CHAPTER 1

INTRODUCTION

1.1 OVERVIEW OF EPILEPSY AND ELECTROENCEPHALOGRAM (EEG) SIGNALS

Epilepsy is a chronic neurological disorder of the brain, approximately 1% of the world population suffers from epilepsy stated by Celement et al (2003). Epilpsy is characterized by recurrent seizures that cause rapid but revertible changes in the brain functions conferred by Gotman (1982). Temporary electrical interference of the brain roots epileptic seizures. The occurrence of an epileptic seizure appears unpredictable. In the circumstance of Epilepsy monitoring, two types of epileptic seizure have to be considered namely behavioural and electrographic. A behavioural seizure is the clinical manifestation of epilepsy, as perceived by the patient and seen by the observer. An electrographic (EEG) seizure is defined as an abnormal bursting EEG pattern discussed by Gotman (1999). The common pattern of neuronal action becomes bothered, causing strange feelings, behaviour, and emotions or sometimes loss of consciousness, convulsions, and muscle spasms stated by Clin (1994).

Classification of epilepsy risk levels, according to International Standard is not easy because individual laboratory findings and symptoms are often unconvincing as conferred in Joel (2004). The EEG is one of the most vital clinical tools for studying the functional conditions of the brain and for monitoring and diagnosing neurological diseases, such as epilepsy stated by
Hazarika et al (1997). The EEG signal is a measure of the added activity of roughly 100 millions of neurons lying in the surrounding area of the recording electrodes discussed by Sleigh (2004). On the whole, the EEG is complex and aperiodic time series holding information of the electrical activity is produced by cerebral cortex nerve cells. The EEG signal is commonly used as a diagnostic indicator for investigating brain activities under different physiological conditions conferred by Pravin (2010).

1.2 COMPUTER BASED DIAGNOSIS OF EPILEPSY

The human Electroencephalogram (EEG) is usually recorded from electrodes attached to the human scalp using high amplifiers, which are typically coupled to the scalp electrodes. The amplified signals are printed on paper using a polygraph, which contains usually 8 to 128 channels. Common subjects usually exhibit alpha, beta, theta, and delta activities, while abnormal activity may be patented by a slow and decrease in amplitude of EEG, increase in the EEG frequency, and the presence of sudden EEG discharges (paroxysmal activity) different from the background either in frequency content or amplitude or pattern. The EEG is a powerful tool for the diagnosis of neurological disorders. Since its discovery, the EEG has been used for the diagnosis of epilepsy, for trauma assessment, for sleep research, and for the analysis of higher brain functions. The EEG is highly dependent upon the availability of high quality instrumentation, and almost from the beginning, automated methods of signal qualification have been applied. One of the primary goals is to help the Encephalographer (EEGer) in the time consuming task of quantifying signal that appears to the eye as a low information content background intermixed with either bursts of rhythmic activity with different frequencies (the EEG rhythms) or short transients of clinical significance (such as spikes). In spite of years of research to produce universal automated detection methods, success has been achieved only in specific areas.
Accomplishments include automatically sleep staging with a high degree of accuracy; counting spikes and wave complexes, and monitoring in intensive care units. However clinicians still rely on visual analysis for clinical applications.

The human eye and brain can be trained to recognize ostensibly defined patterns in multi-channel EEG recordings. However, ostensive definitions are not readily disseminated. A description of a mental image by words is normally poor and lengthy. In clinics, for patients through medically intractable partial epilepsies, time-consuming video EEG monitoring of spontaneous seizures is frequently necessary. Ocular analysis of interictal EEG is, still, time-intensive so the automated detection of seizures in long-term EEG records is extremely useful, as it decreases the information that a specialist has to analyze in order to make a diagnosis about the type of epilepsy or to determine the epileptic source. In clinical practice it is a way of exploring the great pattern recognition of a human visual system and enhancing the efficiency of the visual data communication. Computers can bring quantification to EEG analysis in the form of precise measurements (micro volt and millisecond precision), but at the same time they cannot always use the measured data to identify clinically significant features.

Alison et al (1993) mentioned about the research in the design of computer-based environments that will help the doctor in the visual clinical assessment of multi-channel EEG recordings, and the engineer in the design of better detectors. It is widely accepted that the information available to the physician about his patient and about medical relationships in general is inherently uncertain. Nevertheless, the physician is still quite capable of drawing conclusions, though approximate, from this information. The novel attempt in this research is to provide a formal model of this process using a mathematical approach in implementing the model in the form of a
computerized diagnostic system. The optimized classification of the risk level of epilepsy is achieved by non linear models, Artificial Intelligence, Neural networks, and Hardware implementation wavelet Neural Network.

1.2.1 Background

The Electroencephalogram (EEG) signal is employed for the purpose of epileptic detection as it is a situation related to the brain’s electrical activity. Although the brain’s electrical activity and the abnormal pattern of EEG during the epileptic seizure might vary significantly from the brain’s electrical activity through non-seizure period, the recognition of epileptic seizures is however challenging for a number of causes. A general form of EEG recording used for this reason is an ambulatory recording which contains EEG data for a long duration of even up to a week. It engages an expert’s effort in analyzing the whole data to detect traces of epilepsy as uttered by Zumsteg et al (2000).

The conventional techniques of analysis being tedious and time consuming, many automated epileptic EEG systems have emerged in recent years. Automated classification of EEG data is complicated by a number of causes. The EEG potentials stretch out in the micro-volt range and therefore highly susceptible to physiological and environmental artifacts. The existence of Epileptiform activity in the EEG authenticates the diagnosis of epilepsy, which occasionally confused with other disorders producing similar seizure like activity. Leon et al (2003) discussed many issues associated with epileptic seizure prediction based on dynamic nonlinear nature of EEG signals. In common, the complexity of the dynamics of the neuronal system of the brain is vanished during seizures. Ocak H (2009) used discrete wavelet transforms and approximate entropy to understand the dynamics of epileptic seizures. Adlassnig (1986) mentioned that between seizures, the EEG of a patient with epilepsy may be characterized by occasional epileptic form
transients-spikes and sharp waves. Arthur C. Guyton (1996) specifies that different types of epileptic seizures are characterized by different EEG waveform patterns.

1.3 REVIEW OF EPILEPSY DETECTION TECHNIQUES

Electroencephalography is a well-established clinical procedure, which can provide information pertinent to the diagnosis of a number of brain disorders (e.g. epilepsy or brain tumors). However, despite its widespread use, it is one of the last routine clinical procedures to be fully automated. Analysis of the electroencephalogram (EEG) includes the detection of patterns and features characteristic of abnormal conditions explained by Schuyler (2007). For example, Asymmetries in the amplitude or frequency of background activity suggest a lesion, while the presence of Epileptiform activity supports a clinical diagnosis of epilepsy. Over half the EEG referrals relate to epilepsy, with the EEG being the most useful procedure in its diagnosis.

Recording the EEG during a seizure is particularly helpful in determining whether a patient has epilepsy stated by Rennie et al (2004). Because seizures usually occur infrequently and unpredictably, obtaining such recording might require an EEG extending over several days (long-term EEG monitoring). Techniques have been developed for the automated detection of petit mal seizures and grand mal seizures, which have proven relatively successful. Between seizures, the EEG of a patient with epilepsy may be characterized by occasional Epileptiform transients (spikes and sharp waves) and, consequently, relatively short recording can still be useful in the diagnosis of epilepsy. Mark van Gils et al (1997) stated that a routine recording typically lasts 20-30 minutes, during which some 4 meters of paper record are produced. An Electroencephalographer (EEGer) detects Epileptiform transients by visual inspection of the recording, which requires considerable skill and is time consuming discussed by Harikumar et al (2005).
Thus, automation of this process could save time increase objectivity and uniformity, and enables quantification for research studies.

Automated detection of Epileptiform transients has two primary areas of clinical application conferred by Liu et al (1992). The first is in long term EEG monitoring, where it acts essentially as a daily reduction process. A segment of EEG is recorded only when a transient is detected and all segments are reviewed by an EEGer. Thus, the goal is to detect a high proportion of Epileptiform activity while minimizing false detection. The second area is in routine clinical recordings where, major objective is to minimize the visual inspection process as far as Epileptiform transients are concerned. In this case it is important not to precipitate a misdiagnosis of epilepsy and, therefore, the aim is to eliminate false detections while detecting a satisfactory proportion of Epileptiform transients.

Spikes and sharp waves are defined as transients clearly distinguished from background activity with pointed peaks at conventional paper speeds. Spikes are defined having durations of 20-70 ms, while sharp waves have durations of 70-200 ms. No distinction is made between spikes and sharp waves and, therefore, they are collectively termed Epileptiform transients. Owing to the variety of morphologies of Epileptiform transients and similarities to waves which are part of the background activities and due to artifacts (i.e. extra cerebral potentials from muscles, eyes, heart, electrodes, etc.), the detection of Epileptiform activity in the EEG is far from straightforward.

Several techniques have been applied to the detection of Epileptiform activity in the EEG. These include:

a) Template matching, where detection is made whenever the value relation of the EEG with a template exceeds a threshold.
b) Parametric methods, where a detection is made when the difference between the EEG and its predicted value used on the assumption that the background is stationary exceeds a threshold

c) Mimetic methods, where one or more parameters of each wave are calculated and threshold

d) Syntactic methods, where detections are based on the presence of a structural combination of structures

e) Artificial neural networks trained to detect epileptic waveform transients and

f) Expert systems, which detect Epileptiform activity by mimicking the knowledge and reasoning of the EEGer.

Most of these systems are in the developmental stage, and those in clinical use are restricted to long-term EEG monitoring with all detections being reviewed by an EEGer. Owing to a high number of false detections these systems cannot perform satisfactorily in the routine EEG setting. It is generally accepted that the only way to separate Epileptiform from non-Epileptiform waves is to make use of a spatial and temporal context. Several groups are implementing this approach in an effort to minimize false detections. Glover et al (1989) have developed a system that relies on a wide spatial context, with 12 EEG channels being analyzed together with additional contextual information provided by EKG, Electrooculogram (EOG) and Electromyogram (EMG) signals. Conversely, the system developed by Gotman and Wang (1991) implements extra temporal context, where sections of EEG are classified into one of the five states (active wakefulness, quiet wakefulness, synchronized EEG, phasic EEG, or slow-wave EEG) before independent rules are applied to reject non-Epileptiform activity.
Song et al (2010) have developed a new system, which makes considerable use of spatial and temporal contextual information. This system is proven to be particularly successful at rejecting non-Epileptiform activity during awake and resting EEG’s. It uses a mimetic method to detect candidate transients, which are subsequently trimmed or rejected as Epileptiform by an expert system. Siuly et al (2010) introduces a system integrates both spatial and temporal contextual information to detect definite and probable Epileptiform activities and reject non-Epileptiform waves. Preliminary results state that this system should be capable of performing routine clinical EEG setting.

Because of the difficulty of reliably distinguishing Epileptiform events from all background activities and artifacts and sometimes, because of conflicting clinical requirements or priorities, it was decided to allow two types of output. The first type of output is based on probable events. The aim here is to detect a higher proportion of Epileptiform events, but this is likely to be at the expense of several false detections. The second is definite Epileptiform events. For these, it is essential that all artifacts and background activities are rejected and therefore the subsequent detection rate of Epileptiform events may not be particularly high.

1.4 METHODOLOGY OF THE RESEARCH

The proposed system that detects focal and non-focal Epileptiform events which are epilepsy risk levels in a manner similar to the EEGer. The system consists of four stages:

i) A data collection stage, which samples and digitizes EEG data.

ii) Dimensionality Reduction Techniques such as Singular Value
Decomposition (SVD), Principle Component Analysis (PCA), Independent Component Analysis which reduce EEG data bin.

iii) The reduced EEG data bin is processed through three different types of post classifiers such as Hidden Markov Model (HMM), Neural Networks, and Extreme Learning Machine (ELM), which classifies epilepsy risk levels.

iv) FPGA Implementation of Wavelet Neural Network with Particle Swarm Optimization (PSO) Learning for Epileptic Seizure Detection.

In this thesis, a discussion about a two-level classifier with all the four post processing methods in the optimization of the epilepsy risk levels is carried out. As mentioned by Ludmila Kuncheva (1994) a two-level classifier brings together two pattern recognition ideas. In this case, Dimensionality Reduction Techniques and combination of post processing methods; resulting scheme is expected to possess the following advantages over classical pattern recognition techniques.

i) To achieve higher classification accuracy. It can be proven that under certain conditions the combination of classification decisions can surpass the best single classifier.

ii) To handle information that cannot be conveniently described by conventional techniques. Therefore, it is necessary to use the different types of post processing techniques as the second level optimizer to increase the parametric values.

The need for new therapies and success of similar devices to treat cardiac arrhythmias as mentioned and recommended by Naresh et al (2006) has spawned an explosion of research into algorithms for use in implantable
therapeutic devices for epilepsy. Most of these algorithms focus on either
detecting unequivocal EEG onset of seizures or on quantitative methods for
predicting seizures in the state space, time, or frequency domains that may be
difficult to relate to the Neuro physiology of epilepsy Zumsteg et al (2000).
There are diverged variety of post processing methods using Artificial
Intelligence, and Neural Networks and their applications as mentioned by
Marco Russo (1998). The basic block diagram of the Epilepsy risk level
classification system is shown in Figure 1.1.

![Block Diagram](image)

**Figure 1.1** The Basic Block Diagram of the Epilepsy Risk Level Classification System

As shown in Figure 1.1 the acquired EEG signals are sampled at
200Hz. The two second duration of the EEG samples are considered as an
epoch. Three such an epochs are selected per channel. There are sixteen channels available in our recordings which are explained in the section 1.5 of the thesis. These EEG samples are dimensionality reduced through the SVD, PCA, and ICA methods to overcome the curse of dimensionality. At this juncture, the reduced data patterns are processed through three different types of post classifiers such as Hidden Markov Model (HMM), Neural Networks, and Extreme Learning Machine (ELM). The patients Epilepsy risk level is classified from the post classifier outputs. The performances of the post classifier are adjudged through benchmark parameters such as sensitivity, specificity, Average Detection, and Good Detection Ratio. Higher the benchmark values maketh the better Epilepsy risk level classifier system.

![Figure 1.2](image_url)

**Figure 1.2** FPGA Implementation of Wavelet Neural Network (WNN) for Epilepsy risk level detection.
Figure 1.2 shows the basic block diagram of FPGA Implementation of Wavelet Neural Network (WNN) with Particle Swarm Optimization (PSO) learning ability for Epilepsy risk level detection. The Electroencephalography (EEG) signals were first pre-processed using Dimensionality Reduction (PCA). The features obtained were fed into the input layer of WNNs. Four different activation functions were used in the hidden nodes of WNNs. The Particle Swarm Optimization (PSO) learning method is used in this research. The non-linear activation functions are approximated by the Taylor series and Look-up Table (LUT) to achieve better approximation.

1.5 DATA ACQUISITION OF EEG SIGNALS

The EEG is recorded by placing electrodes on the scalp according to the International 10-20 system. Sixteen channels of EEG are recorded simultaneously for both referential montages, where all electrodes are referenced to a common potential like ear, and bipolar montages, where each electrode is referenced to an adjacent electrode. The EEG recording points on the scalp are illustrated in Figure 1.3. Recordings are made while the patient is awake but resting and include periods of eyes open, eyes closed, hyperventilation and photonic stimulation. Amplification is provided by an EEG- machine (Siemens Minograph Universal). Before placing the electrodes, the scalp is cleaned, lightly abraded and electrode paste is applied between the electrode and the skin. By means of this application of electrode paste, the contact impedance is less than 10 kΩ. Generally disk like surface electrodes are used. In some cases, needle electrodes are used to pick up the EEG signals. The signals are recorded with the speed of 30 mm/s. The obtained signals are filtered by notch filter (low pass filter - 5Hz, high pass filter - 75Hz).
Figure 1.3 EEG Recording by 10-20 system

The EEG is broken down into sections or epochs, for the purpose of feature extraction. An epoch of 2.0 s is used for the following reasons:

i) It is long enough to capture the main statistical characteristics of the EEG and short enough to capture the evolution of seizures

ii) The EEG being digitized at a sampling rate of 200 Hz an epoch of 2s contains 400 samples, which is a convenient length for computation. The software for analyzing the EEG data was implemented using Matlab v7.0. Waveforms of normal and abnormal data are plotted and studied as mentioned by Mark van Gills et al (1997)

The EEG data used in the study were acquired from twenty epileptic patients who had been under the evaluation and treatment in the Neurology Department of Sri Ramakrishna Hospital, Coimbatore, India. A digital record of 16 channel EEG data in European data format is acquired
From a clinical EEG monitoring system through 10-20 international electrode placing method. With the help of neurologist, we have selected EEG records with distinct features. Four types of artifacts were present in our data. These include, eye blink, Electromyogram (EMG) artifacts, chewing, and motion artifacts. Approximately 1% of the data was contained artifacts. In this thesis, artifacts of specific nature and in numbers not selected. The objective of including artifacts was to have spike versus non spike categories of wave forms. The latter could be a normal background EEG and/or artifacts. In order to train and test the signal components extractor and classifier, a suitable segment of EEG data need to be selected. In this research, training and testing were selected through a short sampling window and all EEG signals are visually examined by a qualified EEG technologist. A neurologist’s decision regarding EEG data bin (or normal EEG segment) was used as the gold standard.

Since the EEG records are over a continuous duration of about thirty seconds, they are divided into epochs of two second duration. A two second epoch is long enough to detect any significant changes in activity and presence of artifacts and also short enough to avoid any repetition or redundancy in the signal as studied by Haoqu & Gotman (1997), Donna Hudson (1994), Mark Van Gils et al (1997) and Seunghan Park et al (1990). Figure 1.4 shows the two second epoch waveform and sampled waveform. The EEG signal has a maximum frequency of 50 Hz and so, each epoch is sampled at a frequency of 200 Hz. Each sample corresponds to the instantaneous amplitude values of the signal, totaling 400 values for an epoch. Each channel has 400 samples of EEG signals per epoch and four such epochs of data forms a bin. There are sixteen such bins available per patient. The data volume for a patient is around 25,600 samples. Hence, this large amount of data necessitates the dimensionality reduction technique level for processing the EEG signal. This number is enough to give reliable statistics in mean and
variance calculation. The different parameters used for quantification of the EEG are computed using these amplitude values by suitable programming codes. EEG records of twenty male patients were used for both training and testing. These EEG records had an average length of six seconds and total length of 120 seconds. The patients had an average age of 31 years. A total of 960 epochs of 2 seconds duration are analyzed in this research.

Major contribution of this research is to identify a good Epilepsy risk level classifier system through dimension reduction process and a group of post classifier. Working on the principles of probabilistic theory, machine learning techniques and FPGA Implementation of Wavelet Neural Network (WNN) for Epilepsy risk level detection using Particle Swarm Optimization (PSO) Learning is also discussed in the research.

![Figure 1.4 Two Second Epoch Waveform and Sampled Waveform](image-url)
1.6 ORGANIZATION OF THESIS

Chapter 1 presents an overview of epilepsy detection and some of the diagnostic issues related to the continuous monitoring of epileptic patients.

Chapter 2 exhibits the Dimensionality Reduction technique as a pre-processing step which reduces the dimension of the EEG data through the usage of Conventional decomposition methods such as Singular Value Decomposition (SVD), Principle Component Analysis (PCA), and Independent Component Analysis (ICA).

Chapter 3, investigates the efficacy of non linear model like Hidden Markov Model (HMM) in obtaining classified risk level.

In Chapter 4, three types of post classifiers such as Elman (neural network -Recurrent supervised), MLP (neural network supervised) and Extreme Learning Machine are analyzed. Based on the benchmark parameters the classifiers are evaluated. How ELM outperforms other two method were elucidated. FPGA implementation of Wavelet Neural Network (WNN) with Particle Swarm Optimization (PSO) learning ability is discussed in Chapter 5 for epilepsy risk level classification.

The Results are discussed in Chapter 6. The thesis is concluded in Chapter 7. Better classification methods are ranked based on their performance and convenience of operations.