- **Always Encrypted**

This model was developed to enhance the Column/Cell–Level Encryption. Enabling this option serves in encryption of the data along the network, within the disk and in memory, which ensures a high protection of sensitive data.

For these reasons SQL server was selected to create the Epileptica database that serves in storing patient's electroencephalogram recordings besides their epileptogenic focus detection report.

## B.4 Communication protocol: TCP/IP [272]

The protocols represent a combination of principles about formats of message and the needed proceedings that enables hosts (application programs) to interchange information. These regulation must be carefully followed by each participating host in the communication process, to ensure that the receiving machine can correctly recuperate the transmitted message.

Transmission Control Protocol/Internet Protocol (TCP/IP), represents a series of communication protocols employed for interconnection of network systems on the internet (long distances communications). Moreover, the intranet or extranet (private computer network) used TCP/IP as a communications protocol.

TCP/IP was introduced in the early 1970s and considered as the standard protocol for the Advanced Research Projects Agency Network, known as ARPANET in 1983. The two principle protocols TCP/IP serve in particular functions; TCP specifies the manner in which, applications generate communication channels over a network. Moreover, it coordinates the assembling process of the message to be transmitted into undersized packets at the level of the sender, in addition to the correct reassembling at the receiver level. The IP marks the proceedings of addressing and routing the resulting packets, in order to ensure their arrival in the required destination. Consequently, in the transmission network, each gateway computer, controls the destination IP address to determine appropriately, the next destination to forward the message. In addition, the sub net mask role is to define in the IP address, both network and the hosts portions (network part and host part).

### B.4.1 TCP/IP Model Layers

TCP/IP encompasses four layers, each one describes a specific protocol:

**The application layer:** furnish systematized data interchange applications. In other words, this layer offers an interface (web browsing, file transfer,.. etc.) between the user and the network services, in order to allow him to manage tasks over the network (connections), through several protocols namely; Hypertext Transfer Protocol (HTTP), Post Office Protocol 3 (POP3), Simple Network Management Protocol (SNMP), File Transfer Protocol (FTP), and Simple Mail Transfer Protocol (SMTP). At this level of layer, the payload consists in the substantial application data. This layer verifies as well the employer's accessing authorization and authentication. It deals with certain complicated operations such as data compression, encryption or decryption. Besides the data synchronization at both transmitter and receiver levels.

**The transport layer:** in charge of managing the end–to–end communications along the network. TCP manages communications between machines and ensures reliability, flow control, and multiplexing. The protocols of transport involve TCP and User Datagram Protocol(UDP), which is in some cases employed alternatively of the TCP protocol for particular purposes.

**The network layer:**, known also as **the internet layer**, manages the packets and links independent networks to transmit these packets along network boundaries.

the employed protocols includes; Internet Control Message Protocol (ICMP); used for error reporting and the well known Internet Protocol (IP).

**The physical layer:**, called also as data link layer or the network interface layer, represents the lowest layer of the presented TCP/IP model. It manages the data in bits format, and deals with the machine–to–machine interactions in the network. Moreover, it specifies the medium of transmission (wired or wireless), the communication mode (simplex, half–duplex, or full–duplex.) between hosts, configuration of the line (multi–port or point–to–point), besides the number of bits transmitted per a second (data rate). In this layer, The protocols used changes from network to network.

### B.4.2 Relevance of TCP/IP Protocol

TCP/IP is not a private protocol, and therefore, it can not be dominated by any private company, it is adaptable with any operating systems, easy to modify and enables communication with any other system

TCP/IP Model enables an appropriate connectivity between the computer and the internet and serves in creating virtual network in case of several connected hosts. Moreover, it manages the data transmission procedures and permit long distances communications.

TCP/IP is greatly scalable, frequently employed in actual architecture of internet as an efficient routable protocol, that determines the fastest and effective path through the network.

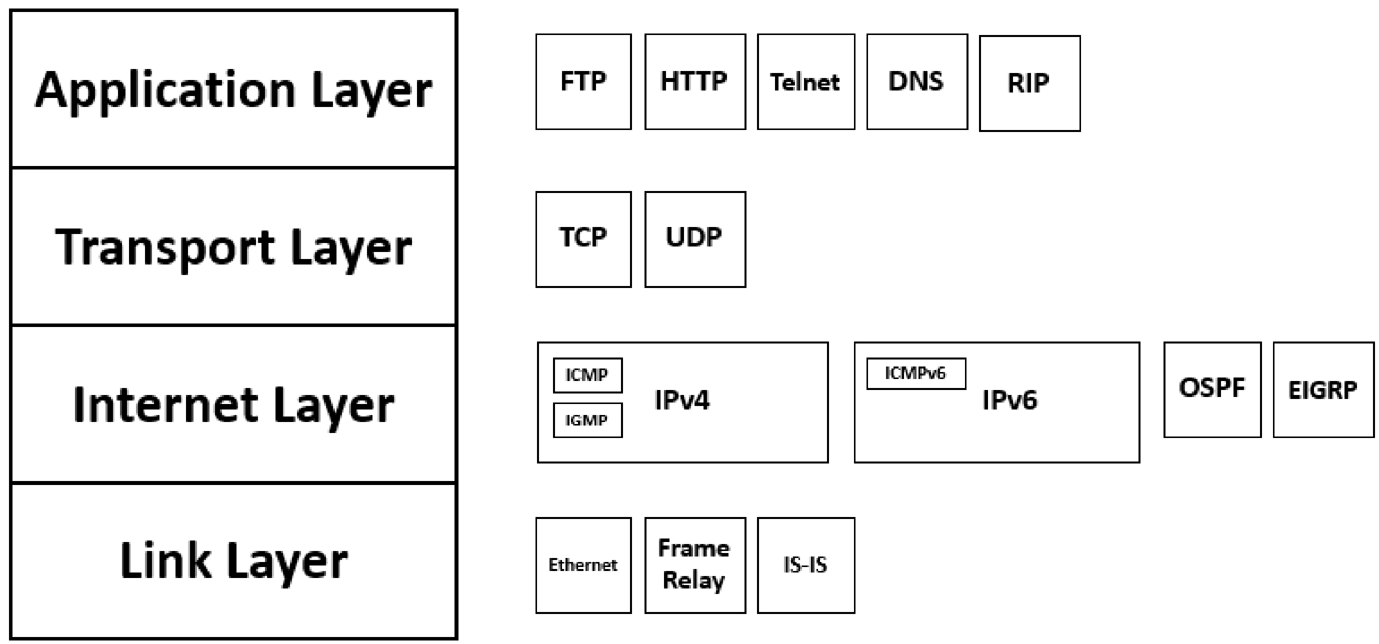


Figure B.2: TCP/IP protocol layers

# Appendix C

# Scientific Achievements

## C.1 International Publications

Hasnaoui, L.H., Djebbari, A. Robust dimensionality-reduced epilepsy detection system using EEG wavelet packets and machine learning. Res. Biomed. Eng. (2024). https://doi.org/10.1007/s42600-024-00355-6

Hasnaoui, L. H., & Djebbari, A. (2024). Leveraging epilepsy detection accuracy through burst energy integration in cwt and decision tree classification of eeg signals. Biomedical Engineering: Applications, Basis and Communications, 2450052.

Hasnaoui, L. H., Benabdallah, A., & Djebbari, A. (2023). INVESTMENT OF BIOMEDICAL APPLICATIONS IN MARKETING: ELECTROENCEPHALOGRAM-BASED CONSUMER DECISION PREDICTION. Biomedical Engineering: Applications, Basis and Communications, 35(04), 2350013.

## C.2 International Conferences

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, “Discrete Wavelet Transform Energy-–based Dimensionality Reduction for Electroencephalogram classification”, Colloque international, Tendances dans les Applications Mathematiques TAMTAM2019, Universite de Tlemcen, 23–27 Février 2019.

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, "Discrete Wavelet Transform and Sample Entropy–Based EEG Dimensionality Reduction for Electroencephalogram classification," 2019 International Conference on Advanced Electrical Engineering (ICAEE), 2019, pp. 1–6,

doi: 10.1109/ICAEE47123.2019.9015166.

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, "Remote EEG signal Analysis for Epileptogenic focus detection: a Client–Server Application", 2021 International Congress on Health Science and Medical Technologies 2021 ICHSMT'21, 15–17 June 2021, Tlemcen, Algeria.
Hasnaoui, L. H., & Djebbari, A. (2022, May). Epileptic Activity Prediction Within Pre–ictal Epochs: Application on Selected Channels. In 2022 7th International Conference on Image and Signal Processing and their Applications (ISPA) (pp. 1-6). IEEE.

## C.3 National Conferences

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, "Seizure Detection using Discrete and Continuous Wavelet Transform of EEG signals", 8ème journée doctorale de génie biologique et médical JD-GBM'2018, Université de Tlemcen, 10 Mai 2018.

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, "Seizure Detection using Discrete and Continuous Wavelet Transform of EEG signals", 7ème journée de la Maintenance Biomédicale (JMB2018), Hopital Central de l'Armée, Dr Mohamed Seghir Nekkache Alger, 04 Oct. 2018.

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, " Epilepsy Detection Within EEG signals using EMD and DWT: A Comparative Study ", The first Conference on Electrical Engineering CEE 2019, EMP Alger, 22–23 Avril 2019.

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, " Epilepsy Prediction by Welch-spectrum of Discrete Wavelet Transform Coefficients of Electroencephalogram Signals ", 9ème journée doctorale de génie biologique et medical JD–GBM'2019, Université de Tlemcen, 13 Join 2019.

Lyna Henaa. Hasnaoui and Abdelghani Djebbari, " Epilepsy Prediction by Welch-spectrum of Discrete Wavelet Transform Coefficients of Electroencephalogram Signals ", 8ème journée de la Maintenance Biomédicale (JMB2019), Hopital Central de l'Armée, Dr Mohamed Seghir Nekkache Alger, 10 Oct. 2019.

Lyna Henaa. Hasnaoui, Amel Benabdallah, and Abdelghani Djebbari, "Impact of neuroscience on marketing advancement: EEG–based prediction study", Colloque national du neuromarketing, Universite de Tlemcen, 2022.

**Abstract**

Electroencephalography (EEG) stands as a cornerstone in non-invasive brain activity monitoring, offering invaluable insights with high temporal resolution. This dissertation focuses on harnessing EEG for the detection of epileptic activity, specifically targeting the precise delineation of epileptic zones responsible for abnormal electrical patterns within the brain. The meticulous mapping of these zones is pivotal for assessing patients with pharmacoresistant epilepsy, paving the way for targeted seizure-free interventions. Thus, this dissertation introduces two complementary subsystems: the Representative EEG Channel Creator (RECC) and the Seizure Affected EEG Channel Detector (SAECD). The RECC contributes to enhanced dimensionality reduction with up to 93.75%, improving the efficiency of epilepsy pattern detection with a sensitivity of 98.46%. Upon a positive response from the RECC indicating epileptic EEG, the SAECD subsystem is activated. Leveraging the Energy-to-Shannon-Entropy ratio and a k-means clustering approach, SAECD precisely localizes the epileptogenic focus and traces the path of seizure diffusion within the brain with a promising average silhouette range of [51.21-88.18]%. In addition to the innovative subsystems introduced, this study places a particular emphasis on the selection of an appropriate mother wavelet. The careful choice of this latter plays a crucial role in enhancing the accuracy and efficiency of the proposed epilepsy detection system. In addition to advanced signal processing techniques, this research incorporates engineered features. These latter are strategically designed to capture nuanced aspects of epileptic activity, contributing to the overall robustness and effectiveness of the proposed methodology. Furthermore, the dissertation embraces the realm of telemedicine with the introduction of Epileptica, an asynchronous application designed for remote access to the results generated by the developed EEG-type-independent system. This telemedical platform enhances accessibility to critical information, supporting neurologists in making informed decisions regarding patient care and the suitability for seizure-free surgery.

**Keywords:** Electroencephalography, EEG dimensionality reduction, epilepsy detection, epileptogenic focus detection, time–scale analysis, wavelet transform, mother wavelet selection, classification, telemedicine, client-server architecture.

**Résumé**

L'électroencéphalographie (EEG) constitue une pierre angulaire dans le suivi non invasif de l'activité cérébrale, offrant des informations précieuses avec une haute résolution temporelle. Cette thèse se concentre sur l'exploitation de l'EEG pour la détection de l'activité épileptique, ciblant spécifiquement la délimitation précise des zones épileptiques responsables des anomalies électriques dans le cerveau. La cartographie minutieuse de ces zones est essentielle pour l'évaluation des patients atteints d'épilepsie pharmacorésistante, ouvrant la voie à des interventions ciblées et sans crises. Ainsi, cette thèse propose deux sous-systèmes complémentaires : le Representative EEG Channel Creator (RECC) et le Seizure Affected EEG Channel Detector (SAECD). Le RECC contribue à une réduction dimensionnelle accrue jusqu'à 93,75%, améliorant l'efficacité de la détection des motifs épileptiques avec une sensibilité de 98,46%. En cas de réponse positive du RECC indiquant un EEG épileptique, le sous-système SAECD est activé. En s'appuyant sur le ratio Énergie/Entropie de Shannon et une approche de regroupement par k-means, le SAECD localise précisément le foyer épileptogène et retrace la diffusion des crises dans le cerveau avec une silhouette moyenne prometteuse allant de [51,21 à 88,18] %. En plus des sous-systèmes innovants proposés, cette étude accorde une attention particulière à la sélection d'une ondelette mère appropriée. Ce choix minutieux joue un rôle crucial dans l'amélioration de la précision et de l'efficacité du système de détection d'épilepsie proposé. En complément des techniques avancées de traitement du signal, cette recherche intègre des caractéristiques conçues sur mesure. Ces dernières sont stratégiquement élaborées pour capturer des aspects subtils de l'activité épileptique, renforçant la robustesse et l'efficacité globale de la méthodologie développée. Par ailleurs, cette thèse s'inscrit dans le domaine de la télémédecine avec l'introduction d'Epileptica, une application asynchrone permettant un accès à distance aux résultats générés par le système développé, indépendant du type d'EEG. Cette plateforme télémédicale améliore l'accessibilité aux informations critiques, soutenant les neurologues dans la prise de décisions éclairées sur les soins aux patients et l'adéquation à une intervention chirurgicale visant l'absence de crises.

**Mots clès:** Electroencéphalographie, réduction dimensionnelle de l'EEG, détection de l'épilepsie, détection du foyer épileptogène, analyse temps-échelle, transformation en ondelettes, sélection de l'ondelette mère, classification, télémédecine, architecture client-serveur.

**الملخص**

يعد تخطيط كهربية الدماغ بمثابة حجر الزاوية في مراقبة نشاط الدماغ غير الجراحي، حيث يقدم رؤى لا تقدر بثمن مع دقة زمنية عالية. تركز هذه الأطروحة على تسخير مخطط كهربية الدماغ للكشف عن نشاط الصرع، واستهداف التحديد الدقيق لمناطق الصرع المسؤولة عن الأنماط الكهربائية غير الطبيعية داخل الدماغ. يعد رسم الخرائط الدقيقة لهذه المناطق أمراً محورياًا لتقييم المرضى الذين يعانون من الصرع المقاوم للأدوية، مما يمهد الطريق لتدخلات مستهدفة خالية من النوبات. وبالتالي، تقدم هذه الأطروحة نظامين فرعيين متكاملين: منشئ قناة تخطيط كهربية الدماغ التمثيلي (ضزرر) وكاشف قناة تخطيط كهربية الدماغ المتأثرة بالنوبات (ضازر). يساهم ضزرر في تعزيز تقليل الأبعاد بنسبة تصل إلى ٥٧.٣٩٪، مما يحسن كفاءة اكتشاف نمط الصرع بحساسية تصل إلى ٦٤.٨٩٪. بناءً على استجابة إيجابية من ضزرر تشير إلى تخطيط كهربية الدماغ الصرع، يتم تنشيط النظام الفرعي ضازر. من خلال الاستفادة من نسبة الطاقة إلى شانون-إنتروبيا ونهج التجميع بالوسائل ك، يقوم ضازر بتحديد التركيز المسبب للصرع بدقة وتتبع مسار انتشار النوبات داخل الدماغ بمتوسط نطاق خيالي واعد يبلغ ﴿١٢.١٥-٨١.٨٨٪. بالإضافة إلى الأنظمة الفرعية المبتكرة التي تم تقديمها، تركز هذه الدراسة بشكل خاص على اختيار المويجات الأم المناسبة. يلعب الاختيار الدقيق لهذا الأخير دوراً حاسماًا في تعزيز دقة وكفاءة نظام الكشف عن الصرع المقترح. بالإضافة إلى تقنيات معالجة الإشارات المتقدمة، يتضمن هذا البحث ميزات هندسية. تم تصميم هذه الأخيرة بشكل استراتيجي لالتقاط الجوانب الدقيقة لنشاط الصرعِ، مما يساهم في متانة وفعالية المنهجية المقترحة بشكل عام. علاوة على ذلك، تتناول الأطروحة مجال التطبيب عن بعد مع تقديم زلِتِ، وهو تطبيق غير متزامن مصمم للوصول عن بعد إلى النتائج الناتجة عن نظام مستقل من نوع زز. تعمل منصة التطبيب عن بعد هذه على تعزيز إمكانية الوصول إلى المعلومات المهمة، ودعم أطباء الأعصاب في اتخاذ قرارات مستنيرة فيما يتعلق برعاية المرضى ومدى ملاءمة الجراحة الخالية من النوبات.

االكلمات المفتاحية :تخطيط كهربية الدماغ، تقليل أبعاد مخطط كهربية الدماغ، اكتشاف الصرع، اكتشاف بؤرة الصرع، تحليل النطاق الزمني، تحويل المويجات، اختيار المويجات الأم، التصنيف، التطبيب عن بعد، بنية خادم العميل.