**Electroencephalogram based epileptic seizures detection and prediction via machine/deep learning approaches**

**Chapter one**

**1-INTRODUCTION**

**1.1 Epilepsy**

**1.1.1 General definition, and etiology**

Epilepsy is one of the most common neurological disorders affecting 70 million worldwide [1]. It was first defined by Jackson in 1873 as “an occasional sudden and excessive discharge of grey matter”. This definition lasted for a long period of time, during which, investigations have given more insights into the characterization and mechanisms of this medical disorder on several levels. The fundamental elements of epilepsy are unprovoked, recurrent seizures [2] resulting from abnormal excessive hypersynchronous neuronal discharges. Seizure manifestations vary greatly depending on the site, intensity and propagation of the seizure discharge. In between seizures, brief (milliseconds) asymptomatic discharges called interictal epileptiform discharges (also known as spikes) may occur [3]. Although epilepsy can appear at any age, its incidence is higher in children and elderly (after the age of 65) [4]. The main causes of epilepsy include genetic mutations, gliosis from acquired brain insults (hypoxia, ischemia/stroke, trauma, and infection), malformations of cortical development, vascular malformations, brain tumors and degenerative disorders.

**1.1.2 Epileptic seizures**

A seizure is defined as a transient disturbance of brain functions due to an abnormal electrical synchronization of groups of neurons. Epileptic seizures can be divided into two main categories: focal and generalized [5]. Seizures are said to be focal when they start from a restricted area of the brain (thus in one hemisphere) while generalized seizures involved the whole of both hemispheres [6]. Focal seizures can be further classified into frontal, temporal, insular, parietal, and occipital, depending on the lobe involved at seizure onset. In generalized seizures, there is impaired consciousness from the onset as the excessive electrical discharge is widespread from the beginning. With focal seizures, earliest symptoms depend on the lobe of seizure onset (ex. visual symptoms with occipital lobe seizures, sensory symptoms in parietal lobe seizures, motor symptoms in frontal lobe seizures etc.). Consciousness is frequently not impaired at the onset of a focal seizure but such impairment may occur as the discharge spreads to larger areas of the brain 2 and even manifest as bilateral tonic-clonic seizures if the discharge spreads to the whole brain [6].

**1.1.3 Electroencephalography**

Because epilepsy is fundamentally the result of abnormal neuronal discharges, EEG is the single most important investigative technique for the study of epilepsy. EEG consists in an electrophysiological recording of the brain’s electrical activity. The electroencephalogram (recorded signal) displays spatial and temporal voltage variations due to ionic currents flowing 3 within brain neurons. It is characterized by a high temporal resolution (order of ms), allowing the evaluation of dynamic cerebral functions [7]. EEG displays neuronal electrical activity resulting from the summation of inhibitory and excitatory postsynaptic potentials of large group of neurons. It is considered to be mainly produced by pyramidal cortical neurons, which are arranged in parallel, perpendicularly to the surface of the brain, and have their cell bodies mainly in layers III and V of the cerebral cortex [8].

**1.1.4 The EEG in focal epilepsy**

Patients with focal epilepsy exhibit focal epileptiform abnormalities. These are usually divided into a) ‘interictal’ discharges (‘spikes’) which are brief (20-200ms) asymptomatic paroxysmal EEG transients clearly distinguished from background; and b) ‘ictal’ discharges which are sudden focal rhythmic activity with characteristic pattern of evolution (with respect to amplitude, frequency and spatial distribution) lasting at least several seconds to minutes. These ictal discharges are generally associated with clinical seizure manifestations (electroclinical seizures) but can sometimes be clinically silent (electrical seizures) [9]. With a routine 30- min EEG, interictal spikes can be found in approximately 50% of epileptic patients (and in up to 84% by the third serial EEG).

**1.1.5 seizure detection**

Due to the time-limited observation period, the patient’s antiepileptic medication is sometimes reduced for facilitating the occurrence of epileptic events within the observation period [10], where the seizures may not be representative of natural conditions. In many cases, patients are asked to keep seizure diaries, as seizure monitoring is crucial for therapeutic decisions. Patient-reported seizure counts and measures derived from these reports, such as reduction in seizure frequency over a defined period, represent the primary endpoint for most clinical trials in epileptology [11].

However, it is well known that most epileptic seizure go unnoticed by the patients and their caregivers, which may affect treatment decisions. Seizure tracking is dependent on a subjective patient and family recall and may be influenced by the capacity of remembering details post seizure, by the level of awareness during the seizure and by the ability to identify seizures [12].

**1.1.6 seizure prediction**

Besides seizure detection, accurately predicting seizures a few minutes before their onset would enable patients to take precautions against injury, and could open the door for development of treatments to prevent or control the incoming seizure. For instance, neurostimulation systems can act quickly as a way of suppressing a high portion of seizures [13]. This prediction should have sufficient precision, specificity and sensitivity to minimize the interruptions on the patient’s life, having minimal unpredicted seizures and false alarms.

**1.2 Problem statement**

People who suffer from epilepsy cannot lead their normal lives because they may be exposed to a sudden seizure that endangers their lives, such as falling in a public place, their workplaces or while sleeping, and damage the parts of their body often leads to death, which makes their lifestyle limited. Some methods which used in epileptic seizures classification and detection varying at accuracy and time of work.

**1.3 Objectives**

The general objective is to design EEG-Based Epileptic Seizure Detection and Prediction Machine/Deep learning models.

The specific objectives are to

1. Achieve accurate classification for epileptic seizures.

2. Achieve high accuracy, less time predicting the occurrence of a seizure.

**Chapter two**

**1- Literature review**

Epilepsy detection has been studied extensively since the 1970s. Early, statistical methods and classical machine learning techniques were used for Epilepsy classification. But due to the data complexity, the researchers started applying deep learning to this problem. Since 2016, many deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Belief Networks (DBN), Autoencoders (AE), Long short-term memory (LSTM), and generative adversarial networks (GAN) have been used to identify epilepsy.

Classification of EEG signals into epileptic and nonepileptic involves extracting features from the EEG signals and using these features in training a machine learning model. In the literature, several feature extraction approaches and several classification methods are used. Several groups used the Discrete Wavelet Transform for feature extraction and then they applied different machine learning algorithms.

In 2017, Sandeep Kumar Satapathy and Alok Kumar Jagadev decided to use a semi-automatic tool in the framework of machine learning to understand the EEG signals and to predict epilepsy seizures. Using Bonn University—EEG Dataset, their primary focus was on two main techniques: neural networks and support vector machine (SVM); for neural network approach probabilistic neural network, radial basis function neural networks, and recurrent neural networks are taken into consideration for empirical analysis on EEG signal to detect epilepsy seizure. Furthermore, for SVM, several kernel methods were studied such as linear, polynomial, and RBF during empirical analysis. With wavelet transform as the data analysis technique and some of the statistical features of many have been extracted from the signals such as Minimum (MIN), Maximum (MAX), MEAN, and Standard Deviation (SD), the efficiency of different machine learning techniques like MLPNN, RBFNN, RNN, PNN, and SVM have been compared, and concluded that SVM is the most efficient and powerful machine learning technique for the purpose of classification of the EEG signal with accuracy of 99.1% but extremely high detection time.[14]

Later that year, another study done by Duo Chen et al. in the hope for developing a framework for automatically searching the adequate DWT settings to improve accuracy and to reduce computational cost of seizure detection, they developed a method to decompose EEG data into 7 commonly used wavelet families. The selection of frequency bands and features removed approximately 40% of redundancies. With two different datasets Bonn University and Children’s Hospital Boston and the Massachusetts Institute of Technology (CHB-MIT) EEG-Datasets, their proposed algorithm is constructed by two main selection blocks, a Wavelet-Level Selection (DWT coefficient features from several frequency bands construct the feature vector of one EEG signal segment) and a Band-Feature Selection. A support vector machine (SVM) and RBF kernel was used as the classifier. To assess the performance of the approach, especially its ability to overcome individual difference, they used leave-one-subject-out cross-validation on MIT dataset which was a fair evaluation scheme to truly reveal the robustness of the classifier on overcoming the individual difference. Since UBonn dataset did not separate the data from different patients, 10-fold cross validation was used instead of leave-one-subject-out. On MIT dataset, decomposition level affects the accuracy substantially regardless of the mother wavelets. On UBonn dataset wavelets could achieve high accuracy (above 95%) at low decomposition level (less than 2). UBonn dataset, Compared with the results in MIT dataset, EEG segments in UBonn could be accurately classified at very low decomposition level, however, in other cases, including this work, these properties of wavelet do not matter at all. On dataset having complex EEG signals (contain hidden information distribution in several frequency bands), like MIT dataset, decomposition level influences accuracy substantially regardless of the mother wavelet and running the process is very time-consuming, especially when using various wavelet families and long-time continuous EEG segments.[15]

Shuang X. Wang et al. on the other hand involved a novel random forest model combined with grid search optimization in the proposed automatic detection framework in 2019. The short-time Fourier transformation visualizes seizure features after normalization and used to conduct the time-frequency analysis of non-stationary EEG signals. The dimensionality of features is reduced through principal component analysis before feeding them into the classification model which was used to classify 500 samples of raw EEG data. In this study, the time-frequency analysis method is used to extract the time-frequency characteristics of EEG signals. At the same time, the statistical characteristics of EEG signals are extracted by statistical techniques, thus the best combination of feature extraction and feature classification is realized. Noninvasive EEG data was obtained at Bonn University from 25 patients with medically intractable partial epilepsy, the dataset was divided into five groups of ictal scalp EEG signals. And EEGLAB toolbox of Matlab was used to preprocess the cEEG. To ensure the credibility of the test results, they performed an arithmetic average processing. This paper uses the improved GSO to identify RF by computer. The GSO algorithm refers to meshing the variable regions, then traversing all the grid points, solving the objective function values satisfying the constraints, and selecting the optimal values. Although the proposed RF-GSO classification model has excellent classification performance with accuracy of 96.7 the model had low sensitivity and specificity for multi-class.[16]

Another approach done by Paschalis Bizopoulos et al. in 2020, beside the choice of the EEG epileptic seizure recognition dataset from University of California, Irvine (UCI) for EEG classification, the implications of this study could be generalized in any kind of signal classification problem. Here we also refer to CNN as a neural network consisting of alternating convolutional layers each one followed by a Rectified Linear Unit (ReLU) and a max pooling layer and a fully connected layer. For the CNN modules with one and two layers, the input is converted to an image using learnable parameters. They restricted the output for the model to a 178 × 178 image to enable visual comparison. CNN DenseNet201 achieved the best accuracy of 85.3% with training time 70seconds/epoch on average. The two layer CNN S2I achieved worse even compared with the 1D variants. Another outcome of these experiments is that increasing the depth of the base models did not increase the accuracy which is inline with previous results.[17]

Until recently, the general belief in the medical community was that epileptic seizures could not be anticipated. Seizures were assumed to be abrupt transitions that occurred randomly over time. However, theories based on reports from clinical practice and scientific intuition, like the “reservoir theory” postulated by Lennox, existed and pointed out to the direction of seizure predictability. Various feelings of auras, that is, patients’ reports of sensations of an upcoming seizure, exist in the medical literature.[18] Even though seizure detection and prediction is an ongoing research. So far many different approaches using machine learning and deep learning have been tried by several researchers on seizure prediction.

In 2017, U. Rajendra Acharya et al. developed a computar-aided diagnosis (CAD) system to distinguish the class of EEG signals from Bonn University, Germany if normal, preictal, or seizure class using machine learning techniques. The EEG signals were normalized with Z-score normalization, zero mean and standard deviation of 1,then they were divided into 10 equal portions, nine out of ten were used to train the CNN while the one tenth was used to test the performance of the system. The model achieved 88.67% accuracy.[19]

Thara D Ka, B G PremaSudhab, and Fan Xiongc in 2019 experienced epileptic seizure detection using Long Short Term Memory (LSTM) approach on BONN university dataset resulting in 99.08% accuracy. Meanwhile seizure prediction was conducted using the same dataset by classifying preictal states of EEG from interictal and ictal states and the model could identify the pre-ictal state with the overall sensitivity: 89.21% and false prediction rate: 0.06.[20]

In this study, I Wijayanto, S Hadiyoso, S Aulia, and B S Atmojo in 2020 extracted the EEG signal pattern by using the Higuchi fractal dimension to classify the ictal and interictal conditions of EEG signals from Bonn University Dataset. The features were extracted from five EEG sub-bands, delta, theta, alpha, beta, and gamma band and fed to support vector machine model. The experiment shows that the use of HFD and the quadratic kernel is suitable for ictal detection with average accuracy of 91.1%. While the use of cubic kernel and HFD is suitable for detecting interictal conditions with average accuracy of 94.1%.[21]

Meanwhile, in 2021, Adnan Salman offers a model based on a two-dimensional Convolution Neural Network (CNN), that provides a reliable strategy for both preprocessing and feature extraction. The model is used to categorize EEG signals from university of Bonn dataset into normal vs intericatl vs ictal instance, and in order to improve training and generalization accuracy, they adopted an augmentation technique to expand the size of the data set. This model achieved 97.8% accuracy.[22].

In this research, H O Lekshmy, Dhanyalaxmi Panickar and Sandhya Harikumar focused on the performance of various machine learning techniques (Logistic regression, Naive Bayes, Random Forest, and K- Nearest neighbor, Artificial neural network, Convolutional neural network, Long short term Memory technique and Auto Encoder) on EEG data to find the best algorithm that perform well on the Bonn university dataset as the primary dataset and CHB-MIT dataset to validate the results. The EEG signals shows different potential at different frequencies, so a conversion from the time- amplitude domain into the frequency-time domain was needed using Wavelet transform (WT). Random Forest classifier has performed remarkably well in terms of specificity, sensitivity and with 97%accracy. Among deep learning algorithms, Long Short Term Memory (LSTM) is the best performing model with 98% accuracy. Random Forest is less computationally expensive when compare with the Long Short-Term Memory (LSTM) model. Long Short-Term Memory (LSTM) model performance can be effectively increased with the help of GPU acceleration. Random Forest supports variability of data, while LSTM is more suitable for time-series data. Long ShortTerm Memory (LSTM) model has a provision for avoiding long dependencies this makes our predictions more accurate when compared with other models. The main problem with Long ShortTerm Memory (LSTM) model is, it requires a large amount of data for training purposes.[23]

**Chapter three**

**3-Theoretical background**

**3.1 Human brain anatomy and physiology:**

The brain is a complex organ that controls thought, memory, emotion, touch, motor skills, vision, breathing, temperature, hunger and every process that regulates our body. Together, the brain and spinal cord that extends from it make up the central nervous system, or CNS.

Weighing about 3 pounds in the average adult, the brain is about 60% fats. The remaining 40% is a combination of water, protein, carbohydrates and salts. The brain itself is a not a muscle. It contains blood vessels and nerves, including neurons and glial cells. The brain has three main parts: the cerebrum, cerebellum and brainstem. Cerebrum: is the largest part of the brain and is composed of right and left hemispheres. It performs higher functions like interpreting touch, vision and hearing, as well as speech, reasoning, emotions, learning, and fine control of movement.

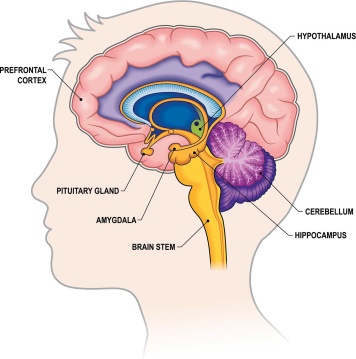


Fig 3.1: shows brain anatomy.

The brain sends and receives chemical and electrical signals throughout the body. Different signals control different processes, and your brain interprets each. Some make you feel tired, for example, while others make you feel pain. Some messages are kept within the brain, while others are relayed through the spine and across the body’s vast network of nerves to distant extremities. To do this, the central nervous system relies on billions of neurons. [24]

**3.2 The electroencephalogram:**

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from the scalp. The recorded waveforms reflect the cortical electrical activity.

**Signal intensity:** EEG activity is quite small, measured in microvolts (µV).

**Signal frequency:** the main frequencies of the human EEG waves are:

1. **Delta:** has a frequency of 3 Hz or below. It tends to be the highest in amplitude and the slowest waves. It is normal as the dominant rhythm in infants up to one year and in stages 3 and 4 of sleep. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions. It is usually most prominent frontally in adults (e.g. FIRDA - Frontal Intermittent Rhythmic Delta) and posteriorly in children e.g. OIRDA - Occipital Intermittent Rhythmic Delta).
2. **Theta:** has a frequency of 3.5 to 7.5 Hz and is classified as "slow" activity. It is perfectly normal in children up to 13 years and in sleep but abnormal in awake adults. It can be seen as a manifestation of focal subcortical lesions; it can also be seen in generalized distribution in diffuse disorders such as metabolic encephalopathy or some instances of hydrocephalus.
3. **Alpha:** has a frequency between 7.5 and 13 Hz. Is usually best seen in the posterior regions of the head on each side, being higher in amplitude on the dominant side. It appears when closing the eyes and relaxing, and disappears when opening the eyes or alerting by any mechanism (thinking, calculating). It is the major rhythm seen in normal relaxed adults. It is present during most of life especially after the thirteenth year.
4. **Beta:** beta activity is "fast" activity. It has a frequency of 14 and greater Hz. It is usually seen on both sides in symmetrical distribution and is most evident frontally. It is accentuated by sedative-hypnotic drugs especially the benzodiazepines and the barbiturates. It may be absent or reduced in areas of cortical damage. It is generally regarded as a normal rhythm. It is the dominant rhythm in patients who are alert or anxious or have their eyes open.

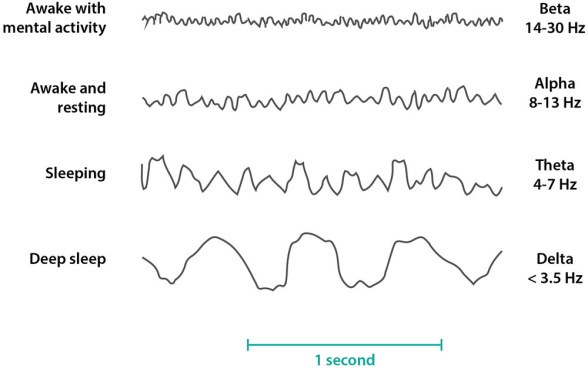


Fig 3.2: the main frequencies of the human EEG waves.

**Variables used in the classification of EEG activity:**

1. **Frequency:** refers to rhythmic repetitive activity (in Hz). The frequency of EEG activity can have different properties including:

Rhythmic. EEG activity consisting in waves of approximately constant frequency.

Arrhythmic. EEG activity in which no stable rhythms are present.

Dysrhythmic. Rhythms and/or patterns of EEG activity that characteristically appear in patient groups or rarely or seen in healthy subjects.

1. **Voltage:** refers to the average voltage or peak voltage of EEG activity. Values are dependent, in part, on the recording technique. Descriptive terms associated with EEG voltage include:
2. Attenuation (synonyms: suppression, depression). Reduction of amplitude of EEG activity resulting from decreased voltage. When activity is attenuated by stimulation, it is said to have been "blocked" or to show "blocking".
3. Hypersynchrony. Seen as an increase in voltage and regularity of rhythmic activity, or within the alpha, beta, or theta range. The term implies an increase in the number of neural elements contributing to the rhythm. (Note: term is used in interpretative sense but as a descriptor of change in the EEG).
4. Paroxysmal. Activity that emerges from background with a rapid onset, reaching (usually) quite high voltage and ending with an abrupt return to lower voltage activity. Though the term does not directly imply abnormality, much abnormal activity is paroxysmal.
5. **Morphology:** refers to the shape of the waveform. The shape of a wave or an EEG pattern is determined by the frequencies that combine to make up the waveform and by their phase and voltage relationships. Wave patterns can be described as being:
6. Monomorphic. Distinct EEG activity appearing to be composed of one dominant activity
7. Polymorphic. distinct EEG activity composed of multiple frequencies that combine to form a complex waveform.
8. Sinusoidal. Waves resembling sine waves. Monomorphic activity usually is sinusoidal.
9. Transient. An isolated wave or pattern that is distinctly different from background activity.

* Spike: a transient with a pointed peak and a duration from 20 to under 70 msec.
* Sharp wave: a transient with a pointed peak and duration of 70-200 msec.

1. **Synchrony:** refers to the simultaneous appearance of rhythmic or morphologically distinct patterns over different regions of the head, either on the same side (unilateral) or both sides (bilateral).
2. **Periodicity:** refers to the distribution of patterns or elements in time (e.g., the appearance of a particular EEG activity at more or less regular intervals). The activity may be generalized, focal or lateralized.[25]

**3.2.1 EEG abnormal conditions:**

Conditions that may be diagnosed with the aid of an EEG include:

* Sleep disorders (such as narcolepsy)
* Head injuries
* Brain infection
* Brain hemorrhage
* Alzheimer's disease
* Degeneration of brain tissue
* Metabolic conditions that affect brain tissue
* Hormonal conditions that affect brain tissue
* Certain disorders of the central nervous system
* Stroke
* Brain tumors
* Brain death.

Normal brain waves occur at a rate of up to 30 per second, but in someone with epilepsy, for example, the EEG may show bursts of abnormal discharges in the form of spikes and sharp wave patterns. Suspected epilepsy is the most common reason for an EEG.[26]

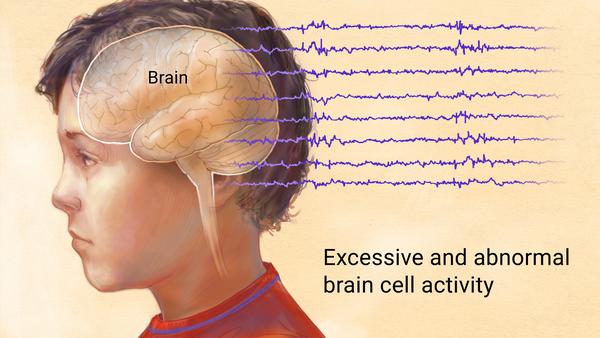


Fig 3.3: shows abnormal brain activity.

**3.3 Epilepsy:**

Epilepsy is a central nervous system (neurological) disorder in which brain activity becomes abnormal, causing seizures or periods of unusual behavior, sensations and sometimes loss of awareness. Anyone can develop epilepsy. Epilepsy affects both males and females of all races, ethnic backgrounds and ages. [3.4] An epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. The definition of epilepsy requires the occurrence of at least one epileptic seizure.[28]

Seizure symptoms can vary widely. Some people with epilepsy simply stare blankly for a few seconds during a seizure, while others repeatedly twitch their arms or legs. Having a single seizure doesn't mean you have epilepsy. At least two seizures without a known trigger (unprovoked seizures) that happen at least 24 hours apart are generally required for an epilepsy diagnosis.[27]

Missed medication, lack of sleep, stress, alcohol, and menstruation are some of the most common triggers for epileptic seizures, but there are many more. Flashing lights can cause seizures in some people, but it’s much less frequent than you might imagine. In fact, only 3% of people with epilepsy are photosensitive (react to flashing lights). Other less common seizure triggers include: Herbal Medications and Supplements and Nutrient Deficiencies. [29]

Normal EEG can be distinguished from abnormal (epileptic seizure) EEG:

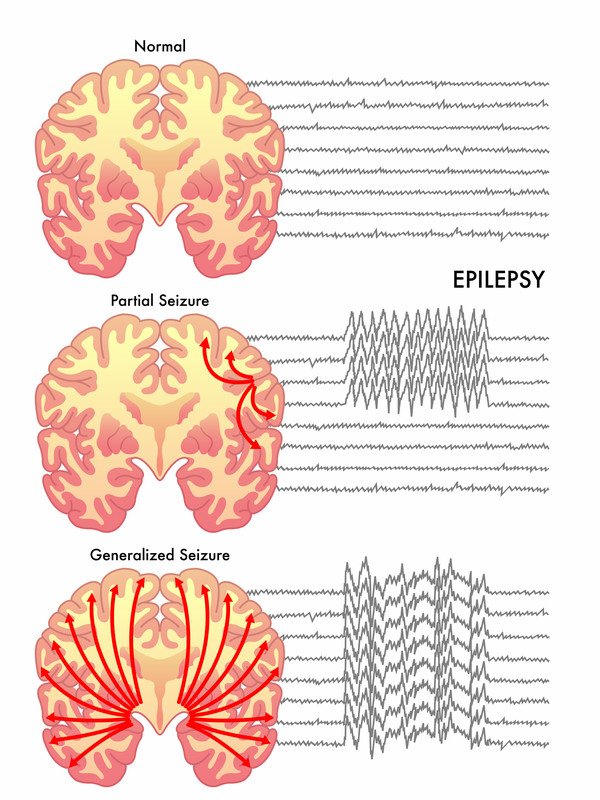


Fig 3.4: ​Comparing a normal EEG signal to an abnormal one.

EEG signals record the electrical activity of the brain using EEG electrodes placed on the scalp. They are noisy, have artifacts, and, above all, they are not the type of signals people are used to deal with (images, charts,...). Doctors, neuroscientists, and biomedical engineers usually receive training for years to understand and extract meaningful information from EEG data. Even in these cases, the raw recorded data needs to be processed before specialists look at it. Temporal and spatial filtering is usually applied, as well as artifact rejection procedures, even if the participant is still during recording. This processed EEG can then be visually inspected to detect anomalies (e.g. episode of epilepsy), changes in the mental state (e.g. sleep phases) or to study grand average responses of groups of people. Visual inspection is a long, expensive, and tedious process. It does not scale up well and cannot be transferred to Brain Computer Interface (BCI) applications. AI and machine learning tools are the perfect companion to automate, extend, and improve EEG data analysis. Indeed, BCI systems such as spellers or brain-controlled devices are based on decoding pipelines that use extensively different machine learning algorithms.[30]

**3.4 Artificial intelligence (AI):**

**Learning process:** Among the many interesting properties of a neural network is the ability of the network to learn from its environment and to improve its performance through learning. A neural network learns about its environment through an iterative process of adjustments applied to its synaptic weights and thresholds. We define learning in the context of neural networks as: a process by which the free parameters of a neural network are adapted through a continuing process of stimulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place.

**Supervised learning:** An essential ingredient of supervised is the availability of an external teacher, which is able to provide the neural network with a desired or target response. The network parameters are adjusted under the combined influence of the training vector and the error signal. This adjustment is carried out iteratively in a step-by-step fashion with the aim of eventually making the neural network emulate the teacher. This form of supervised learning is in fact an error-correction learning, which was already described.

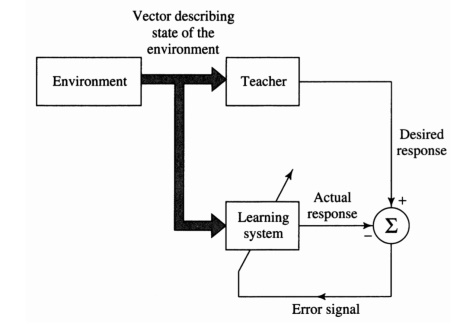


Fig 3.5: Supervised learning.

**Unsupervised learning:** In unsupervised or self-organized learning there is no external teacher to oversee the learning process. In other words, there are no specific samples of the function to be learned by the network. Rather, provision is made for a task-independent measure of the quality of representation that the network is required to learn and the free parameters of the network are optimized with respect to that measure. Once the network has become tuned to the statistical regularities of the input data, it develops the ability to form internal representations for encoding features of the input and thereby creates new classes automatically.

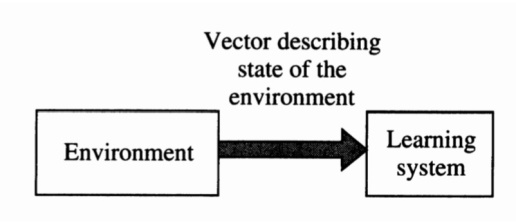


Fig 3.6: Unsupervised learning.

**Pattern recognition:** Pattern recognition is formally defined as the process whereby a received pattern/signal is assigned to one of a prescribed number of classes (categories). A neural network performs pattern recognition by first undergoing a training session, during which the network is repeatedly presented a set of input patterns along with the category to which each particular pattern belongs. Later, a new pattern is presented to the network that has not been seen before, but which belongs to the same population of patterns used to train the network. The network is able to identify the class of that particular pattern because of the information it has extracted from the training data. Pattern recognition performed by a neural network is statistical in nature, with the patterns being represented by points in a multidimensional decision space. The decision space is divided into regions, each one of which is associated with a class. The decision boundaries are determined by the training process. The construction of these boundaries is made statistical by the inherent variability that exists within and between classes.[32]

**3.4.1 AI models:**

**3.4.1.1 K-Nearest Neighbors (KNN):** is a machine learning algorithm used for classification and regression tasks. It is a non-parametric and lazy learning algorithm, meaning it does not make any assumptions about the underlying distribution of the data and does not have a separate training phase to build a model. In KNN, the class or value of an unknown instance is predicted by finding the k nearest instances (neighbors) in the training set based on a distance metric, and then taking a majority vote (in classification) or an average (in regression) of their labels or values. The choice of k is a hyperparameter that can be tuned to optimize performance. KNN is simple to implement and can be effective for low-dimensional data or when the decision boundary is nonlinear and complex. However, it can suffer from the curse of dimensionality and become computationally expensive as the number of features or instances grows. It also requires a distance metric that is appropriate for the data and may be sensitive to outliers or imbalanced classes.



Fig 3.7: k-nearest-neighbor-algorithm-for-machine-learning

**3.4.1.2 Long Short-Term Memory (LSTM):** is a type of recurrent neural network (RNN) architecture that is designed to address the problem of vanishing gradients in traditional RNNs. LSTM networks are widely used for modeling sequential data, such as natural language, speech, and time series data. The key feature of LSTM is the presence of memory cells that are capable of storing information for a long time and selectively forgetting or updating that information. The memory cells are controlled by gates, which are layers of neural networks that control the flow of information into and out of the memory cells. The gates include an input gate, which decides which information to add to the memory cells, a forget gate, which decides which information to forget from the memory cells, and an output gate, which decides which information to output from the memory cells. LSTM has become popular in many applications due to its ability to capture long-term dependencies in sequential data and its ability to handle vanishing gradients, which can be a problem in traditional RNNs. LSTM has also been extended and modified in various ways to improve its performance, such as adding attention mechanisms, using multiple layers, and incorporating convolutional layers.

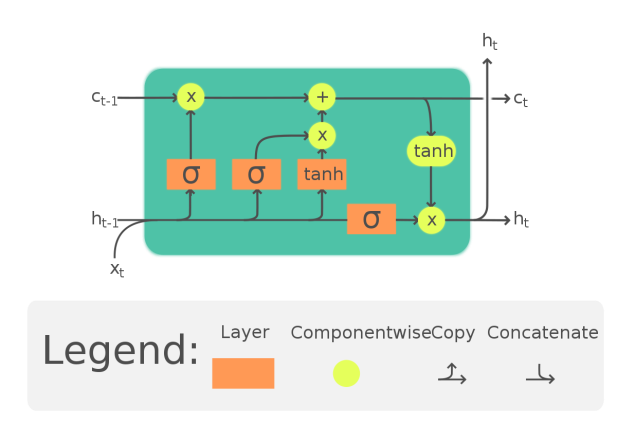


Fig 3.8: Long short term memory cell

**3.4.1.3 Support Vector Machine(SVM):** is a powerful and widely used supervised machine learning algorithm used for classification, regression, and outlier detection tasks. It is a parametric algorithm, meaning it builds a model based on training data that can be used to make predictions on new, unseen data. The core idea of SVM is to find the optimal hyperplane that separates the data into different classes or predicts the target value in the case of regression. The hyperplane is chosen to maximize the margin, which is the distance between the hyperplane and the closest data points from each class. The SVM algorithm can handle both linear and nonlinear boundaries by using different types of kernels, such as polynomial, radial basis function (RBF), and sigmoid. SVM is a versatile algorithm that can handle high-dimensional and complex data, and it is known for its ability to handle small and medium-sized datasets. It also has a strong theoretical foundation and is able to generalize well to new, unseen data. However, SVM can be computationally expensive, especially for large datasets, and requires careful tuning of the kernel and other hyperparameters to achieve optimal performance.



Fig 3.9: support vector machine algorithm

**3.4.1.4 “Artificial” neural networks (ANNs):** are inspired by the organic brain, translated to the computer. It’s not a perfect comparison, but there are neurons, activations, and lots of interconnectivity, even if the underlying processes are quite different.

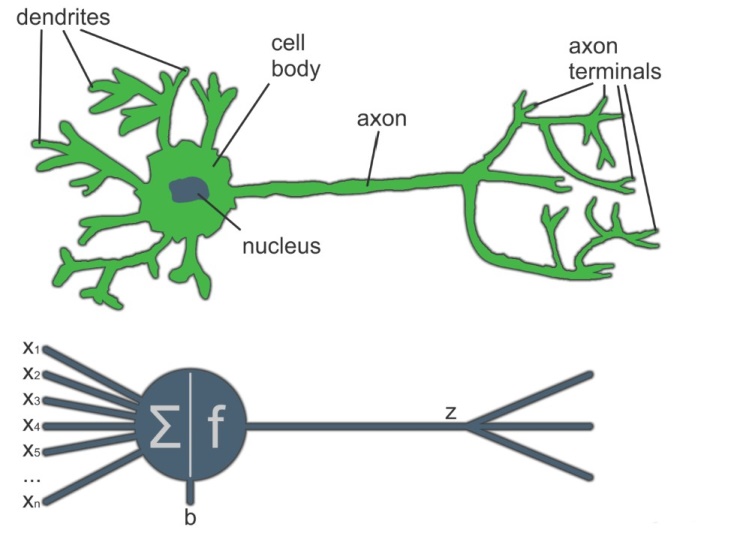


Fig 3.10: ​Comparing a biological neuron to an artificial neuron.

A single neuron by itself is relatively useless, but, when combined with hundreds or thousands (or many more) of other neurons, the interconnectivity produces relationships and results that frequently outperform any other machine learning methods.

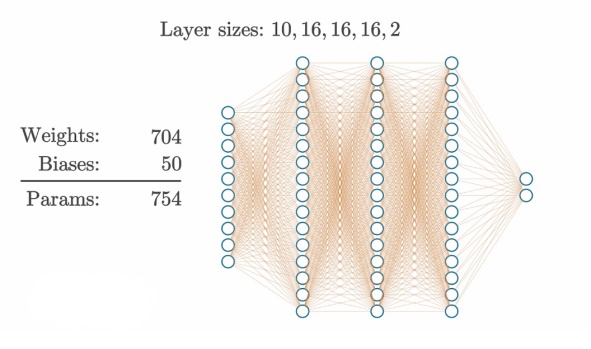


Fig 3.11:​ Example of a neural network with 3 hidden layers of 16 neurons each.

The above animation shows the examples of the model structures and the numbers of parameters the model has to learn to adjust in order to produce the desired outputs. The details of what is seen here are the subjects of future chapters. It might seem rather complicated when you look at it this way. Neural networks are considered to be “black boxes” in that we often have no idea why ​ they reach the conclusions they do. We do understand how ​ they do this, though.[31]

**3.4.2 Evaluation of neural network’s output:**

The evaluation of a neural network's output typically depends on the specific task and the type of data involved, one of the general approaches that can be used to evaluate the performance of a neural network is Confusion matrix: A confusion matrix is a table that shows the number of true positives, false positives, true negatives, and false negatives for a classification task. It can be used to calculate evaluation metrics such as accuracy, precision, recall, and F1 score. These metrics compare the predicted outputs with the true labels or categories and measure the performance of the model in terms of its ability to correctly classify the data.

**Accuracy:** Accuracy is the proportion of correctly classified instances, calculated as the number of true positives and true negatives divided by the total number of instances.

**Precision:** Precision is the proportion of true positives among the instances predicted as positive, calculated as the number of true positives divided by the sum of true positives and false positives.

**Recall:** Recall is the proportion of true positives among the instances that are actually positive, calculated as the number of true positives divided by the sum of true positives and false negatives.

**F1 score:** F1 score is the harmonic mean of precision and recall, calculated as 2 \* (precision \* recall) / (precision + recall).

These are just some of the many evaluation metrics used in machine learning. The choice of metric depends on the specific task and the desired performance criteria.

With the use of modern technologies such as machine learning, it is now possible to classify and predict epileptic seizures and therefore preventing diagnostic mistakes and accidental hazards. This research aims to design integrated AI software for both detection and prediction of epilepsy. The following chapter of this thesis illustrates the methodology applied to design the software.

**Chapter four**

**4-Mehodology**

**4.1 Materials and methods for classification**

The purpose of our work is to compare a number of machine learning and deep learning techniques to find out which is more accurate in classifying EEG signals as an epileptic seizure or not an epileptic seizure.

Figure 1. explains the general flow chart of machine learning models.

Figure 2. explains the general flow chart of deep learning models.

**4.1.1 EEG Database**

In this study, a multi-channel scalp EEG database was used for the experiment. The EEG database we used is from Bonn University. The data be accessed at https://github.com/apurvnnd/Epileptic-Seizure-Recognition-Using-ANN. The unique dataset from the reference includes five special folders, every with one hundred files, with every record representing a single subject/person. Each record is a recording of mind interest for 23.6 seconds. The corresponding time-collection is sampled into 4097 records factors. Each records factor is the value of the EEG recording at a special factor in time. So, we've got general 500 people with every has 4097 records factors for 23.5 seconds. We divided and shuffled each 4097 records factors into 23 rows, every row includes 178 records factors for 1 second, and every records factor is the value of the EEG recording at a special factor in time. So now we've got 23 x 500 = 11500 portions of records(row), every records includes 178 records factors for 1 second(column), the closing column represents the label y {1,2,3,4,5}. The reaction variable is y in column 179, the Explanatory variables X1, X2, …, X178 y includes the class of the 178-dimensional enter vector. Specifically y in {1, 2, 3, 4, 5}: 5 - eyes open, way after they had been recording the EEG sign of the mind the affected person had their eyes open, 4 - eyes closed, way after they had been recording the EEG sign the affected person had their eyes closed, 3 - Yes, they become aware of wherein the area of the tumor changed into within side the mind and recording the EEG interest from the wholesome mind place, 2 - They recorder the EEG from the place wherein the tumor changed into located ,1 - Recording of seizure interest. All of the cases in classes 2, 3, 4, and 5 have never had an epileptic seizure. Only class 1 has epileptic seizures. All of cases have an equal number of samples.

**Classification**

**KNN, SVM, LSVM**

**Feature extraction**

**Data splitting**

**Dataset**

**Preprocessing Data**

**Result and analysis**

**Figure 1.** Proposed Model for machine learning techniques

**Classification**

**ANN,LSTM**

**Dataset**

**Data splitting**

**Preprocessing Data**

**Result and analysis**

Figure 2. Proposed Model for deep learning techniques

**4.1.2 Preprocessing**

This dataset is a pre-processed version of a very commonly used dataset featuring epileptic seizure detection. Biomedical indicators which include EEG have been infected through artifacts and noise, and accordingly a pre-processing step is wanted to smooth the data. Many sign-filtering algorithms were proposed to enhance the overall performance of fitness devices (EEG, ECG, EMG...) besieged through artifacts.

-During the pre-processing of biomedical indicators, the maximum hard trouble is to extract excessive decision EEG indicators from noisy measurements and keep the EEG waveform sharpness.

**4.1.3 classification**

We built our models (ANN, KNN, SVM, LSVM and LSTM) and trained them to be ready to test any EEG signal.

**ANN:**

**-**ANNs are a network shape composed of a sequence of interconnected factors known as neurons, every of which has an enter and output and plays an exceedingly easy operation. Neural networks normally study their feature via learning process. Any ANN has an input, output and hidden layers, in our model we made two hidden layers. ANNs have the capacity to learn and model non-linear and complicated relationships that is clearly crucial due to the fact in real-life many of the relationships among inputs and outputs are non-linear in addition to complicated.

**-Formula for artificial neural network:**

**Y=W1X1+W2X2+b)**

This summed function is applied over an Activation function. The output from this neuron is multiplied with the weight W3 and supplied as input to the output layer.

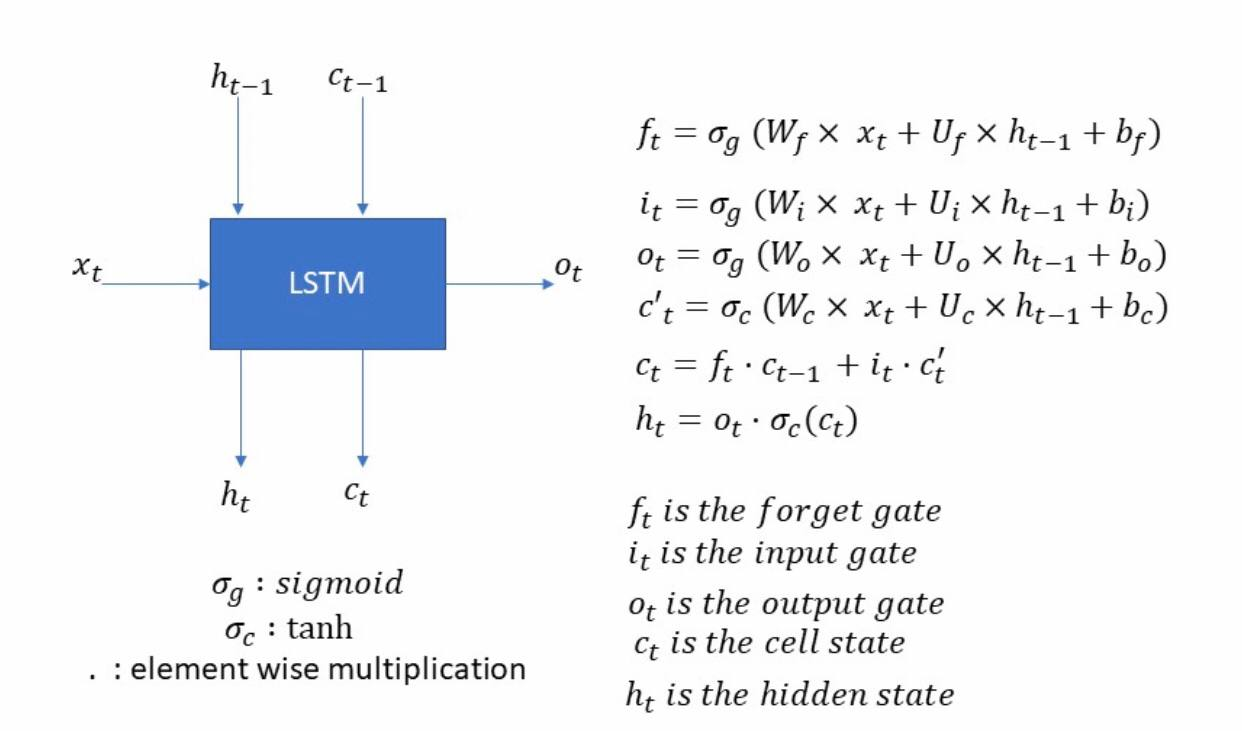
To train a neural network to carry out a few task we have to modify the weights of every unit in the sort of manner that the error among the desired output and the real output is reduced.

**LSTM:**

LSTM models are a subtype of Recurrent Neural Networks. They are used to recognize patterns in data sequences. A unique structure lets in the LSTM version to determine whether or not to preserve preceding facts in short-time period reminiscence or discard it. It is unique form of recurrent neural community this is able to mastering long time dependencies in facts. This is accomplished due to the fact the habitual module of the version has a mixture of 4 layers interacting with every other. They're now no longer well-suitable for on-line mastering obligations which includes prediction or category obligations wherein the enter facts, isn't a sequence. LSTM stands for Long Short Term Memory.

In LSTM we will have 3 gates: Input Gate, Forget Gate, Output Gate. Input Gate which tells us that what new information we’re going to store in the cell state. The forget gate which tells the information to throw away from the cell state. The output gate which is used to provide the activation to the final output of the LSTM block at timestamp ‘t’.

**-Formula for LSTM:**



**KNN:**

KNN is a completely easy set of algorithm used to clear up classification problems. KNN stands for K-Nearest Neighbors. K is the number of neighbors in KNN. Does not work well with big dataset. In big datasets, the cost of calculating the distance between the new point and every current points are big which degrades the overall performance of the set of algorithm. Does not work well with excessive dimensions due to the fact with big variety of dimensions it becomes difficult for the set of algorithm to calculate the space in every dimension. Need function scaling, we want to do feature scaling (standardization and normalization) earlier than making use of KNN set of rules to any dataset. If we do not do so, KNN can also additionally generate incorrect predictions. Sensitive to noisy statistics, lacking values and outliers: KNN is touchy to noise with inside the dataset. We want to manually impute lacking values and cast off outliers.

**Formula for KNN:**

The k-nearest neighbor classifier essentially is predicated on a distance metric. The higher that metric displays label similarity the higher the categorized will be. The maximum not unusual place desire is the Minkowski distance, dist (x, z) =(d∑r=1xr−zrp)1/p.

**SVM:**

A support vector machine (SVM) is a supervised machine studying model, that makes use of category algorithms for two-institution category problems create the great line or selection boundary which can segregate n-dimensional area into instructions in order that we are able to without problems positioned the brand new records factor in the best class with inside the future, SVM set of rules isn't always appropriate for big records sets. SVM does now no longer carry out thoroughly while the records set has extra noise.

**Formula for SVM:**

**SVM Lagrange problem**

**f(w)=12‖w‖2, g(w,b)=yi(w⋅x+b)−1,i=1... m.**

Minimizing w\_2 corresponds to maximizing the margin. right here x1\* and x2\* are the closest factors inside the hyperplanes of the 2 extraordinary instructions and w\_2 is L2 norm of the load matrix. Here we see the very last shape of classifier hold in thoughts that is for ideal linear classification.

**LSVM:**

Linear, SVM: Linear SVM is used for linearly separable records because of this that if a dataset may be labeled into lessons via way of means of the usage of a single instantly line, then such records, is called as linearly separable records and classifier is used referred to as Linear SVM classifier LSVM works via way of means of mapping records to a high-dimensional function area in order that records factors may be categorized even if the records aren't in any other case linearly separable. A separator among the types is found, then the records are converted in any such manner that the separator may be drawn as a hyperplane.

**Formula for LSVM:**

X+b=0

wherein w is a vector regular to hyperplane and b is an offset. If the cost of w. x+b>0 then we are able to say it is a positive factor in any other case it is a negative factor. Now we need (w, b) such that the margin has a most distance.

We splitting our dataset into training set and testing set at a ratio of 80%, 20% respectively.

We used the Binary classification to obtain that class 1 epileptic seizure otherwise 0.

**4.2 Materials and Methods for prediction**

This work used EEG recording data obtained from Bonn University [32].

**4.2.1. EEG Database**

In this study we used the epilepsy dataset from the University of Bonn. This dataset recorded from five patients and has five classes of EEG recording named Set A-E. Each set has 100 recordings with 23.6 seconds in length of brain signals. All EEG signals were recorded with the same 128- channel amplifier system. Set A and set B was recorded from healthy patients with eyes open and closed respectively, and marked as a normal condition. The electrodes used to record these sets were the scalp EEG method (sEEG). The other three series were recorded using the intracranial method (iEEG). EEG signals in Set C were recorded in the hippocampal formation of the brain, while set D was in the epileptogenic zone. These two groups are called the interictal condition. Set E, was recorded from patients in seizure condition and called as an ictal condition. Each set has 4097 samples, and is the sampling rate is 173.61 hertz. The data set is in text format, with 100 text files in each category. Figure (1, 2, 3, 4, 5) illustrates a representative sample for each group

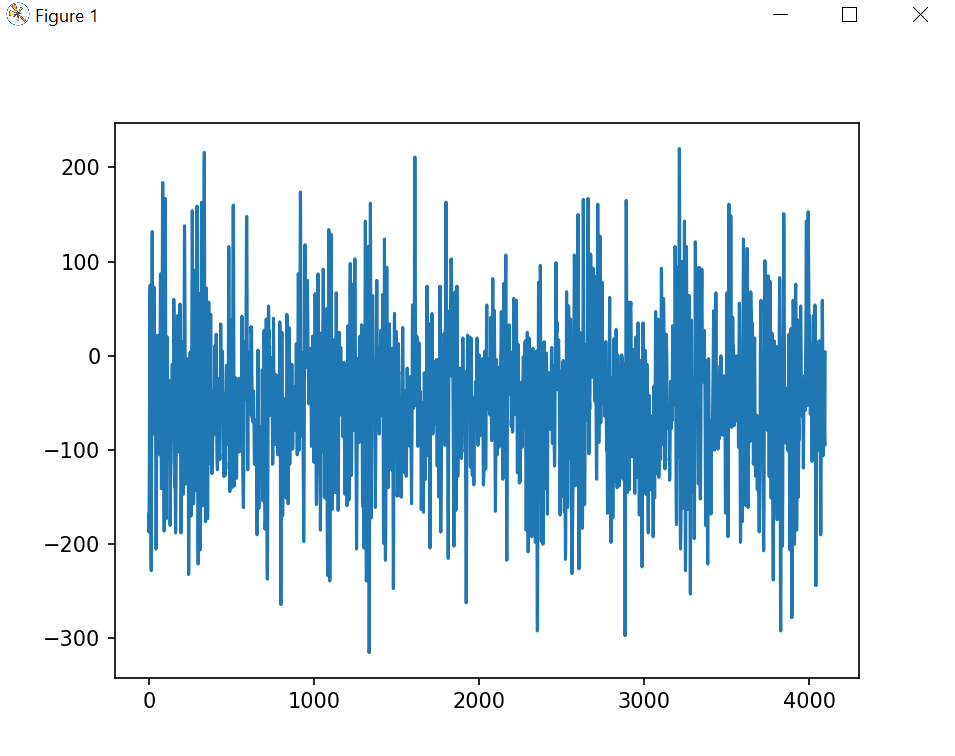


Figure (1) Set C – interictal hippocampal formation (C)\*400=3

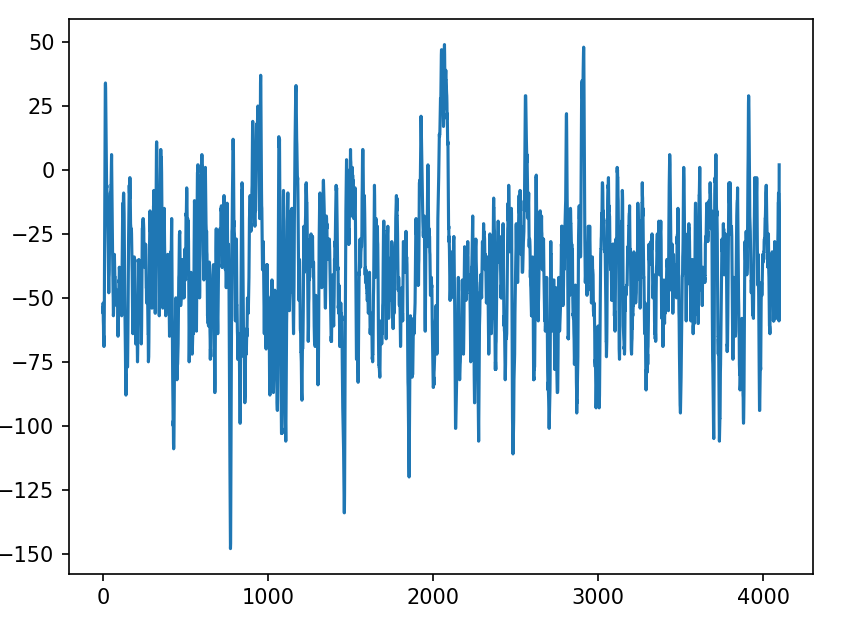


Figure (2): Set E – Signals of unhealthy person during a seizure 252=2

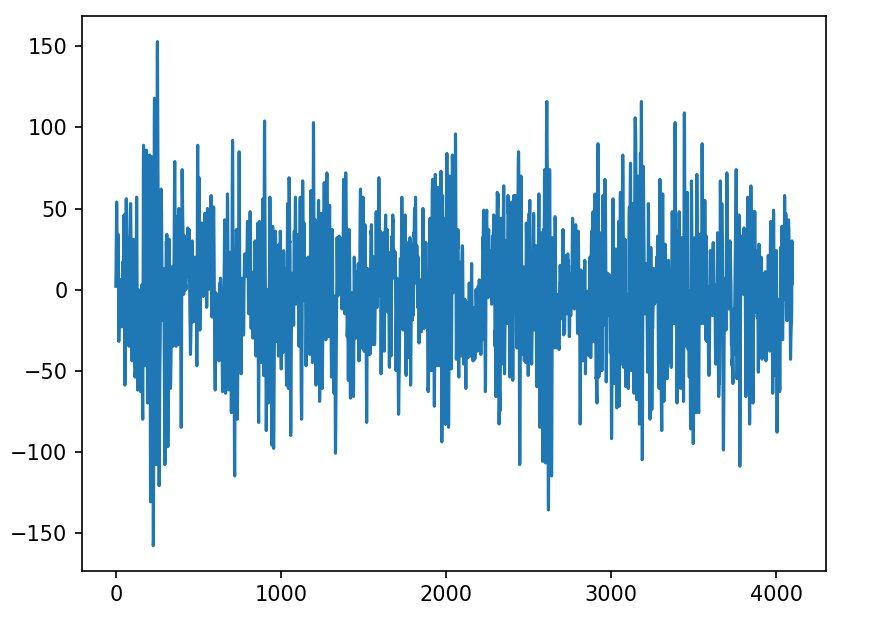


Figure (3): Set A – Person not suffering from Epilepsy with open eye 104=5

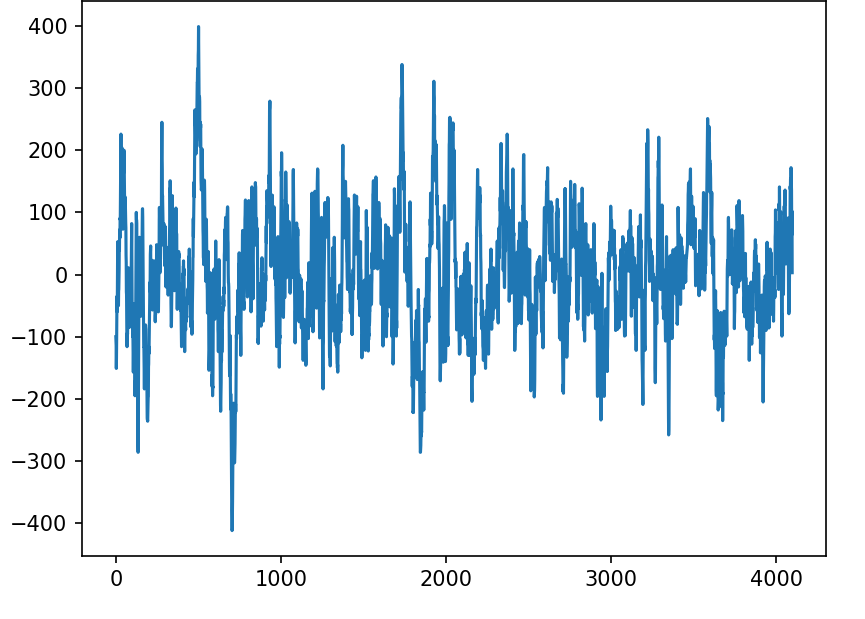


Figure (4): Set D – interictal epileptogenic zone 18=1

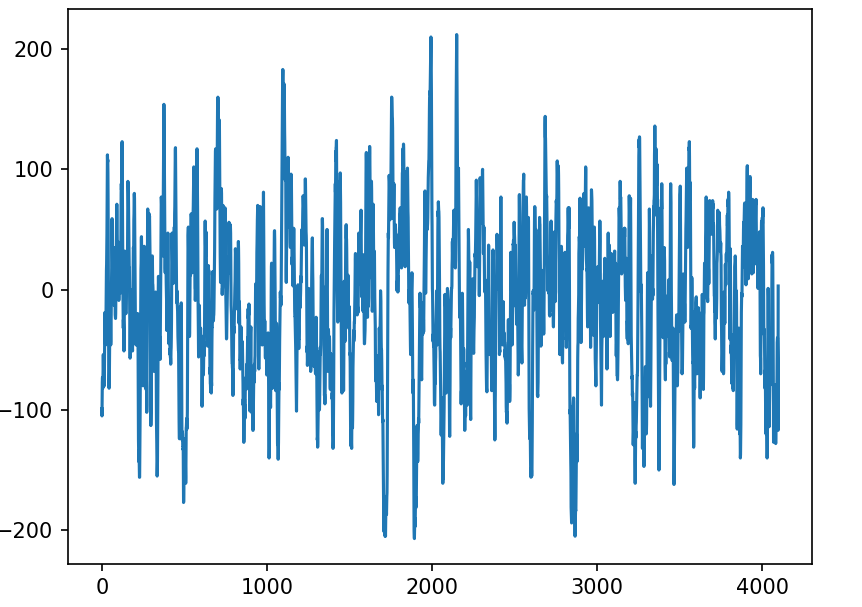


Figure (5): Set B – Person not suffering from Epilepsy with closed eye 453=4

**4.2.2. Preprocessing**

In this study we focus on the ictal condition so we used a binary classification method. The data has five class so we reduces the class to two class by grouped the data together as (A, B, C, E) and (D).

In order to make a classification task we divided the data to pre ictal state (D) and other brain condition (A, B, C, E) .

When we download the data we found that its content five files every file have 100 files in excel sheet. In order to make the classification task easy we combined all this files in one file, to do that first when we plot the signal in python IDEL we faced a problem because tha arranged of data is inversed .the excel file contains (2 columns and 4097 rows) so if we want to plot tha signals we must make every excel file contains (4097 columns and 2 rows) to all the excel files. Instead of have 100 files to each file class we but every class together in one file so we have five files. The last step is to combined all the files together in one file contain all the data instead of five files. The last thing is to add a new column to the data set to make the classification easier and fast. We renamed the classes of data by give a number to each class. Tha detail in table (1).

|  |  |  |
| --- | --- | --- |
| Label | Class Name | New label |
| A | Healthy Open Eyes | 5 |
| B | Healthy closed Eyes | 4 |
| C | Inter-Ictal | 3 |
| D | Pre-Ictal | 1 |
| E | Ictal | 2 |

Table (1):describe the new label of data.

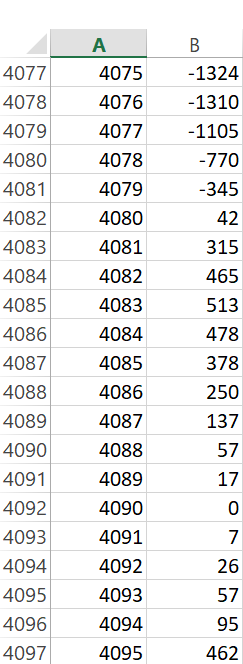


Figure (6): the original data

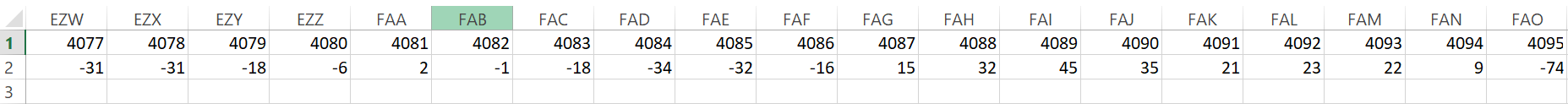


Figure (7) : the inversed data

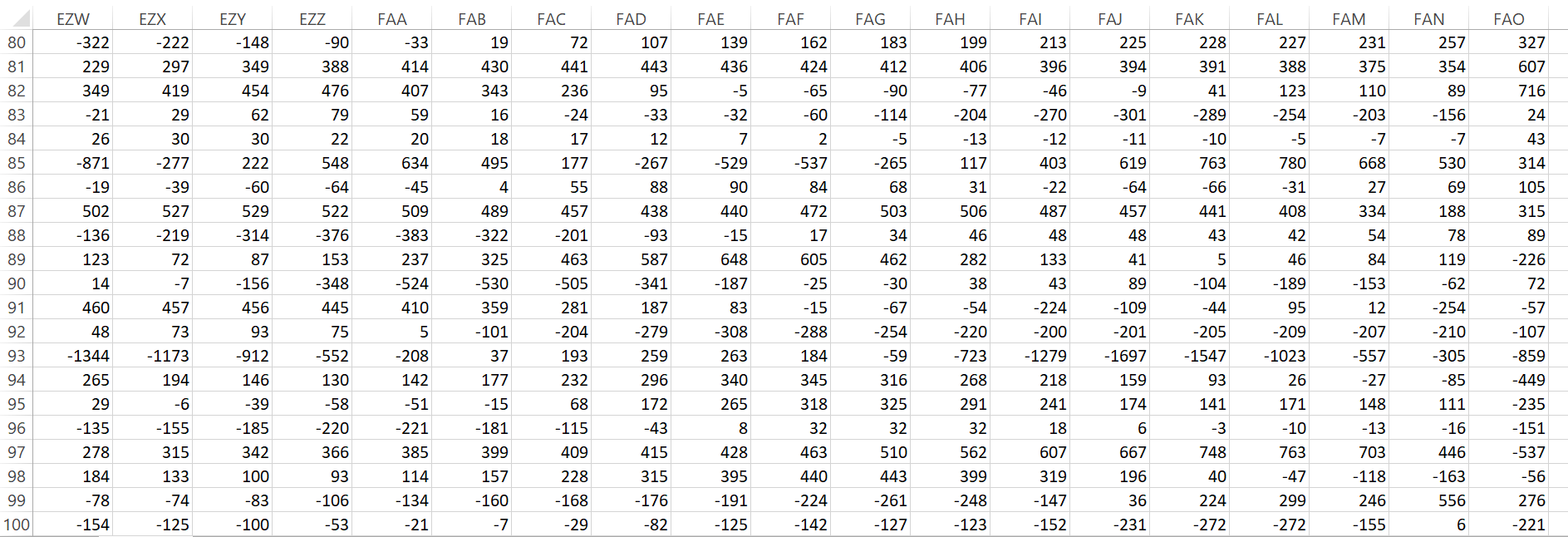


Figure (8): one file contain one class

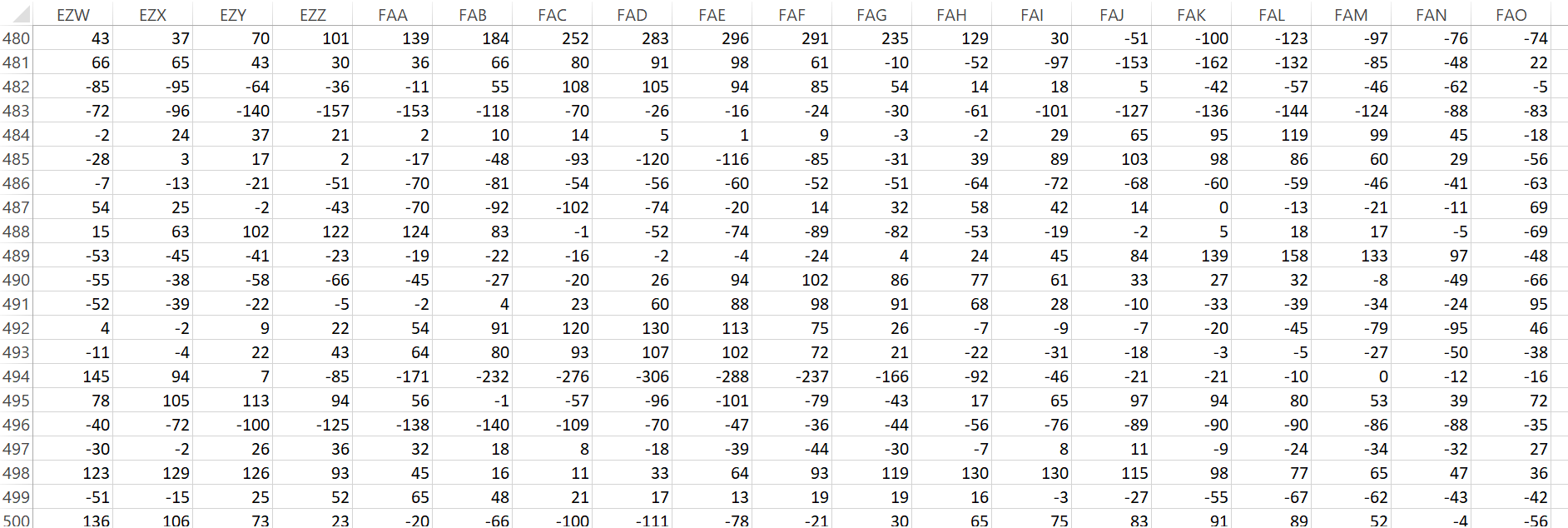
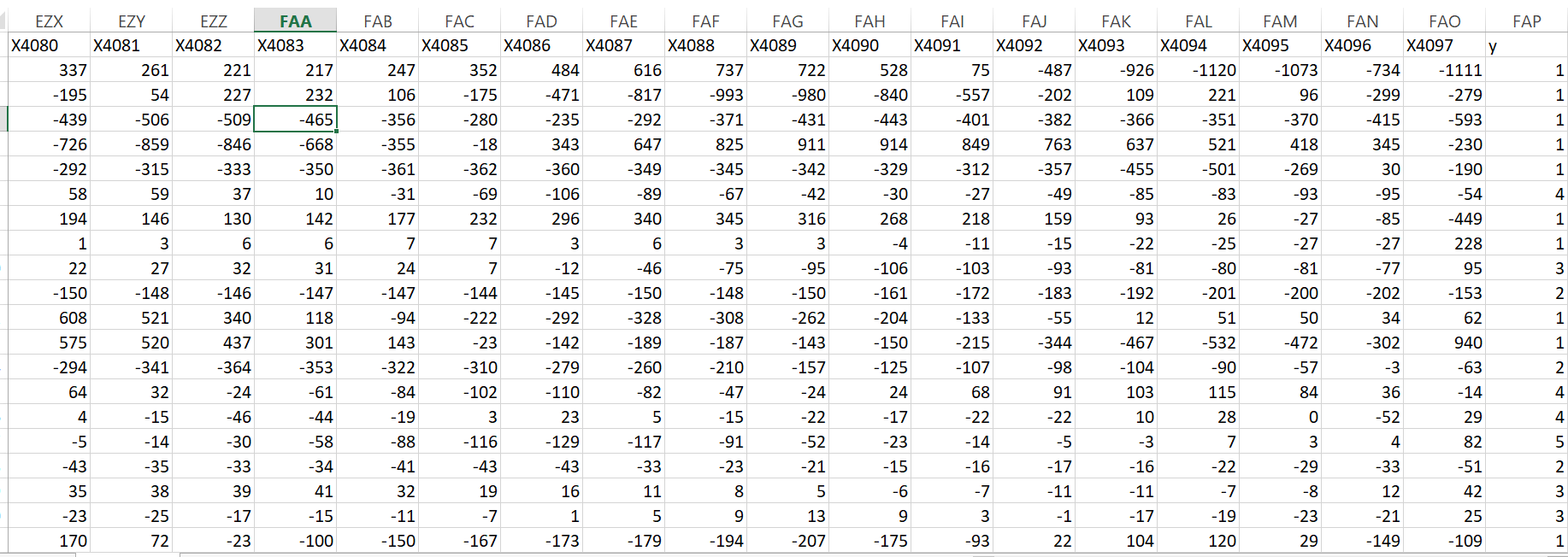


Figure (9): one file contain the five files

Figure (10): the new column with the new label

**4.2.3 Performance Evaluation**

Epileptic EEG signals can be divided into three stages, namely, interictal, preictal, and ictal. In our seizure prediction task, we mainly focused on the preictal periods.

In order to evaluate the prediction effect of the prediction system, we introduce some performance evaluation indexes. In this paper, Accuracy, Sensitivity, Specificity, Precision, Recall, and F1-Score are used as the evaluation indexes for the model.

In case of binary classification, the confusion matrix is a table with 4 different combinations of predicted and actual values. The elements of the matrix TP, TN, FP, and FN correspond to the True Positive, True Negative, False Positive, and False Negative counts, respectively.

These measures are defined as follows:

Accuracy:

The fraction of predictions our model got right. It is measured using the following formula:

TP + TN/ TP + FP + TN + FN

Recall:

or True Positive Rate (TPR): (also known as sensitivity which explains from all the positive classes how many we predict correctly). Calculated by the equation:

TP /TP + FN

Precision:

also known as positive predictive value which demonstrates how many from all the predicted positive classes are actually positive), calculated by the equation:

TP/ TP + FP

F1 – score:

also known as the harmonic mean of precision and recall). It combines precision and recall into a single number using the formula

F1 = 2 × Recall × Precision/ Recall + precision

In real life, however, it is necessary to warn patients and doctors in advance of the impending seizure, so that the medical doctors can be prepared to properly manage the episode. In order to evaluate the performance of the seizure prediction model, we introduced seizure occurrence period (SOP) and seizure prediction horizon (SPH). SOP is defined as the time-period for predicting seizures, while SPH refers to the period between the alarm and the beginning of the SOP that is, the period of clinical intervention. Figure (11).

For a correct prediction, a seizure onset must be after the SPH and within the SOP. If there is a seizure during SPH or no seizure in SOP, it is considered a false alarm.

In clinical use, the SOP should not be set too long, otherwise it will increase the anxiety of patients and cause mental stress. The setting of SPH should provide doctors with enough time for clinical interventions [33]

According to the survey in [34], the optimal warning time is 3–5 min. Nesaei [35] proposed that SPH + SOP should be more than 10 min and less than 90 min to provide treatment for patients and avoid undesirable anxiety. Furthermore, the SOP in many seizure prediction studies [36,33,37] is generally 30 min.

However, the SOP and SPH are usually unknown clinically, and researchers usually chose values based on assumptions [37]. Studies have shown that the electrical changes that occur in the brain before seizures are difficult to capture with the human eye [38]. Furthermore, due to the specificity of seizures, the length of the pre-onset period will vary from a few minutes to a few hours [39].

A seizure is correctly predicted if at least one sample segment inside the corresponding preictal interval is classified as positive .The metrics used to test the proposed approach are sensitivity and FPR with an SPH of 5 min and an SOP of 30 min. We evaluate our model with the following metrics: sensitivity, false prediction rate (FPR).

To have a robust evaluation, we follow a leave-one-out cross-validation approach for each subject.

The false positive rate (FPR):

Is the percentage of negative cases in the data that were mistakenly reported as positive. It is measured using the following formula:

FPR=FP/ (FP+TN)

Sensitivity or Recall or TPR (True Positive Rate):

It measures the ability of the classifier to find all the positive samples. . It is measured using the following formula:

TRP=TP/ (TP+FN)

**Chapter fife**

**5. Result and Discussion**

**5.1 Result and Discussion for classification:**

In our work, five sets-explained in table1- each containing 100 single- channel EEG segments of 23.6-sec duration, were composed for the study. These segments were selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| classes | The class description | The patient state | Number of cases | Binary case |
| 1 | Seizure activity recorded from epileptic patient | General epilepsy with seizure | 2300 | 2300 |
| 2 | EEG recorded from tumor region in epileptic patient | Partial epilepsy (no seizure) | 2300 | 9200 |
| 3 | EEG recorded from healthy area in epileptic patient | Partial epilepsy(no seizure) | 2300 |
| 4 | Eyes closed EEG recording | Healthy subject | 2300 |
| 5 | Eyes open EEG recording | Healthy subject | 2300 |

Table (1): Data set description and number of cases in each class

Results of using multiple classifiers to classify the epilepsy data set and the performance of the classifications are analyzed in this section.

**5.1.1 Metrics used to evaluate the classifiers:**

|  |  |  |
| --- | --- | --- |
| Acronym | Detection type | Real-world scenario |
| TP | True positive | A seizure detected correctly |
| FP | False positive | Falsely detected seizure |
| TN | True negative | A person who has no seizure diagnosed correctly |
| FN | False negative | A person who has a seizure and it is not detected |

Table (2): classification outcomes

**5.1.2 Performance measures:**

**Accuracy :**

is the fraction of predictions our model got right. It is measured using the following formula:

**Accuracy =**.

**Precision** :

(also known as positive predictive value which demonstrates how many from all the predicted positive classes are actually positive), calculated by the equation:

**Precision =**.

**Recall**:

(also known as sensitivity which explains from all the positive classes how many we predict correctly). Calculated by the equation:

**Recall=**.

**F1-Score**:

(also known as the harmonic mean of precision and recall). It combines precision and recall into a single number using the formula:

**F1-Score=**

**5.1.3 Confusion matrix:**

The below figures represented the confusion matrix of our models that shows the actual and predicted values from the classifier \_ showing number of true positive(TP),false positive(FP),true negative(TN)and false negative(FN).

Figure (1):The confusion matrix of svm

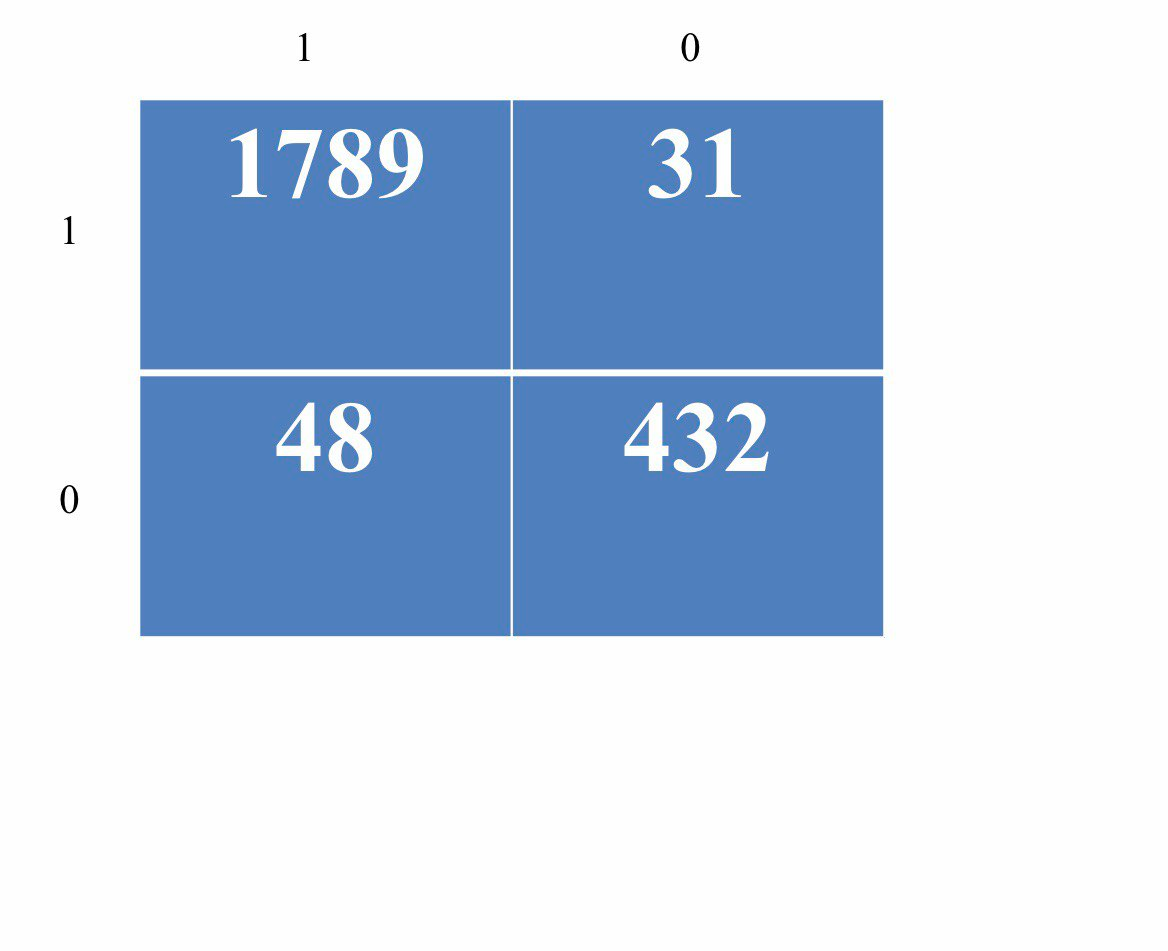


Figure (2): The confusion matrix of KNN

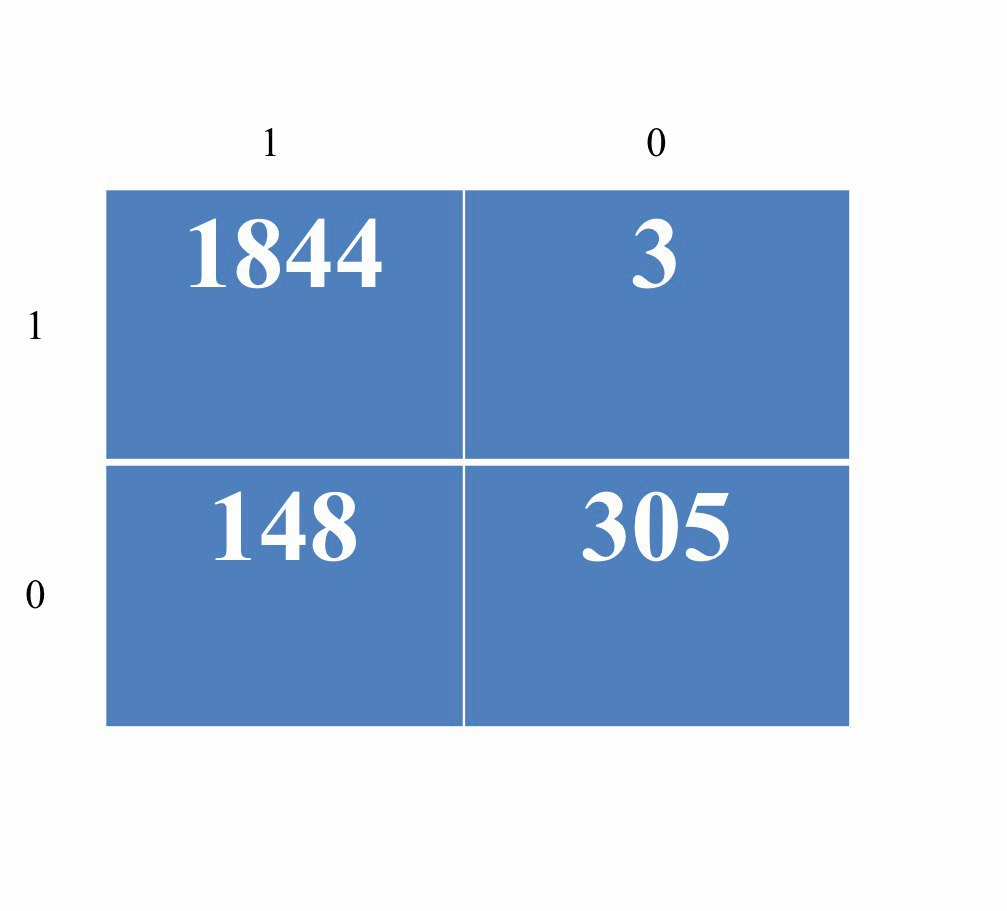


Figure (3): The confusion matrix of lsvm

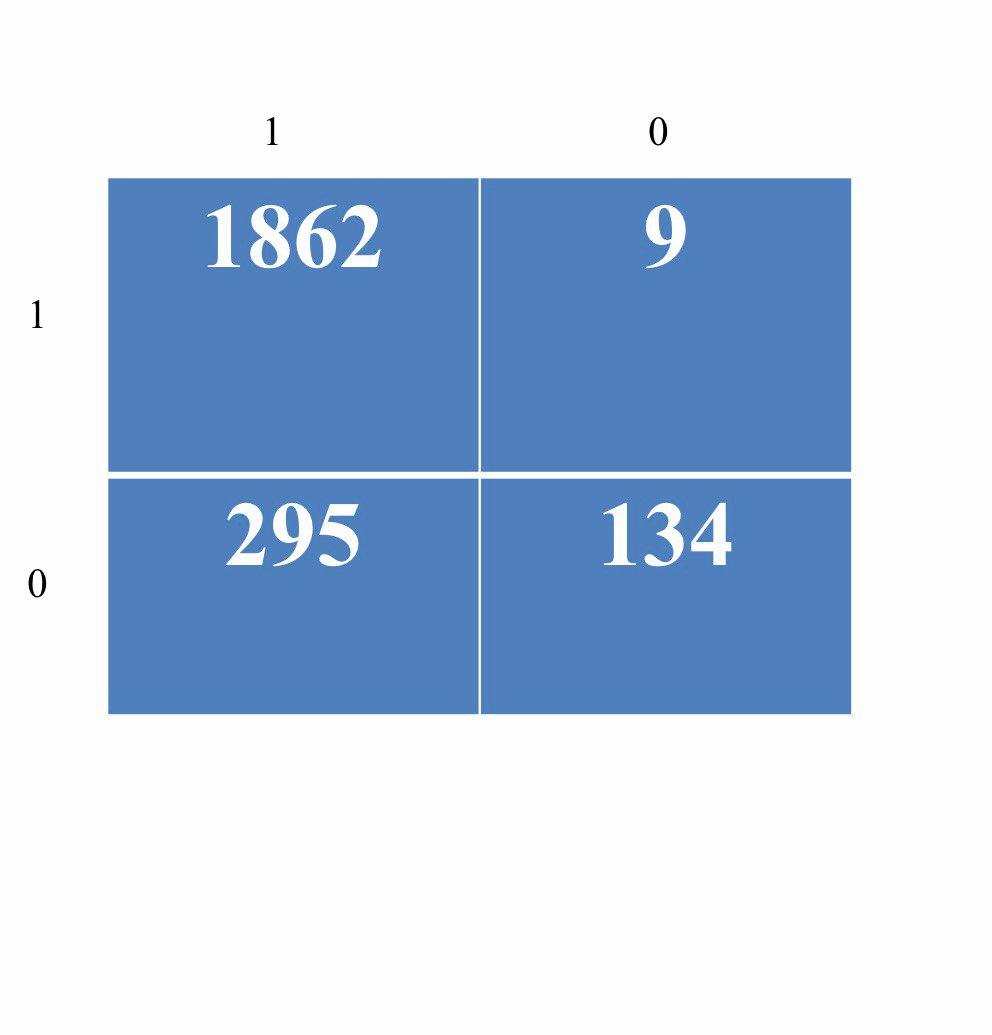


Table (3) and figure (1) illustrate the comparison between the different classification techniques with setting 80% of the dataset for raining and 20% for testing. As shown in table (3) the ANN algorithm achieving accuracy of 97.35 shows the best result. While LSTM and SVM resulted in 96% accuracy with the SVM having the best F1 score. Finally, the KNN and Linear SVM had 93.4% and 86.7% respectively.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classification techniques | Accuracy | Recall | Precision | F1 score |
| KNN | 93.43 | 67 | 99 | 80 |
| SVM | 96.57 | 98 | 97 | 98 |
| ANN | 97.35 | 93 | 93 | 93 |
| LSTM | 96 | - | - | - |
| Linear SVM | 86.78 | 31 | 97 | 47 |

Table (3): Comparison of the different Classification Techniques

Figure (5): Comparison of the different Classification Techniques

Another outcome of these experiments is that we could not derive the confusion matrix for the LSTM approach and so could not determine its precision, recall and F1-score. But since our experiment is based on accuracy comparison it did not pose a problem.

**5.2 Result and Discussion for prediction:**

The model proposed in this paper was built in a Python 3.7 environment using Google colab 1.9.we used the Keras-Tensorflow and scilearn Implementation. We divided the EEG segments from all patients into a training set and a test set at a ratio of 9:1.The proposed seizure prediction method has been tested Bonn University database, as described in Section II.

We process the EEG signal from the Bonn University database, which has five classes. The classes then grouped into two general conditions. The first is the preictal condition, which consists set (D). Set (A ,B,C,E) are grouped as other brain conditions. We first evaluate our model with standard metrics and then compare it with two other works that achieves state-of-the-art performance. Sensitivity, false prediction rate (FPR) are evaluated in this study.

The workflow of the seizure prediction system is shown in Figure (12)

Classification

To pre ictal and other brain condition

RAW EEG DATA SET

Prediction alarm

**Performan**ce **Evaluation**

**Discussion:**

Information extracted from EEG signals in frequency and time (synchronization) domains has been used widely to predict seizures.

Sharif et at [40] This approach achieved a high sensitivity Sharif and a low FPR of 0.05–0.08 in testing with the Freiburg Hospital iEEG dataset.

Zhao et al. [41] used a binary single-dimensional convolutional neural network (BSDCNN) to predict seizures with a sensitivity of 88.89% and an FPR of 0.39 per hour.

Zhang et al. [42] used a simple CNN model to classify the correlation matrix obtained by calculating the Pearson correlation coefficient to distinguish the preictal states from the interictal ones and obtained a sensitivity of 92.9%.

Truong et at [43] achieved a high sensitivity of 91.8–96.6% and a low FPR of 0.05–0.08 in testing with the Freiburg Hospital iEEG dataset.

Jianzhuo et at[44] achieved prediction sensitivity and FPR were 96.01% and 0.047/h, respectively using database obtain from CHB-MIT scalp EEG database.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Year | Authors | Feature | Classifier | No. of Patients | No. of Seizures | Sen 1 (%) | FPR (h−1) |
| 2017 | Sharif |  | SVM |  |  |  | 0.05–0.08 |
| 2018 | Truong | STFT | CNN | 13 | 64 | 81.2 | 0.16 |
|  |  |  |  |  |  |  |  |
| 2020 | Zhao | **-** | BSDCNN | 6 | **-** | 94.69 | 0.095 |
| 2021 | Zhang | Pearson correlation coefficient matrices | CNN | 19 | **-** | 92.9 | **-** |
| 2022 | Jianzhuo | STFT | Three tower transformer | 21 | 111 | 96.01 | 0.047 |
|  | This work |  |  | 10 or 5 | 100 |  |  |

**Chapter six**

**6.conclusion:**

Epileptic seizures are currently one of the leading reasons for morbidity and mortality in the world. With the rise of epileptic seizures around the world and their effect on people's lives, it's more important than ever to get an accurate and timely diagnosis.

The fundamental goal of this thesis was to discover the best classification algorithm for epileptic seizures by compare a number of machine learning and deep learning techniques to find out which is more accurate in classifying EEG signals as an epileptic seizure or not an epileptic seizure. We found that a customized ANN with personalized cost function that learns from the imbalanced data and achieves high accuracy in automated seizure detection. ANN Which it is deep learning technique the best classifier with highly accuracy of 97.35.

Epileptic seizure prediction is very useful to control seizures that are non-treatable with medicines or surgery. Predicting an epileptic seizure with an increased sensitivity and the low false positive rate remains a challenge due to multiple factors that include the lack of effective preprocessing of the EEG signals, class imbalance problem.

Deep learning techniques provide a way of extracting robust features and generate feature maps using kernels. It provides good accuracy results and accuracy is very important in case of health domain.

An effective seizure prediction method will not only better help doctors diagnose and reduce the pain of patients, it can also help them avoid dangerous activities such as driving or swimming before the onset of seizures.

Seizure prediction capability has been studied and improved over the last four decades. A perfect prediction is not yet available, but with current prediction performance it appears possible to provide patients with a warning so they can take some precautions for their safety.

The proposed approach showed its good generalization in working well with both iEEG and sEEG data. This gives more patients the opportunity to possess a seizure prediction device that can help them have a more manageable life.

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