SEIZURE PREDICTION BASED ON MORPHOLOGICAL FEATURES USING ONE-DIMENSIONAL LOCAL BINARY PATTERN ON LONG-TERM EEG SIGNALS

A PROJECT REPORT

submitted by

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of

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with specialisation in

Industrial Instrumentation and Control

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DECLARATION

I undersigned hereby declare that the project report entitled "**Seizure Prediction Based On Morphological Features Using One-Dimensional Local Binary Pattern On Long-Term EEG Signals**", submitted for partial fulfillment of the requirements for the award of degree of Master of Technology in Electrical and Electronics Engineering with specialisation in Industrial Instrumentation and Control, APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of *Dr. Muhammed Shanir P P*, Assistant Professor, Department of Electrical and Electronics Engineering. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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CERTIFICATE

This is to certify that the report entitled " **Seizure Prediction Based On Morphological Features Using One-Dimensional Local Binary Pattern On Long-Term EEG Signals** " submitted by **ALANDUTT V R** , **(Reg. No. TKM20EEII04)** of fourth semester to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Electrical and Electronics Engineering with specialisation in Industrial Instumentation and Control, is a bonafide record of the project work done by him under my guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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Abstract

After stroke, epilepsy has become the most prevalent disease in the world. Recurrent seizures are the hallmark of epilepsy, which is an aberrant neural activity of a brains. This illness causes abnormal, uncontrollable brain and body activity that can put a person in a coma or possibly cause death. Electroencephalography (EEG) is frequently used to diagnose epilepsy. By analysing the EEG data to find features that will detect the aberrant activity, seizures can be detected. This study analyses EEG signals to find the greatest qualities that can foretell seizures far before they start. Early seizure recognition can reduce the severity of injuries and help in the treatment of epilepsy patients. There are several ongoing studies in this field, but the accuracy of the results is very low in all of them. Therefore, increase the performance the study, LBP is being utilised to anticipate epileptic seizures by extracting morphological features. LBP assigns a sample point a perfect decimal value by weighting the binary values after quantizing the adjacent sample with current sample point. These LBP values help to capture the EEG signal's rising and falling edges, using the sum of absolute difference of the LBP values and the interquartile range processed EEG signals per epoch is determined. K-nearest neighbour classifier is utilised for classification, and performance is assessed using data from the CHB-MIT continuous EEG dataset. In the subject wise experiment an average best accuracies of 93.66%, and in the subject dependent experiment, the best accuracies of 92.22%, and in the subject independent experiment, the best accuracies of 81.16% is obtained form KNN classifier.

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Abbreviations

ANN	Artificial Neural Network
CNN	Convolution Neural Network
ECG	Electrocardiogram
EEG	Electroencephalogram
FN	False Negative
FP	False Positive
FPR	False Prediction Rate
KNN	K - Nearest Neighbor
LBP	Local Binary Pattern
TN	True Negative
TP	True Positive
WHO	World Health Organization

Notations

$p\left(x\right)$	Probability of x point
x_i	x coordinate of i^{th} point
y_i	y coordinate of i^{th} point
$\hat{y}_i{}^t$	Prediction value at iteration t

Chapter 1

INTRODUCTION

A neurological condition that is socially stigmatised is epilepsy. The World Health Organization (WHO) observes epilepsy as a chronic, non-communicable brain condition that affects individuals of any age. Organization Over fifty million individuals suffer from epilepsy worldwide, with over 80% of them residing in third-world countries. Recurrent seizures affect over 50 million people worldwide, with 4 to 10 cases per 1,000 persons. Additionally, only 70% of the various epilepsies may be treated with medication. Epileptic seizures affect patients daily lives since they are unexpected, resulting in unanticipated mistakes and emotional stress. Early seizure detection can help reduce the seizures can cause physically and psychological suffering, and early medical detection of seizures can help. As well, Unprovoked seizures with fast aberrant neuronal discharges in the brain are the hallmark of epilepsy and a number of health problems, including death, can result from it.

Electroencephalography (EEG) is a technique for analysing variations in brain activity and identifying both normal and pathological occurrences in the human brain. EEG is also very affordable, making it a great option for people with epilepsy. To identify seizure occurrences, Long-term EEG data collection necessitates skilled supervision and meticulously controlled experimental conditions. The technique of electroencephalography (EEG) is frequently employed to investigate changes in brain activity and to help distinguish between normal and abnormal occurrences in the human brain. electroencephalography is also quite inexpensive, makes it the best test for epilepsy sufferers. Longer duration EEG signals must be recorded, under expert supervision, in confined experimental settings in order to reliably identify seizure occurrences. The four primary stages involved in an epileptic seizure event are shown in Figure 1.1 along with the issue description for prediction of an epileptic seizure. The issue of epileptic seizure detection, which is distinct from seizure prediction, is also shown in the same picture. The patient's regular brain state is refers to as the interictal state. Pre-ictal state refers to the mental state just prior to a seizure occurrence.

Depending on the issue, this state may continue for a few minutes or several hours. The brain moves to the post-ictal state following the seizure event from the ictal state, is the circumstance in which the seizure takes place. Making models that differentiate between the pre-ictal and interictal stages of the brain of the specific person is a step in seizure prediction., as shown in Figure 1.1. Pre-ictal duration in proposed algorithms becomes a design decision because the pre-ictal state duration is arbitrary. As a result, if the classifier determines that the input EEG data is pre-ictal, the model is predicting that a seizure will happen within the designated pre-ictal time (duration). Depending on how long is considered to be the pre-ictal time, the developed classifier has varying early prediction capabilities. For instance, If the pre-ictal duration is set to 60 minutes, the generated classifier can detect seizures within a 1 hour prediction window.

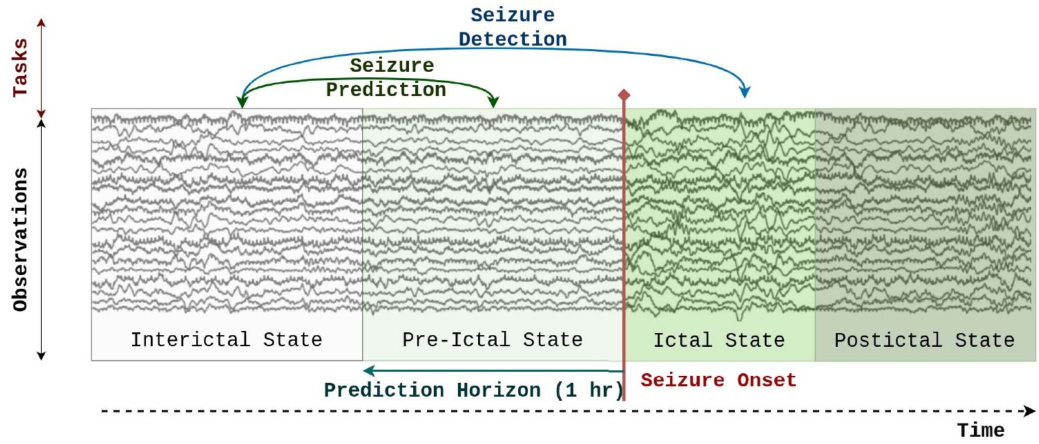

Figure 1.1: Comparing seizure prediction to seizure detection

Seizure prediction aims to predict the mental stage just before a seizure takes place. Additionally, four hours before or after the start of a seizure is frequently considered the interictal brain state by researchers.

There are the three methods for predicting epileptic seizures:

- **Patient-Independent**: Research attempts to create a classifier that can identify seizures in a variety of subjects. These models are developed using the entire dataset, and the collection comprises a wide range of subjects. The objective is to produce a global predictive model function that can do cross-sectional prediction.

- **Patient-Specific**: Studies focus on creating a classifier for each subject while taking into account the large level of inter-subject variability in EEG data. For each subject, a single classifier architecture is created and optimised in this case. The final performance of the model is measured by the average accuracy obtained after training and testing the classifier on all or a various quality of participants in the dataset. By concentrating on each subject separately while creating a model, this strategy simplifies the issue, although these techniques are hindered by the lack of readily available data.

- **Patient-Dependent**: To create a classifier that can identify seizures in a subjects and the complete dataset is used to create the models, the goal is to develop a predictive model functions that can be its own prediction.

The study's main contribution is the suggestion of a patient-independent model for epileptic seizure prediction. As it learns consistently from subjects with comparatively more samples and subjects with less samples, the method can pay attention to all the individuals in the dataset. It should be noted that if the number of recordings available for each patient is constant across the dataset and those recordings have longer lengths, developing a patient-specific model is a potential approach. However, medical datasets sometimes include a variety of recordings for each individual,Therefore, the ability to create a global function that takes the entire dataset into account is essential for use in real life scenarios.

The "preictal state" is the state right prior to onset of the seizure, while "interictal state" is patient's regular condition. Numerous studies on prediction of epileptic seizures have focused on identifying the preictal states using EEG. The EEG can be divided into two categories: intracranial and scalp, depending on where the electrodes are placed. Unlike intracranial EEG, which places the electrodes inside the scalp, scalp EEG places the electrodes over the scalp. Under the dermal layer,Strip, grid, or electrodes of piercing depth are frequently implanted by neurosurgeons. Contrary to brain activity captured by scalp EEG, intracranial EEG data reflect activity on a different scale. While intracranial electrodes offer local information from the structure of the brain, scalp electrodes provide global information. In order to improve the clinical usability of the prediction approaches, methods depend on EEG Signal have also been investigated. Non-linear similarity, phase space similarity measures, average spiking rate, phase synchrony measures, wavelet coherence values, variational Gaussian mixture model, statistical moments, spectral information, and spectral power are some of the features that can be used to predict seizures using scalp EEG.

LBP(Local binary patterns) has been frequently used for texture classification of 2D images because of its discriminative power.1D-LBP (One dimensional local binary pattern) , which is produced from LBP, has been successfully applied to vocal activities in voice signal that are non-stationary in nature. As a result, it can be regarded as a successful method for feature extraction from EEG signals, which are by their very nature non-stationary. The goal of this effort is to develop a new algorithm that has the maximum sensitivity and forecast time for epileptic seizures. A method based on 1D-LBP is put forth in this research to extract features from scalp EEG data recorded during interictal and preictal periods. These characteristics are used to forecast epileptic episodes. The two stages of the suggested scheme are feature extraction from EEG signals and feature-based categorization. Interictal and preictal EEG waves are first processed to determine their individual features. Finally, a feature-based procedure was carried out before the K-nearest neighbour (KNN) classifier classified the dataset. The proposed method is assessed using a dataset of scalp EEG from the Massachusetts Institute of Technology. Up till now, the study has used information from 13 epileptic patients who have experienced a total of 47 episodes. The performance of seizure prediction is evaluated for sensitivity, predictability, and false prediction rate (FPR).

1.1 Objective

The widely used approach for identifying anomalies in brain signals is EEG, and multichannel EEG is frequently used to identify epilepsy. Epileptic seizures are occurred by a brain function abnormality, which may be harmful to the patient's health. Predicting epileptic seizures before they start can be very helpful in using medication to prevent them. The objective of a seizure prediction system is to precisely identify the preictal brain state, which occurs before a seizure onset. To boost sensitivity, we must use better discriminating features. The brain signals are converted to decimal values by using LBP in three different features RFEC, IQR, SAD. This output is given to a classifer known as KNN and values are grouped by using a confusion matrix in three different ways patient dependent, patient independent and patient specific. The objective of this work is to develop a feature extraction and prediction technique that can able to predict the seizure in three above mention ways.

1.2 Organisation of the report

The literature survey done for this work is explained in the chapter 2. In the chapter 3, the EEG signal and epilepsy, LBP, proposed block diagram, data preparation, feature extraction and classification methods are explained. In chapter 4, obtained results are mentioned and discussed and finally in chapter 5,the conclusion and the future works of this thesis is described.

Chapter 2

EPILEPTIC SEIZURE PREDICTION "AN OVERVIEW"

Previous chapter deals with the overall information about the Seizure prediction involves creating models between pre-ictal and interictal stages.Current chapter focuses on understanding of methods by analysing the different works that have been conducted by many authors all around the world, on the area of seizure prediction and seizure detection. The works related to thesis such as different classification methods, different classes etc is been studied in this chapter.

2.1 LITERATURE REVIEW

In this chapter the literature review of the several seizure prediction technique with the proposed method (using EEG signals) is investigated. And observed that all works are based on feature extraction and these features are used to quantify the information. The issues may rise due to this is also observed. Using Scalp EEG Signals, Deeper Training for Patient-Independent Epileptic Seizure Prediction paper provide two deep learning architectures that are independent of the patient and can train a global function using data from several subjects. On the CHB-MIT-EEG dataset, proposed models provide community efficiency for seizure prediction with accuracy rates of 88.81% and 91.54%, respectively[1].

Using features from the scalp electroencephalogram's one-dimensional local binary pattern (1D-LBP), a new technique for automatic seizure prediction is provided in this research (EEG).

The preictal and interictal EEG data were converted to the 1D-LBP region and statistical characteristics were extracted during the feature extraction stage. Two distinct classifiers linear logistic regression and support vector machine were given these features to process .[2] A basic post processing stage was been added to help lower the false prediction rate .
The detection work suggests a brand-new method for extracting morphological features that is built just on local binary pattern operator. By weighing the binary results after thresholding the adjacent samples with the current sample point, LBP assigns a distinct decimal value to a sample point. These LBP values help to capture the rising and decreasing margins of the EEG signal, resulting in a pattern that is morphologically featured and can be used to detect epilepsy. The variance in the LBP readings is quantified in the current work by summing the absolute differences between the successive LBP values[3]. To determine the signal's dispersion, the interquartile range is computed over preprocessed EEG data.
Does the level of vigilance affect false seizures predictions Report on Two Seizure-Prediction Techniques and Suggested Treatments Both seizure-prediction approaches under investigation have limitations in terms of specificity due to variations in the Brainwave dynamics associated with the sleep-wake cycle[4]. This might offer a hint for enhancing prediction techniques more generally. The combination of reference states produces encouraging findings and may present potential to improve the effectiveness of prediction algorithms even more.
employing wavelet-based features and some features are extracted without wavelet decomposition, a method for automatically detecting the commencement and event of epileptic seizures. Using a linear classifier, normal and abnormal EEG data were distinguished. The EEG database from Bonn University has been used to detect seizure events. EEG signals from healthy volunteers with their eyes open, epileptic individuals in the epileptic seizure during a seizure-free period, and epilepsy patients experiencing epileptic episodes were all classified into one of three categories. Calculations of significant characteristics like energies, efficiency, variance, maximum, minimum, and mean at various subbands were made, and a linear classifier was used to classify the results[5].

This chapter reviews the research on various prediction techniques and also looks into the suggested approach (using EEG signals). The majority of research on predicting epileptic seizures is based on various deep learning and machine learning algorithms. Since the effectiveness of such methods is unsatisfactory, one dimensional local binary patterns are used in this work to enhance system performance.

Table 2.1: Contains the investigated information of some works done with eeg signals for the seizure prediction.

Authors	Signal	Method	Dataset	Remarks
Theekshana Dissanayake, Tharindu Fernando [1]	EEG	MFCC featuremap, CNN, Multitask Deep Learning Architecture	CHB-MIT-EEG	Demonstrating 88.81% and 91.54% accuracy respectively.
Thasneem Fathima, Paul Joseph K et al.[2]	EEG	linear discriminant analysis (LDA) support vector machine (SVM)	CHB-MIT-EEG	sensitivity of 96.15%
P. P. Muhammed Shanir Kashif Ahmad Khan et al.[3]	EEG	1D-LBP domain, KNN	CHB-MIT-EEG	sensitivity of 99.2% Mean accuracy of 99.7%
Schelter B, Winterhalder M [4]	EEG	the dynamic similarity index and the mean phase coherence	CHB-MIT-EEG	86% of all false predictions occurred during sleep for the dynamic similarity index
Nabeel Ahammad et al.[5]	EEG	KNN	CHB-MIT-EEG	overall accuracy was 84.2%
World Health Organization (WHO) et al.[6]				
Niedermeyer et al.[7]	EEG			

Authors	Signal	Method	Dataset	Remarks
Finnigan, Simon et al.[8]	EEG		CHB-MIT-EEG	overall accuracy was 84.2%
Zhang, Zisheng et al.[9]	EEG	SVM	CHB-MIT-EEG	overall accuracy was 90.2%
Ahmedt-Aristizabal et al.[10]	EEG			
Daoud et al.[11]	EEG	DCNN, BI LSTM	CHB-MIT-EEG	overall accuracy was 91.2%
Jiang, Zhen et al.[12]	EEG		CHB-MIT-EEG	overall accuracy was 89.5%
Hassan, Ahnaf Rashik et al.[13]	EEG	CEEMDAN	CHB-MIT-EEG	
Roy, Yannick et al.[14]	EEG	CNN	CHB-MIT-EEG	
Rasheed, Khansa et al.[15]	EEG		CHB-MIT-EEG	overall accuracy was 90.5%
Tsiouris, Kostas M et al.[16]	EEG	LSTM, DenseNet	CHB-MIT-EEG	
Kuhlmann, Levin et al.[17]	EEG		CHB-MIT-EEG	
Bomela, Walter et al.[18]	EEG		CHB-MIT-EEG	overall accuracy was 92.5%
Dissanayake, Theekshana et al.[19]	EEG		CHB-MIT-EEG	

Authors	Signal	Method	Dataset	Remarks
Sridevi, Veerasingam et al.[20]	EEG	SVM, KNN	CHB-MIT-EEG	overall accuracy was 92.5%
Truong, Nhan Duy et al.[21]	EEG	CNN	CHB-MIT-EEG	overall accuracy was 89.5%
Chatlani, Navin et al.[22]	EEG	SVM	CHB-MIT-EEG	overall accuracy was 93.5%
Kaya, Yılmaz et al.[23]	EEG		CHB-MIT-EEG	overall accuracy was 95.5%
Samiee, Kaveh et al.[24]	EEG	SVM	CHB-MIT-EEG	overall accuracy was 92.5%
Michel, Christoph M et al.[25]	EEG		CHB-MIT-EEG	
Lascano, Agustina Maria et al.[26]	EEG		CHB-MIT-EEG	overall accuracy was 92.5%
Kurian, Mary et al.[27]	EEG		CHB-MIT-EEG	
Anderson, Nicholas R et al.[28]	EEG		CHB-MIT-EEG	overall accuracy was 89.5%
Majumdar, Kaushik [29]	EEG		CHB-MIT-EEG	
Adeli, Hojjat et al.[30]	EEG		CHB-MIT-EEG	overall accuracy was 92.5%
Li, Shufang et al.[31]	EEG	ANN	CHB-MIT-EEG	overall accuracy was 88.5%
Qu, Hao et al.[32]	EEG	NN	CHB-MIT-EEG	overall accuracy was 90.5%
Yadav, Rajeev et al.[33]	EEG		CHB-MIT-EEG	overall accuracy was 91.9%

Chapter 3

METHODOLOGY

The investigation of the different methodology, classifiers and works including their performance is done in the previous chapter. This chapter deals with the method with which the work is done, also discusses the dataset, emotion classification, classifiers etc. which are used in the work.The block diagram of the proposed method is mentioned in the Figure 3.1. First of all, the dataset is pre-processed, the dataset may contain some irrelevant channels that do not add any meaningful information, in that case we must eliminate those channels, the dataset using this work uses 23 channels, on those 23 channels only 22 channels are relevant ones. The EEG signals of 22 channels are recorded and converted to using 1D-LBP method in order to do the feature extraction of the converted output, there are three methods are used which include RFEC, IQR, SAD. The extracted output is given the classifier that is KNN.

3.1 Electroencephalogram

A popular non-invasive technique for keeping tabs on the brain is the electroencephalogram (EEG). It is based on placing metal electrodes on the scalp to detect the mins electrical potentials brought on by brain activity that occurs outside of the skull. The fact that it can monitor events in the head with minute accuracy and that it is theoretically portable are its two key benefits over earlier brain imaging techniques. This makes it possible to conduct real-world neuroimaging from outside clinical and laboratory settings. As a result, it is a popular sensing approach for many applications in the field of health and welfare, such as tracking mood and diagnosing epilepsy.

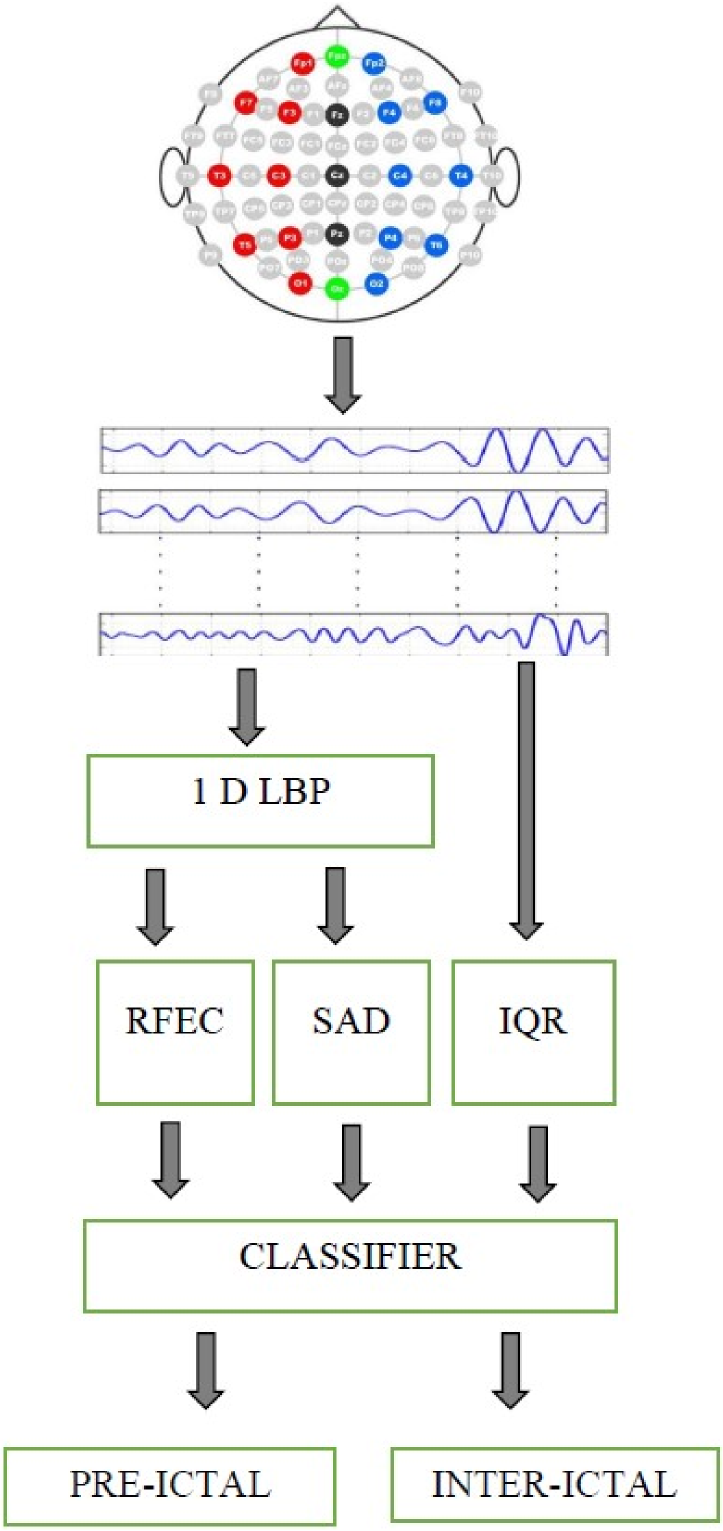

Figure 3.1: Block diagram of the proposed method

3.1.1 Origin of EEG

The German psychiatrist Hans Berger performed the EEG for the first time in 1929, and it has a lengthy history of development and application.Fundamentally, the EEG (electroencephalogram) is similar to the well-known ECG (electrocardiogram), which is used to monitor the heart, but it is carried out on the head rather than the chest. In a nutshell, brain activity is defined by electrical impulses that pass along nerve cells and postsynaptic responses that occur when neurons connect with one another.Electrodes affixed to the skull are used to detect the accumulated electrical currents associated with these impulses, and the potential fluctuations they may generate can be magnified and stored to create different pictures of brain activity. It is a sensing method that is frequently used for a range of health and well-being applications, such as mood monitoring and epilepsy diagnosis. The particular brain source of Eeg data that are visible outside of the skull still has a lot to be discovered. The fact that potassium and sodium ions pass through synapses and that there are numerous voltage-gated ion channels present in the cell components of neuron, which produce action potentials, suggests that the brain has a large number of electrical sources. With volume conduction effects affecting the size of the brain area under consideration, the electrical impulses recorded by the EEG is an extremely large-scale sum of electrical activity from massive populations of synchronize neurons and glial cells. It is not required to take into account the particular cellular origins of these EEG signals in order to make effective use of them. Neuron action within the brain causes an output voltages with its own unique shapes and features to appear on the scalp.For practical purposes, the EEG can be seen as an emerging characteristic of these groups and networks. This is often done by assuming that a finite number of electrical sources called dipoles are responsible for EEG activity, and then posing an inverse problem to calculate the amount that each dipole contributed to the present EEG trace. Each dipole in this situation is an mathematical/electrical construct that is utilised to map the scalp EEG on to rather than being a concept to production that provides precise data on the cellular level origin. While some methods for analyzing EEG data are focused on estimating the dipoles and utilizing them as the foundation for signal processing, others are based on immediately evaluating the period EEG captured from the scalp. Both EEG analysis techniques are valid and often employed. The diagram of the electroencephalogram reading process is mentioned in the Figure 3.2.

Using electrodes that are frequently fixed on an EEG cap, an EEG permits measuring the electrical activity on the scalp. Depending on where the reference electrode is placed, there are two different ways to capture an EEG.

- **Bipolar Montage** : The voltage difference between the electrodes is monitored while both electrodes are applied to a scalp area that is electrically active.
- **Unipolar Montage/Monopolar Montage**: One functional electrode or every or more reference electrodes that are linked. The reference electrode must be as electrically isolated as is practical when compared to brain activity. The recorded signals serve as a representation of the differential between both the working electrode and the activated regions of the brain. Common reference points include the balancing non-cephalic sterno-vertebral leads, right or left mastoid, tip of the chest, nose, and ear lobe.

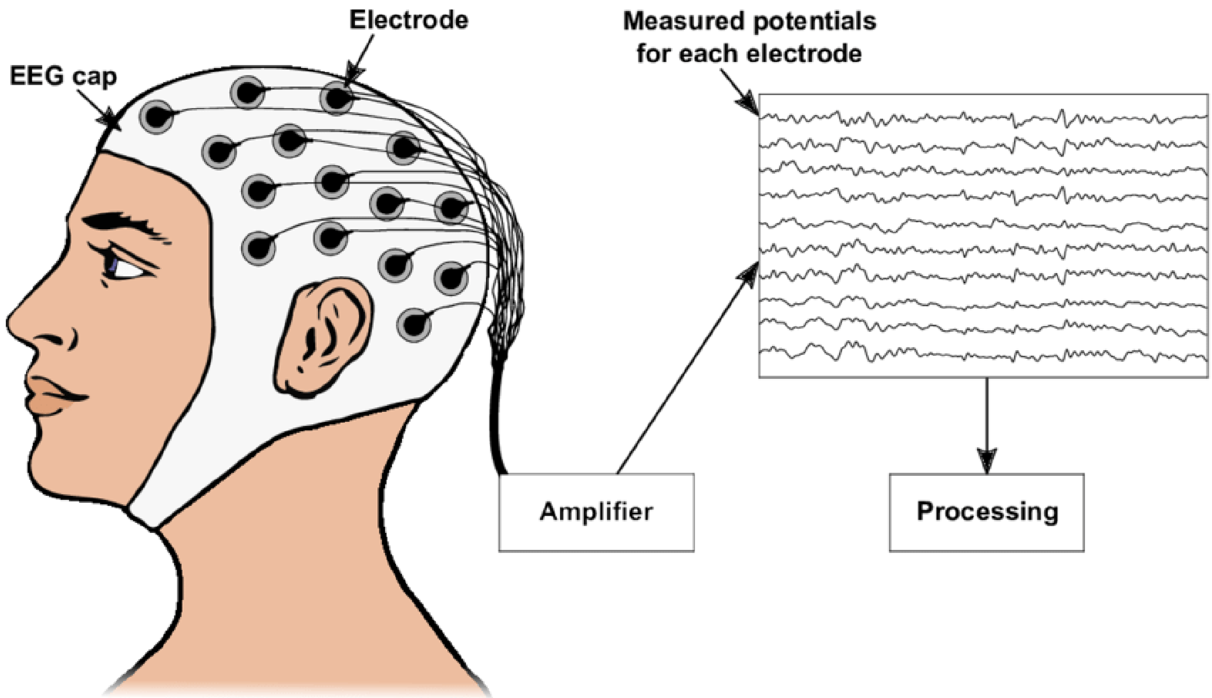

Figure 3.2: Diagram of the electroencephalogram recording process

3.1.2 Typical Signals

The EEG signal that forms on the scalp can take on a wide variety of signal morphologies and is recorded as a volt in the temporal domain. Despite the fact that only a few samples could ever fully capture the wide variety of waveforms that are seen in practise, Figure shows a number of example waveforms. There is an atlas with many more instances accessible. The EEG signal does not generally have a pleasing appearance. To the untrained sight, it frequently just appears to be noise, and it necessitates a lot of practise to be able to identify something other than the plainly visible coarse features. Different categories may be employed according to the application area to classify these features in a range of ways. The EEG is frequently broken down into evoked, hybrid components and free-running,. The brain activity that is present as a result of the brain's regular operation is known as free-running EEG. As the brain functions, it is present always. This EEG is unique in that it is divided into frequency bands, each of which is named after a Greek letter:

- Delta: less than 4 Hz
- Theta: between 4 and 8 Hz
- Alpha: between 8 and 13 Hz
- Beta: between 13 and 30 Hz
- Gamma: over 30 Hz

The dominant frequency in preterm infants is infra-slow oscillations (ISOs), which are less than 0.5 Hz in frequency and are known as spontaneous activity transients (SAT). SATs are examples of endogenously motivated, spontaneous activity at an early, premature stage, when sensory information has little or no influence on the formation of neuronal connections. Additionally, ISOs at a wide range of (0.02 to 0.2 Hz) frequencies , stage of evolution with high frequencies EEG activity, are present during non-REM sleep.

The majority of low-frequency signals research has concentrated on a variety of different tasks and states, including motor motions (Bereitschafts potential), contingent stimulation (contingent negative variation, CNV), and the orienting paradigm. These slow scalp potentials can last for many seconds and frequently have an amplitude of only a few microvolts, necessitating the use of FbEEG in addition to electrodes and skin-electrode connections with true DC characteristics for accurate recording.

Delta (0.5 to 4Hz): The frontocentral head areas of the body physically exhibit a pronounced delta rhythm during deep sleep. When there is localised brain dysfunction and a widespread encephalopathy, a delta rhythm appears in wakwup states. Adults experience FIRDA (frontal intermittent rhythmic delta activity), whereas children experience OIRDA (occipital intermittent rhythmic delta activity). In people with temporal lobe epilepsy,TIRDA (temporal intermittent rhythmic delta activity) is frequently observed.

Theta (4–7Hz): Both drowsiness and the N1 and N2 phases of early sleep trigger this pattern. Early tiredness causes a rhythm that gradually migrates backward, taking the place of the alpha rhythm, and is especially noticeable in the inferior frontal head areas. Increased anxiety states can also enhance frontal rhythm theta rhythm in children and young adults. When awake, the presence of focused theta activity is a sign of focal brain damage.

Alpha (8–12 Hz): The rear dominant alpha pulse can be seen in normal active EEG recordings posterior head region. It is what sets the regular background rhythm of adults apart from other rhythms. By the time a person is three years old, their posterior rhythm has reached the alpha frequency of 8Hz, and it doesn't begin to slow down until they reach their ninth decade of life. Fast changes in the backstory alpha rhythm are seen in the overall population. It is believed that a slowdown of the back - ground alpha rhythm signifies damage of the entire brain. Alpha rhythms vary in amplitude both between individuals and within the same individual. Reactivity, which characterises the alpha rhythm, aids in its identification.It is usually lessened by opening the eyes and exerting mental effort, and is most easily observed when the eyelids are closed and the brain is at ease. Generalized-alpha activity, also referred to as a "alpha coma," may occur in individuals with diffuse encephalopathy and is unresponsive to either internal or external stimuli.

Beta (13 to 30Hz): The beta beat is the one that more commonly noticed in both healthy adults and youngsters. It is most noticeable in the front and central head regions, and as it advances backward, it becomes less noticeable. The amplitude of beta activity normally ranges from 10 to 20 μv, seldom going above 30 microvolts. Prior to amplitude reduction in N2 and N3 sleep, it typically increases during tiredness and N1 sleep. Barbiturates, chloral hydrate, and benzodiazepines are among the sedative medicines that increase beta activity in people's bodies. Beta attenuation may be focal, regional, or hemispheric due toanomalies, ortical traumas, epidural, subdural or subgaleal fluid accumulations.

Sigma waves: This activity, also known as sleep spindles or sigma waves, is observed physiologically during N2 sleep. They are most noticeable the fronto-central head regions and can be either 12 to 14Hz (slow) or 14 to 16Hz (fast). Spindle coma, or pathological spindle rhythm, is a symptom of widespread encephalopathy.

Higher-than-30Hz High-Frequency Oscillations (HFOs): These can also be categorised as 80 to 200Hz(ripples) ,30 to 80Hz (gamma), and 200 to 500Hz (fast ripples). Gamma rhythm has been linked to the integration of several sensory areas in perception. HFOs have been the subject of substantial research across the globe, especially in relation to epilepsy. It is well known that epileptic foci produce extremely high-frequency activity. The location of an epileptic focus can also be determined by activity bursts at a comparatively 60 to 100 Hz lower frequency range. Interictal HFOs may serve as indicators of human brain tissue that is epileptogenic, according to the available evidence. The position, morphology, amplitude, continuity, frequency, symmetry, synchronisation of EEG waveforms can all be used to describe them. However, frequency is the way that is most usually used to categorise EEG waveforms; in fact, Greek numerals are employed to designate EEG waves in order to reflect their frequency range. The waveforms delta, theta, alpha, sigma, and beta are among the most frequently studied waveforms. The comparison of EEG bands is mentioned in the Figure 3.3.

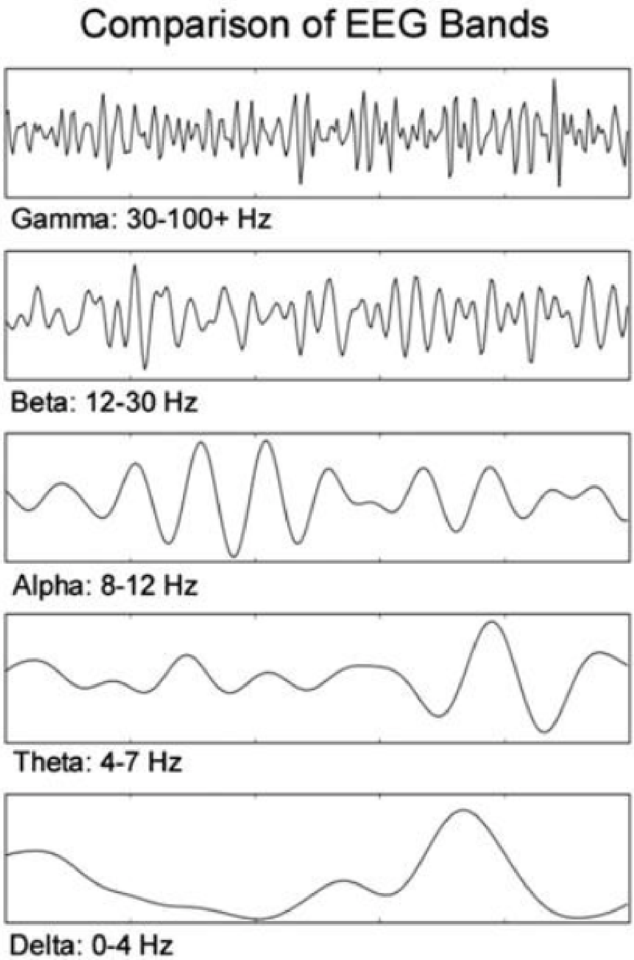

Figure 3.3: Comparison of EEG bands

3.1.3 Electrode Placement

The long-term recording of the brain's activity using a multitude of scalp electrodes is known as an EEG, or electroencephalogram. Diagnostic application frequently focus on the EEG or event-related potentials' spectrum content. The first examines possible variations that might be connected to a certain event, such as "button press" or "stimulus onset". "In latter, various cerebral oscillations often referred to as "brain waves are examined. These oscillations can be seen in the frequency range of EEG recordings.

Electrodes used to measure or record EEG ; however, placement of the electrodes cannot be done at random; there are a set of guidelines for that. The 10-20 system, also referred to as the International system of electrode placement (10-20), is a method that is commonly used to describe and implement scalp electrode placement.

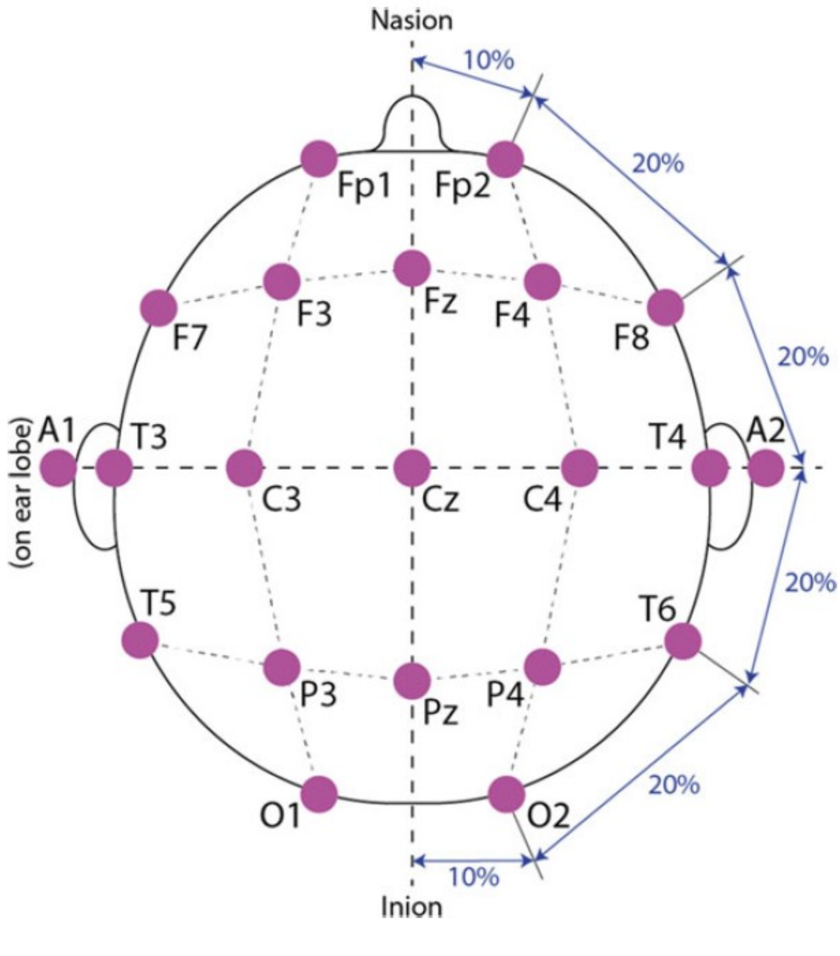

Figure 3.4: The standard 10–20 electrode system for electrode placement

The 10-20 system, which is mentioned in Figure 3.4 Ojala et al. established the local binary pattern (LBP) in 1996 for texture analysis, which they characterised as a grey scale texture measure generated from comparison with local neighbourhood. According to Guo et al. (2010), LBP has also been utilised for shape localisation, dynamic texture identification, and face recognition.1, is based on the relationship of an electrode's position and the region of the cerebral cortex beneath it. Each site is identified by a letter (denote the lobe) and a number or additional letter (denote the position of the hemisphere). The letters F, T, C, P, and O stand for frontal, temporal, central, parietal, and occipital. Even numbers (2,4,6,8) are associated with the right hemisphere, while odd numbers (1,3,5,7) are associated with the left. The z denotes the centre electrodes. Be aware that number decreases closer a position is near the centreline. The diagram of the ictal scalp EEG recording is mentioned in the Figure 3.5.

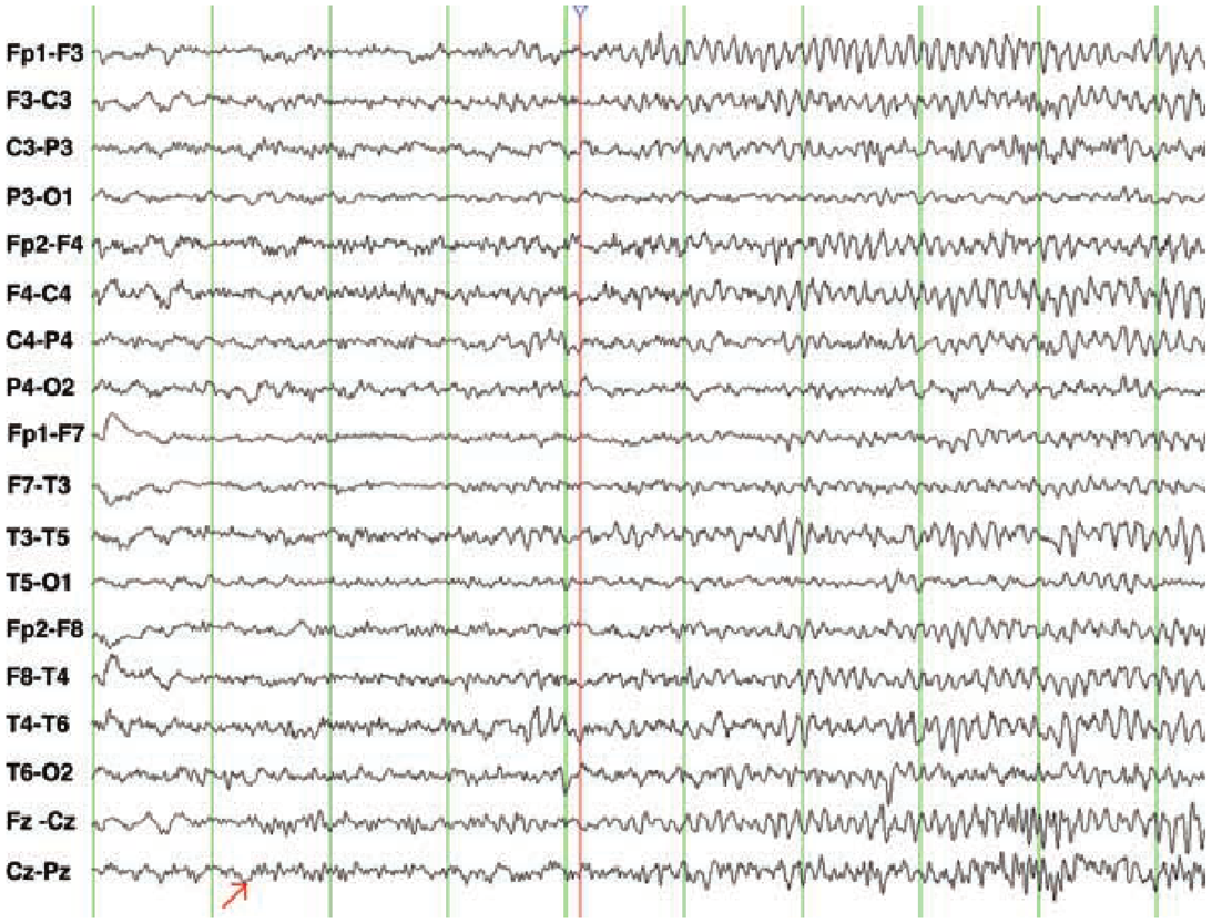

Figure 3.5: Ictal scalp EEG recording

3.1.4 EEG is used to Diagnose Epilepsy

EEG assists patients with epilepsy in identifying the type of seizure and epilepsy syndrome, which helps with antiepileptic drug selection and prognosis prediction. EEG results are essential to the multi-axial diagnosis of epilepsy because they help identify whether the seizure disease is localised or general, idiopathic or symptomatic, or a part of a specific epilepsy syndrome. There is some overlap in the clinical and electrographic symptoms of focal and general seizure disorders, and the condition known as normally have a high epileptic further obscures the distinctions. In the clinical situation, the conceptual distinction among minor and general seizures types is still useful. Based on the patient and witness accounts, the clinician will typically be able to determine the type of seizure.

After a clinical evaluation and a standard EEG, patients who present diagnostic or treatment challenges are often assessed with long-term video or ambulatory EEG. The following are some clinical uses for EEG monitoring:

- Paroxysmal neurological attack diagnosis
- Differentiating parasomnias from nocturnal epilepsy
- Psychogenic non-epileptic seizure diagnosis
- Seizure type classification
- IED or seizure frequency measurement
- Examination of potential epilepsy surgery candidates

Using available commercially spikes and seizure detection techniques can reduce the amount of information needed to be analyzed from long-term surveillance. Currently, methods that can detect non-linear variations in Dataset at least just few min before to a seizure are being investigated. These approaches' specificity and sensitivity have not been well examined, and it is yet unclear what role they will play in clinical settings.

3.2 Epilepsy

A brain illness called epilepsy is characterised by recurrent seizures. A seizure is typically described as an abrupt shift in behaviour brought on by a transient disruption in the electrical activity of the brain. The brain typically continuously produces minute electrical impulses that follow a predictable pattern. Chemical messengers known as neurotransmitters carry these signals along neurons, the network of nerve cells in brain, and throughout entire body. Recurrent seizures are a common symptom of epilepsy, which is characterised by an imbalance in the electrical rhythms of the brain. In individuals with seizures, abrupt and synchronised electrical energy bursts that may momentarily alter their awareness, movements, or sensations disturb the regular electrical pattern.

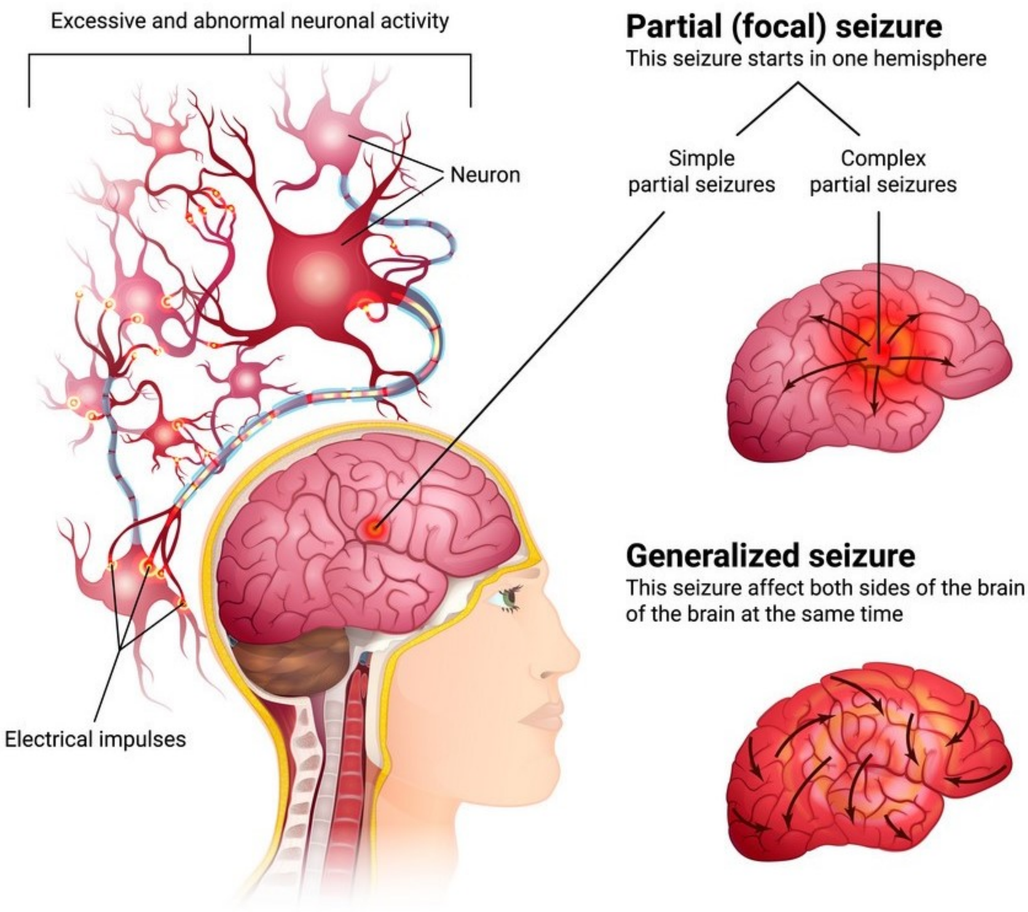

Figure 3.6: Types of epileptic seizures

When a person experiences at least two seizures that are not related to another known medical condition, alcohol withdrawal or extremely low blood sugar, an epilepsy diagnosis is typically made. The earliest symptoms of a seizure that originate from a particular part of the brain frequently correspond to that part's functions. Left half of the brain governs right side of the body, while the right half governs the left side. A seizure might start with a jerking of the left thumb or hand, for instance, if it originates on right side of the brain in the region that regulates thumb movement.The types of epileptic seizures is mentioned in the Figure 3.6.

Epilepsy doctors routinely reclassify seizure categories due to the wide range of seizures. Primary generalised seizures and partial seizures are the two main types into which seizures typically fall. The way they start varies across different categories. A vast electrical discharge that simultaneously affects both sides of the brain in primary generalised seizures' first stages. A small portion of the brain experiences an electrical discharge to start a partial seizure. Primary generalised epilepsy type of epilepsy in which both sides of the brain experience seizures at the same time. Partial generalised epilepsy, which is more likely to involve genetic causes than partial epilepsy, a disorder in which the seizures are caused by a specific region of the brain, is influenced by hereditary variables. Although some partial seizures are linked to head trauma, brain infections, strokes, or tumours, the cause is typically not recognised. The state of awareness (the capacity to react and remember) is one factor that is used to further classify partial seizures. There are many levels of consciousness impairment or preservation, despite the apparent difference.
In those who are prone to seizures, the following elements may raise the risk of seizures:

- Stress
- Lack of sleep or weariness
- Inadequate dietary intake
- Using alcohol or abusing drugs
- Refusal to take anticonvulsant medication as directed

About half of individuals who experience one seizure without a known cause go on to experience another, typically within six months. If a person has a known brain damage or other form of brain abnormalities, they are twice as likely to experience another seizure. There is a roughly 80% likelihood that the patient may experience additional seizures if they do have two. The likelihood that the patient would develop epilepsy is higher if the patient's first seizure happened as a result of a brain injury or infection than if it did not. Three million individuals in the United States and 50 million people worldwide are affected with epilepsy, according to the Epilepsy Foundation. The aetiology of epileptic seizures is unknown in 70% of cases, while they may be linked to heredity or brain damage. 10% of people will experience seizures at some point in their lives, according to the Epilepsy Therapy Project. More than three lakhs kids under the age of fifteen have epilepsy, and more than ninty thousand of these kids experience seizures that cannot be effectively treated. As people get older, especially as they experience strokes, brain tumours, or Alzheimer's disease—all of which can result in epilepsy—the incidence rate begins to rise. According to reports, the disorder affects more than 570,000 persons over 65. Epilepsy affects more men than women. Children and teenagers are more prone to suffer from genetically based or undiagnosed epilepsy. Epilepsy can occur at any age as a result of a brain injury or illness. According to the Epilepsy Foundation, after going five years or longer without a seizure while taking medication, 70% of children and adults with newly diagnosed epilepsy can be predicted to go into remission. In addition, 75% of individuals who are seizure-free while taking medicine can gradually wean themselves off of it. The National Institute of Neurological Disorders and Stroke estimates that 20% epilepsy sufferers experience intractable seizures, or seizures that do not improve with medication.

3.2.1 Risk factors for epilepsy

- Birth defects or low birth weight
- Birth-related trauma (such as lack of oxygen)
- Seizures in the first month of life congenital defects in the brain's structure
- Blood loss in the brain
- Abnormal brain blood vessel development
- Severe brain damage or brain oxygen deprivation
- Brain cancer
- Brain infections like encephalitis and meningitis
- Stroke brought on by artery obstruction
- Spinal palsy

- Mental illnesses
- Seizures that start a few days after a brain injury
- Family history of epilepsy or convulsions brought on by fever
- Alzheimer's condition (late in the illness)
- Long-lasting fever-related seizures
- Overuse of drugs or alcohol

Up to 25 percent of cases, according to the World Health Organization (WHO) Reliable Source, can be avoided. Although this does not apply to genetically based epilepsy, the WHO lists several steps that could help prevent epilepsy, such as:

- Avoiding brain traumas
- To decrease birth injuries, prenatal care must be improved.
- Ensuring access to suitable treatments and drugs to lower paediatric fevers and avoid febrile seizures
- Lowering cardiovascular risks from drinking, smoking, and obesity
- Treating infections and getting rid of parasites that can lead to epilepsy from infections of the central nervous system

3.2.2 Analysing EEG Signals for Epilepsy

The basic technique for locating ES activities in the brain is the analysis of the EEG signals. Over the past 20 years, numerous investigations have provided experimental proof that alterations in EEG's spatial and temporal properties precede seizures. It has also been extensively examined how the spike rate of EEG signals changes before epilepsy, and this evidence supports the presence of a pre-ictal state. However, the EEG states are not characterised by one or more distinct properties. It is currently unclear how to effectively categorise these situations and identify the distinct trait. Below is a quick description of phases.

Pre-ictal State: When a seizure is about to happen and becomes visible; it does not happen at other times. It might not always be visible to the naked eye. However, it would be able to forecast seizures within the certain range of values and would reflect changes in underlying signals. Pre-ictal states must be identified early enough in order to reduce the amount of time that patients experience erroneous warnings before they can be used clinically in a warning system.

Pro-ictal State: Seizures are more likely, but not always, to occur in this state.

Ictal and Interictal States: During a seizure, the EEG signals change to an ictal state, and the interictal state is the interval between two subsequent seizure onsets. The number of epileptogenic neurons, cortical area, and seizure duration can all change for the same person.

Post-Ictal State: This condition occurs after a seizure has take place

3.3 Local Binary Pattern

The LBP (Local Binary Pattern) texturing operator labels each pixel in an image by thresholding its immediate surroundings and treating the result as a binary number. The Local Binary Pattern, that threshold typically results according to the value of the current pixel, is a helpful texture descriptor for images. LBP descriptors are good in capturing the regional spatial characteristics and the contrasts in the gray scale image in a picture. Initiated as a texture descriptor, the Local Binary Pattern methodology has now been used in a number of different computer vision applications, including face identification, facial expression detection, modelling motion and movements, and medical picture analysis. For a wide range of applications, the fundamental LBP methodology has undergone several modifications and improvements, and LBPs have been suggested for signals processes other than image analysis.

Ojala et al. established the local binary pattern (LBP) in 1996 for texture analysis, which they characterised as a grey scale invariant texture measure generated from comparison with the local neighbourhood. According to Guo et al. (2010), LBP has also been utilised for shape localisation, dynamic texture identification, and face recognition. A two-dimensional image's pixels are given an LBP code for each one by thresholding the values of the surrounding pixels with the value of the centre pixel. The term "LBP" is expanded to encompass any circular neighbourhoods, regardless of the number of pixels. LBP's fundamental version only takes eight neighbours into account.The LBP operator marks each pixel as shown in Fig. by utilizing the values of the central pixel as a target value. 3.7. A pixel receives the value 1 if its value is greater or equal to the given threshold, else it receives the value 0. In order to provide the structure information surrounding the chosen pixel, the binary code is produced utilising these values. The decimal value corresponding to this binary code is substituted for each pixel value (Chatlani and Soraghan, 2010).

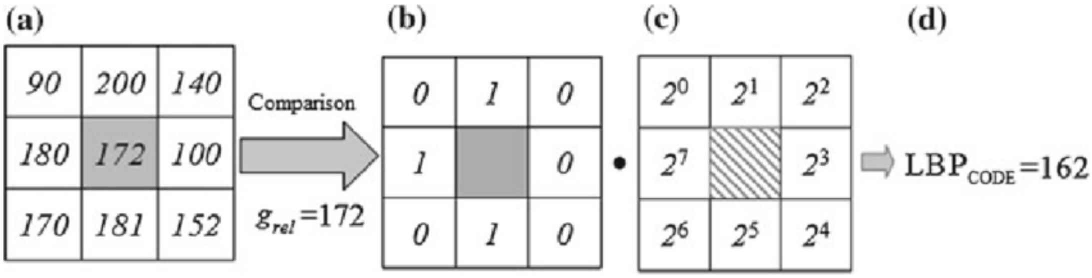

Figure 3.7: The LBP operator labels each pixel, value of the center pixel as a threshold value

The so-called uniform pattern is a helpful addition to the original operator that can be utilised to shorten the feature vector and build a straightforward rotation invariant descriptor. The fact that some binary patterns appear in texture images more frequently than others serves as the inspiration for this theory. If there are no more than two 0-1 or 1-0 transitions in a local binary pattern, the binary pattern is said to be uniform.

3.4 One Dimensional Local Binary Pattern(1D-LBP)

The ideal applications for 1D-LBP are non-stationary voice signals, which it was originally used for in (Chatlani and Soraghan, 2010). From of the 2D LBP implementation processes, it has been modified. The LBP code for a neighbor of sampled data is obtained by quantizing the nearby values against the core sample of a treatment window. This technique, which is done repeatedly to the entire signal, results in a region of the 1-D signal that has a simpler occurence histogram of LBP codes. The LBP procedure was applied to an EEG signal by taking into consideration N consecutive examples from the time - series data to calculate the numeric LBP values for the (N +1) / 2 th example, acting as the centre sample. While 1D LBP is mathematically formulated similarly to how pictures are represented, for EEG time - series data, the amplitude values at each test point rather than pixel value for the pixels in the grid is taken into account. This calculation is carried out consecutively throughout the whole time series, accounting for 9 successive samples at a period, producing an eight bit value for each sample. When this value is converted to decimal, the LBP values vary from 0 to 255. Figure 3.8 depicts the LBP application method to a 1D EEG time - series data signal. Pc and the subsequent 9 points (P1–P8) are taken into account. Figure 3.8 shows that P1 to P4 are smaller than Pc and give a return of $(0000)_2$, while P5 to P8 are larger than Pc and give a return of $(1111)_2$. Consequently, Pc's LBP value is $(15)_{10}$ or $(00001111)_2$.

Similar results are obtained for the complete signal's LBP values.
The associated LBP value for this is 240, which is equivalent to the binary number $(11110000)_2$. The LBP value is determined similarly for each sample. It is evident from EEG signal that the downward-moving signal is represented by the 9 consecutive samples chosen. If the signal exhibits a downward tendency, the LBP value will be repeated. Another example, at Pc = 25, depicts the lowest point for a period of 9 consecutive samples as the binary number $(11111111)_2$. The wave shape will also be shown by each LBP value. The original signal's many patterns can be captured thanks to the LBP value's singularity.

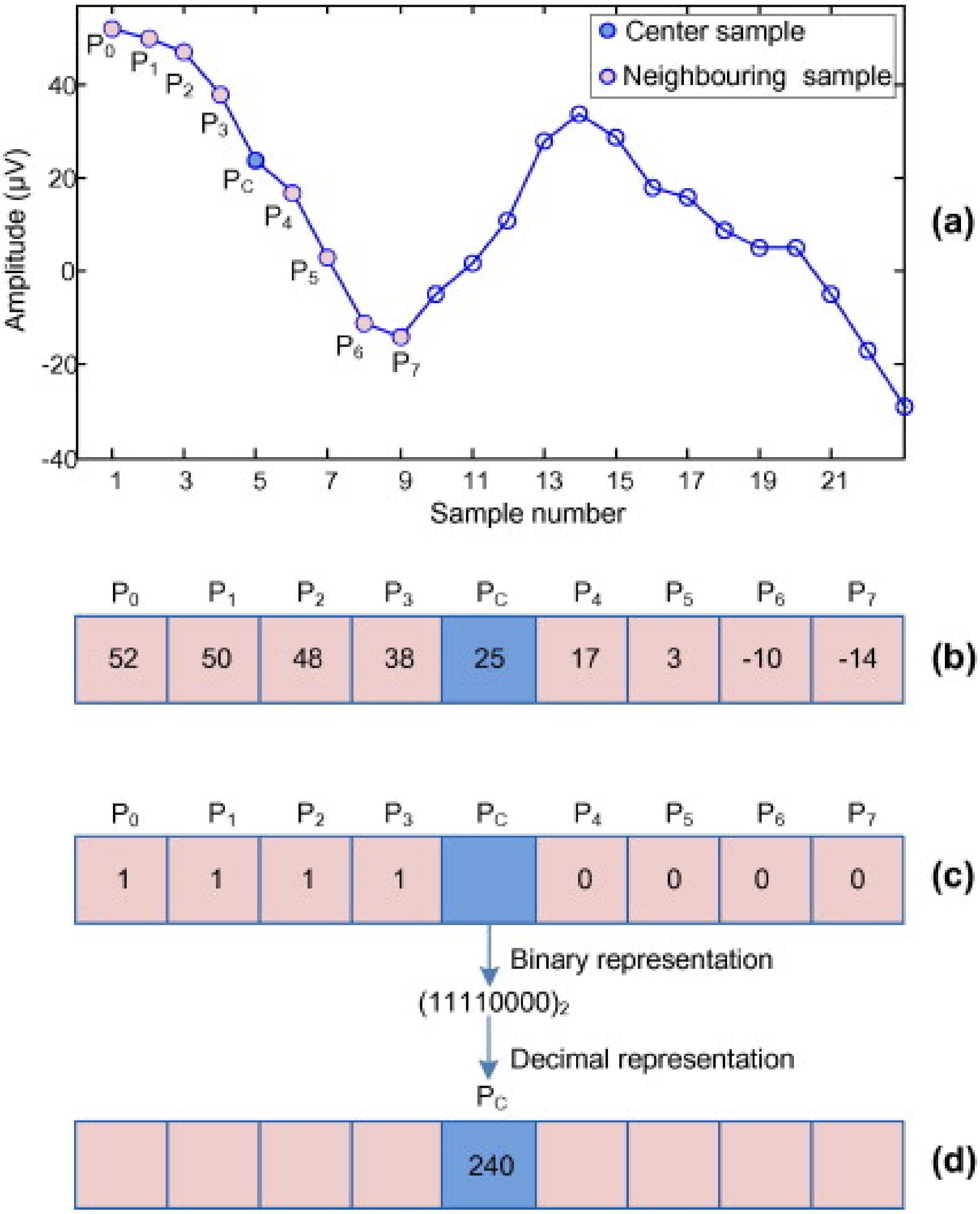

Figure 3.8: Implementation of a local binary pattern (LBP) on a segment of the patient 2's channel 1 EEG signal that was randomly chosen.

3.5 Data Preparation

We use the Children's Hospital Boston-MIT EEG collection recordings. This dataset contains 24 EEG recording data that were collected from 23 persons, including a subsequent non-annotated sample. The participants were split into 5 male participants between age of three and twenty two and Seventeen female subjects between ages of 1.5 and 19. A secondary sample was collected from subject 1 after 1.5 years, and according to current research, this was treated as a brand-new recording made from a separate subject, yielding 24 cases/subjects. Dataset was created with the intention of being stored as an ongoing EEG database. As a result, it includes comments on the start and end times of each capture for each subject. However, due to hardware restrictions, some samples have gaps ranging from 10s to several hours. The 10-20 system's 22 EEG-channel recordings are also present in certain people. By calculating the average across the 22 accessible channels, we added another channel for those subjects in order to be consistent with other examples. We took this action to guarantee that the dataset was consistent because removing one channel from the EEG spectrum's 23 channels might have eliminated significant seizure-related features.

We make the same assumptions as Daoud and Bayoumi's study, namely that each patient's pre-ictal state lasts for at least an hour prior to the start of their seizures, and that their brain's interictal state lasts for four hours prior to or following those seizures. The pre-ictal state of the brains is individual and can happen hours before the seizure encounter, therefore this criterion will ensure that we select the most appropriate samples to accurately portray the patient's interictal brain state. We selected pre-ictal and interictal data from each patient and combined them to create a 158,902-sample balanced dataset. There are 23 channels and a 10s duration for each sample. Because there were few pre-ictal signals in the original data, we employed 2s overlapping while windowing these signals to produce this balanced dataset . While our interictal data are non-overlapping 10s signals, the balanced dataset includes data from all of the Recordings that are presently available in the database.

3.6 Feature Extraction

Several properties, referred to as features, must be extracted from the data in order to distinguish between the seizures and non-seizure signals. After pre-processing, feature extraction comes before categorization as the most crucial phase. A waveform that is generally slower, with rising magnitude, spiky phases, and rhythmical wave characterises the bulk of epileptic EEG patterns. These structural alterations in the EEG signal can be measured using the RFEC (rising and falling edge count) and the SAD (sum of absolute difference)of the LBP value. The IQR (inter quartile range) of the pre-processed EEG signal for each epoch is calculated to accounting for dispersion in the EEG data.

3.6.1 Rising and Falling Edge Count

RFEC stands for rising and falling edge count per epoch. The large amplitude EEG waveform's tendency to slow down during seizures is assessed with the use of RFEC. The rising and decreasing edge of the EEG waveforms can be determined using the LBP value, which ranges from 15 to 240. The quantity of alternative runs with LBP value of 240 and runs of Fifteen is used to explain the RFEC of EEG data. The other LBP value that occur between continuously increasing or decreasing edges (runs of 15 or 240) are considered as 15 or 240, respectively, because our objective is to identify only the increasing and decreasing trend. The frequency of these following sequences show different numbers over an epoch for seizures and non-seizure EEG. This provides an epilepsy patient with a morphological feature that can be utilised to anticipate seizures.

3.6.2 Sum of Absolute Difference

The SAD between any two consecutive LBP values across a period is the total absolute differences between them. Absolute difference is determined to only occur when the LBP value changes, and it predominately happens when the original EEG signal's phase changes (from rising to dropping or vice versa). These values depend on the curve's smoothness. SAD therefore serves as an example of the original EEG signal's phase change, smoothness, and rhythmical character. The figure makes it evident that the non-seizure SAD values cluster in a distinct area than the seizure SAD values.It implies that SAD may be a distinguishing factor between seizure-related and non-seizure-related EEG data.

3.6.3 Interquartile Range

During a seizure, the EEG signal's amplitude's dynamic range normally rises, boosting the signal's dispersion. Using interquartile range (IQR), a trustworthy statistical dispersion parameter, this feature has been used to differentiate here between normal and seizure EEG data. The difference between both the higher and lower quartile values for a 1-second timeframe constitutes the IQR value. The IQR values for normal EEG are concentrated in the lower range because the dynamic range of the EEG data during a seizure is larger than that of normal EEG. IQR can therefore be utilised as a classifying attribute.

3.6.4 K-Nearest Neighbours (KNN)

The KNN uses the distance between features in a data set to classify the data into groups. When the distance inside the data is small, a group forms, however when the distance is large, multiple groups develop. K Nearest Neighbour is one of the best machine learning algorithms that is very straightforward, understandable, and versatile. KNN is utilised in a wide range of fields including politics, banking, healthcare, handwriting recognition, image recognition, and video recognition. Financial institutions will forecast a customer's credit rating in credit ratings. Banking institutions will forecast whether a loan is dangerous or safe at the time of disbursement. Political scientists divide prospective voters into two groups: those who will vote and those who won't. Both classification and regression problems are handled by the KNN algorithm. Based on a feature similarity method, using KNN algorithm. KNN is a popular classifier used in EEG research to categorise the EEG data. The non-parametric k-Nearest neighbour algorithm (k-NN) identifies objects based on comparing training and test sets of data. When a majority of an item's neighbours agree to classify it, the object is put into the category with the most support from its k nearest neighbours (k is a positive number). The value of k was changed to select the category that perfectly matches training and testing data. If k equals 1, the object is simply put into the class of closest neighbour.

K is the quantity of closest neighbours in KNN. The primary determining element is the number of neighbours. Generally speaking, if there are two classes, K will be an odd number. The algorithm is referred to as the nearest neighbour algorithm when K=1. The simplest scenario is this. Assume P1 is the point for which the label must provide a prediction. Finding the nearest point to P1 comes first, followed by identifying the label that belongs to that point. Assume P1 is the point for which the label must provide a prediction. The k points that are closest to P1 are found first, and points are then categorised based on the votes of their k neighbours. Each object casts a vote for the class they belong to, and the prediction belongs to the class with the most votes. To determine the distance between two points and find the ones that are closest to each other, you can use distance metrics such the Hamming distance, Euclidean distance, Minkowski distance and Manhattan distance. The basic steps of KNN are as follows:

- Measure the distance
- Find nearest neighbours
- Pick labels

There is no one number of neighbours that works best for all types of data sets, according to research. Each dataset has specific needs. When there are fewer neighbours, the noise will have a greater impact on the outcome, and there are more neighbours, the computational cost increases. While a smaller number of clusters will be the most flexibility fit, which will have low variance but high variation, a large number of neighbours will have a smoother boundary, meaning lower variance but higher bias.The KNN algorithm's benefits include its ease of implementation, robust behaviour in the presence of noisy training data, and increased effectiveness with larger training data sets.The diagram of the knn classifier mentioned in the Figure 3.9. The KNN algorithm has a few drawbacks: The value of K must be found repeatedly, and it can occasionally be complicated. For each training sample, the distance between each data point is calculated, which raises the computing cost.
K value determines how many neighboring points have to be considered, depending on the number of points and the distance between them, the method operates by calculating the distance

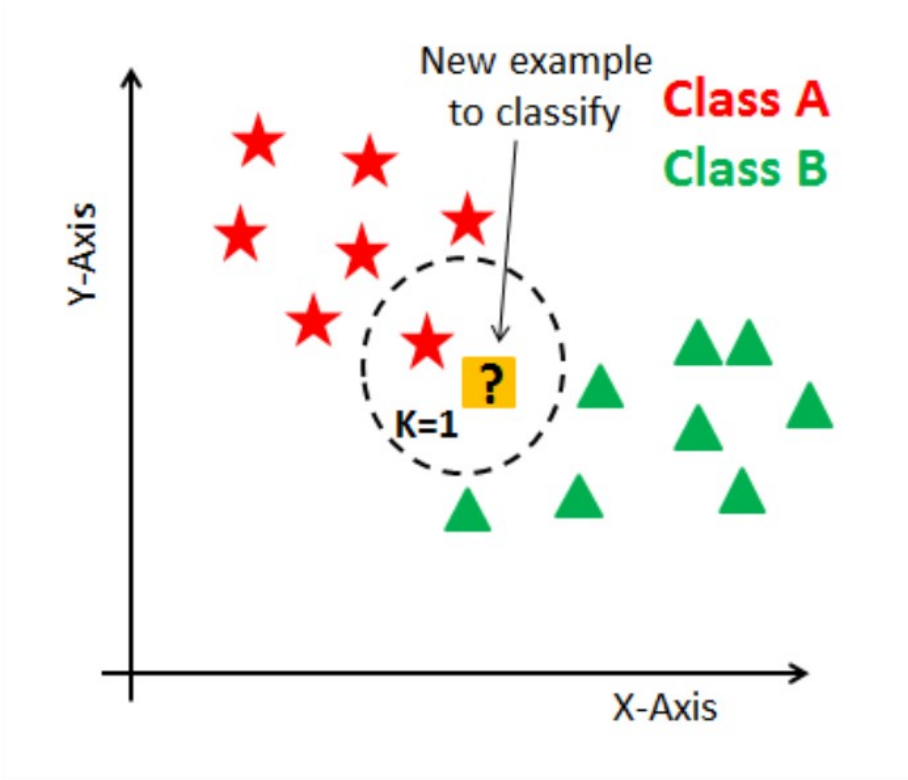

Figure 3.9: knn classifier

between these points' mathematical values. Figure 3.10 shows the working of KNN classifier. It determines the chance that each data point will be similar to the test data by first calculating the distance between each data point and the test data. The highest probability points are used for classification. The distance function can be Hamming, Minkowski, or Euclidean. Euclidean is used as a default method.

If $(\mathrm{x}_1, \mathrm{y}_1), (\mathrm{x}_2, \mathrm{y}_2)$ are the coordinates of two points, then the formula for Euclidean distance, D is

$$D = \sqrt[2]{(\mathrm{x}_1 - \mathrm{x}_2)^2 + (\mathrm{y}_1 - \mathrm{y}_2)^2} \tag{3.1}$$

The input x is then assigned to the class with the highest probability once the distance D has been calculated by the equation 3.1. The formula for probability is shown in equation 3.2:

$$P(y = j \mid X = x) = \frac{1}{K} \sum_{i \in \mathcal{A}} I\left(y^{(i)} = j\right) \tag{3.2}$$

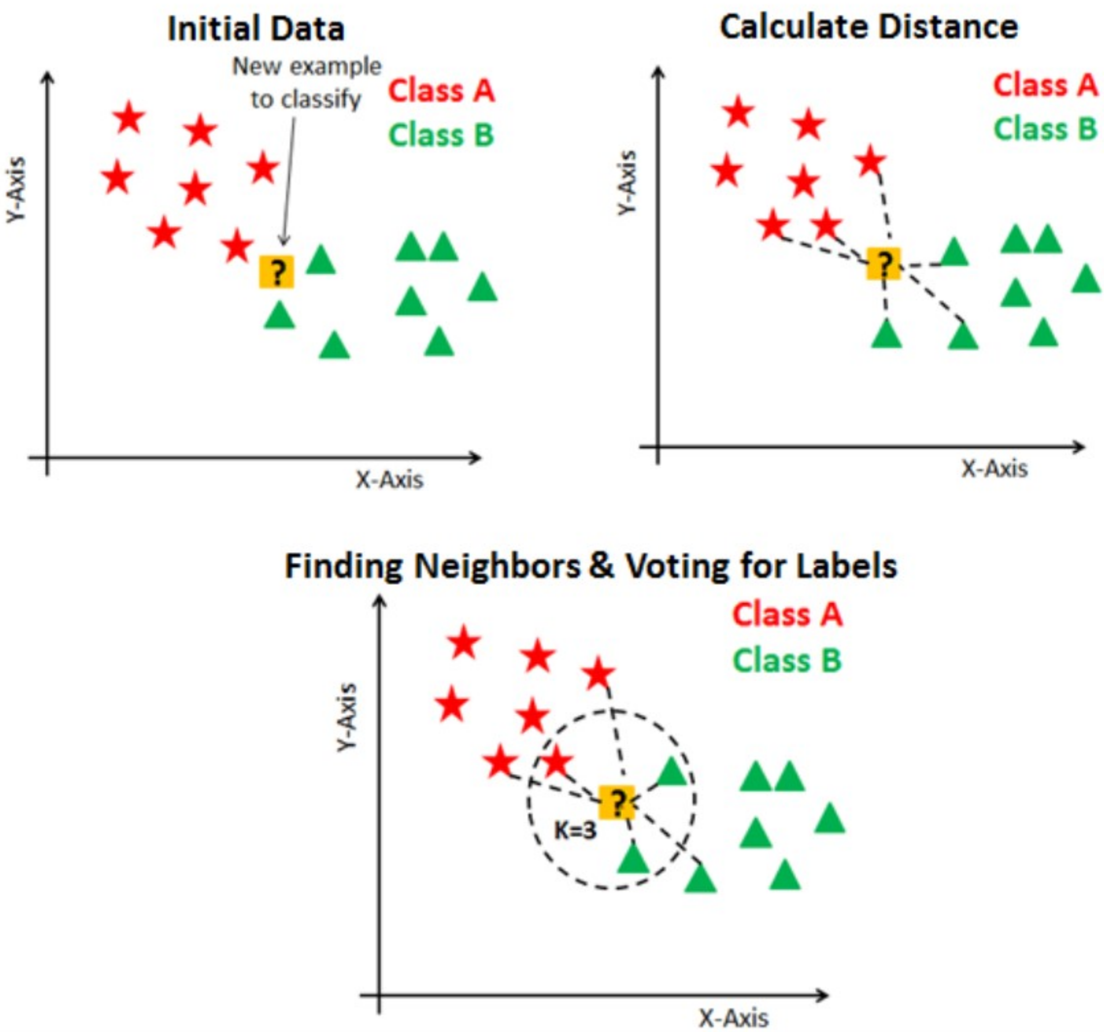

Figure 3.10: Calculate Distance and Voting for Labels

3.7 Performance evaluation

To evaluate the efficacy of a classification model, a N x N matrix known as a confusion matrix is utilised, where N is the total list of predefined classes. The actual objective values and those predicted by the computer vision model are compared in the matrix. This gives us a thorough grasp of the shortcomings of our categorization model and the types of errors it is committing.

Precision and sensitivity are equally crucial for information retrieval because it requires both. When compared to the negative class, it also prioritises the positive classes. In terms of precision and sensitivity, just the real positive (TP), false positive (FP), and false negative (FN) are considered; the true negative is not taken into account (TN).

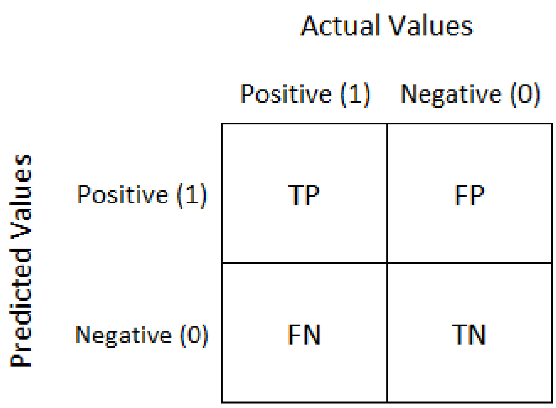

Figure 3.11: A 2X2 Confusion matrix showing the TN, TP, FN, FP

- True positive - Predicted class and actual class both are positive
- True negative – Predicted class and actual class both are negative
- False positive – Predicted positive but actual class is negative
- False negative - Predicted class is negative but actual class is positive.

Figure 3.11 is a 2x2 confusion matrix that just includes the TP, TN, FP, and FN for class 0. This allows for the calculation of numerous performance evaluation criteria. While sensitivity provides the projected positive percentage out of all the positive, precision determines the proportion of the genuinely positive out of all the better predicted. The harmonious mean of sensitivity and precision is known as the F1-score. Specificity and sensitivity reflect the possibility of incorrect negatives and false positives. The analytical analyses of precision and accuracy of a test demonstrate its essential reliability. The terms used to describe the origins of variability are not interchangeable. A test method may be specific (accurately repeated in what it measures) without being accurate (capable of measuring what it was intended to measure), or vice versa.

Measurements such as accuracy, sensitivity, specificity, f1-score, and precision have been used to validate the suggested emotion classification algorithm's performance. The mathematical representation of these parameters are shown in the equation 3.3 to 3.7

$$Precision = \frac{TP}{TP + FP} \tag{3.3}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{3.4}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3.5}$$

$$Specificity = \frac{TN}{FP + TN} \tag{3.6}$$

$$F1 - score = \frac{2TP}{2TP + FP + FN} \tag{3.7}$$

3.8 Summary

This chapter discussed about the method like LBP, proposed block diagram, 1D-LBP, and such as dataset preparation, feature extraction, KNN classifier and performance evalution etc, are studied in this chapter. The next chapter deals with the results obtained using this method.

Chapter 4

RESULTS AND DISCUSSION

In the previous chapter, the experimentation methodologies are mentioned along with the performance evaluation method. The accuracies of the different models and their performance for each classes are verified in this chapter. As mentioned above, mainly three experiments are conducted to understand the efficiency of the classifier with the proposed model.

1. Subject-specific

2. Subject dependent

3. Subject independent

In the former one, the channel data of that specific subjects are only considered for learning and testing, randomly chosen channels of all subjects are used for the training/learning stage and testing stage.

4.1 Performance analysis

4.1.1 Subject specific

After taking the readings from each classifier, evaluation of the model performance is done by using the result of subject (a randomly chosen subject), that is by analysing the confusion matrix obtained from the classifier and evaluated by finding precision, sensitivity, f1-score, specificity and accuracy of the classes. The classes 1 and 2 are the names given for in confusion matrix which represents the classes prediction, not predicted, respectively.

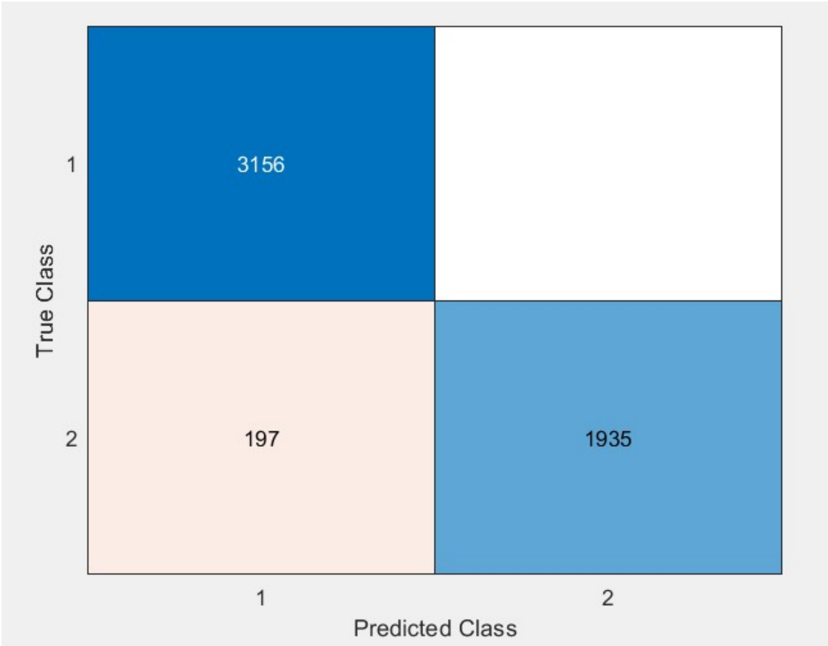

Figure 4.1: Confusion matrix of patient 1

From the obtained confusion matrix (Figure 4.1), the performance of the models are evaluated by finding precision, sensitivity, f1-score, specificity and accuracy of the classes, tabulated in the Table 4.1

While sensitivity provides the projected positive percentage out of all the positive, precision determines the proportion of the genuinely positive out of all the positive predicted. The harmonious mean of sensitivity and precision is known as the F1-score. Specificity and sensitivity reflect the possibility of false negatives and false positives. The analytical assessments of precision and accuracy of a test demonstrate its essential reliability.

Table 4.1: Performance analysis of Subject 5 based on the obtained confusion matrix.

Patient 1	Precision	1.00
	Sensitivity	0.94
	f1-score	0.97
	Specificity	0.91
	Accuracy	96.27
Patient 5	Precision	1.00
	Sensitivity	0.9
	f1-score	0.95
	Specificity	0.89
	Accuracy	94.67
Patient 14	Precision	1.00
	Sensitivity	0.86
	f1-score	0.93
	Specificity	0.90
	Accuracy	91.48
Patient 15	Precision	1.00
	Sensitivity	0.81
	f1-score	0.89
	Specificity	0.95
	Accuracy	96.13
Patient 22	Precision	1.00
	Sensitivity	0.86
	f1-score	0.93
	Specificity	0.82
	Accuracy	89.77

4.1.2 Subject dependent

After the classification with the data of 22 subjects, the obtained confusion matrix is used to evaluate the performance of the model on KNN classifier algorithm. The testing and training data used consist of all 22 subjects, therefore the result will be a generalised one compared with the previous method. Also, it is expected that the results will not reach upto the level of subject specific method because it deals with the data of a unique individual.

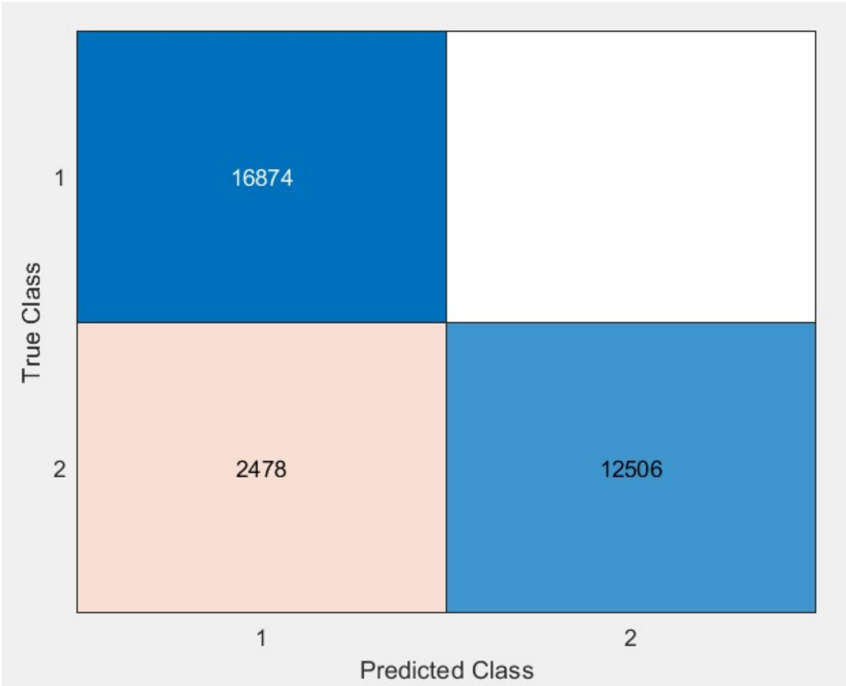

Figure 4.2: Confusion matrix of patient dependent

From the obtained confusion matrix figure 4.2, the performance of the models are evaluated by finding precision, sensitivity, f1-score, specificity and accuracy of the classes Table 4.2

Precision determines the fraction of the truly positive out of all the expected positive, whereas sensitivity gives the predicted positive percentages out of all the positive. The F1-score is the symmetrical average of sensitivity and precision. The likelihood of false negatives and false positives is reflected in specificity and sensitivity. Analytical evaluations of a test's precision and accuracy show that it is fundamentally reliable.

Table 4.2: Performance analysis of the models based on the obtained confusion matrix.

Patient Dependent	Precision	1.00
	Sensitivity	0.87
	f1-score	0.93
	Specificity	0.84
	Accuracy	92.22

4.1.3 Subject independent

Following classification using the data from 22 participants, the confusion matrix that was created is used to gauge how well the model performs using the KNN classifier technique. All 22 participants were included in the training and testing data, so the outcome will be more generalised than with the prior method. Additionally, because it uses data from a single individual, it is anticipated that the results may fall short of subject-specific methods.

The performance of the models is assessed by determining precision, sensitivity, f1-score, specificity, and accuracy of the classes from the resulting confusion matrix, figure 4.3. and is compiled in Table 4.3.

As we can see that by varying the number of classes may affect the accuracy of the model. Accuracy decreases as the number of classes is increased. The proposed technique is tested in 4 class model and obtained a very impressive result.

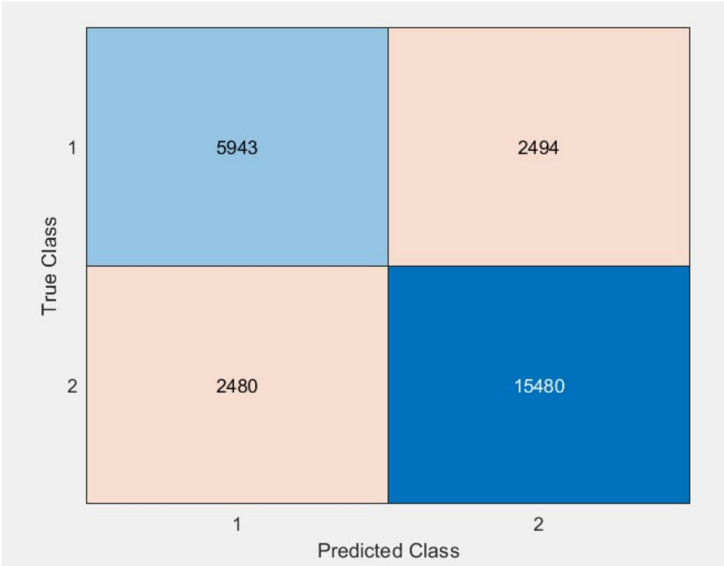

Figure 4.3: Confusion matrix of patient independent

Table 4.3: Performance analysis of the models based on the obtained confusion matrix.

Patient Independent	Precision	0.70
	Sensitivity	0.71
	f1-score	0.70
	Specificity	0.86
	Accuracy	81.16

4.2 Summary

This chapter verified the result obtained from the different experimentation conducted. Three methods are performed which is subject specific and subject dependent, subject independent KNN classifiers are considered in these methods. Performance of the model is also analysed using various parameters and the comparison of the proposed model with previous works is tabulated to highlight the upper-hand of the proposed work. Each model selected in this work is comparable with any previous work as it can provide a better performance in categorization task.

Chapter 5

CONCLUSION AND FUTURE SCOPE

The findings of studies into seizure prediction conducted over the previous 25 years have solidly laid the groundwork for direct therapeutic applications to epilepsy. The timing of an intervention is essential for the successful control of seizures, and as seizure prediction algorithms also can deliver this crucial information online and in real time, they will likely play a significant role in the development of epilepsy treatment in the future. The suggested approach ignored the manual feature extraction method and the feature that was extracted in order to quantify the data. Compared with other works, the proposed model gives good performance and accuracy in the considered problem. For the proposed model, the performance of the machine learning algorithm with the dataset were analysed and selected classifier KNN is used. The results obtained were impressive and very much high compared with other works. The average accuracy of 96% for KNN is obtained for subject specific experiment. For the subject dependent test, the best accuracy of 92.22% is obatined for KNN. The average accuracy of 82% for KNN is obtained for subject independent experiment.

The project's future goals provide determining the best feature-classifier combination possible in order to further enhance performance.

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List of Publications

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