

An overview of machine learning methods in enabling IoMT-based epileptic seizure detection

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Abstract

The healthcare industry is rapidly automating, in large part because of the Internet of Things (IoT). The sector of the IoT devoted to medical research is sometimes called the Internet of Medical Things (IoMT). Data collecting and processing are the fundamental components of all IoMT applications. Machine learning (ML) algorithms must be included into IoMT immediately due to the vast quantity of data involved in healthcare and the value that precise forecasts have. In today's world, together, IoMT, cloud services, and ML techniques have become effective tools for solving many problems in the healthcare sector, such as epileptic seizure monitoring and detection. One of the biggest hazards to people's lives is epilepsy, a lethal neurological condition that has become a global issue. To prevent the deaths of thousands of epileptic patients each year, there is a critical necessity for an effective method for detecting epileptic seizures at their earliest stage. Numerous medical procedures, including epileptic monitoring, diagnosis, and other procedures, may be carried out remotely with the use of IoMT, which will reduce healthcare expenses and improve services. This article seeks to act as both a collection and a review of the different cutting-edge ML applications for epilepsy detection that are presently being combined with IoMT.

Keywords Internet of Things \cdot Internet of medical things \cdot Healthcare \cdot Machine learning \cdot Epileptic seizures

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1 Introduction

Over the past several years, there has been a lot of excitement about the Internet of Things (IoT) in the field of healthcare technology, which is called the Internet of Medical Things (IoMT). The healthcare industry is extremely practical, and IoMT offers a wide range of options to improve it. A wide range of modern medical sensors and gadgets may communicate through different networks, giving access to crucial data regarding patients' ailments. Then, by having a better understanding of the symptoms, this information may be utilized to anticipate disease and recovery, monitor patients from a distance, and overall enhance the diagnostic and treatment process by increasing automation and portability. IoMT-based epileptic seizure detection is one particular instance of health care [1, 2].

One of the most prevalent neurological disorders is epilepsy, which tends to impact the human brain by causing unpredictable and spontaneous seizures. A number of causes have recently been put up. The main factor is the brain's internal electrical activity being disturbed. This could be caused by a number of factors, including abnormalities, low blood sugar, and a shortage of oxygen during childbirth [3, 4]. Around 50 million people around the world possess epilepsy, and 100 million have had it at least once throughout their lives [5]. The primary characteristic of this condition is recurrent seizures, which are caused by an electrical imbalance in the brain. Typically, it causes bodily parts to shake and can even result in fainting. The human brain's typical neural activity pattern is disrupted by epilepsy disease, which causes a rise in important clinical symptoms such as unusual sensations, emotions, abnormal behavior, and memory loss. Even routine actions like driving a car, swimming in a pool, crossing a road, and so forth become so challenging for people with epilepsy that they frequently result in major injuries, sometimes even catastrophic ones. For an epileptic patient, losing consciousness could be fatal. They have a lower quality of life and must rely exclusively on their caregivers for the remainder of their lives. To avoid any form of injury or accident caused by an unclear seizure, this seizure must thus be watched over and identified before it occurs. In order to prevent difficulties connected to seizures, researchers are particularly interested in seizure prediction systems [6]. The seizure recording is shown in Fig. 1.



Fig. 1 A general methodology of epileptic seizure recording

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As shown in Fig. 1, recordings are frequently used to detect epileptic seizures using the electroencephalography (EEG) technique. Analysis of EEG waves is crucial for identifying neurological conditions like epilepsy. Electric signals from EEG monitors are used to capture the neural activity of the human brain. The brain's electrical activity is analyzed by EEG, which creates patterns to categorize it as normal or abnormal. EEG typically captures the patterns of brain waves and a piece of equipment that is implanted, such as electrodes positioned on the head, collects the signals [7].

Based on the symptoms, neuro experts have divided seizures into two principal classes: partial seizures and generalized seizures [8, 9]. The symptoms of a partial seizure, which are mostly brought on by damage to the cerebral hemisphere, can be utilized to define it. Additionally, there are two basic categories into which a partial seizure can be classified: simple-partial and complex-partial. In the case of simple-partial, a human appears alert and can typically speak, whereas the patient acts strangely in the complex-partial, becomes disoriented, and frequently chews and mutters. A generalized seizure comprises two main components as well. While conclusive seizures are challenging to diagnose because they lack motor signals, apparent motor signs can be used to rule out conclusive seizures. The person is unable to move or say anything other than to stare [10]. Figure 2 lists the different seizure types and their subcategories.

Because EEG data is a time series, epilepsy is typically detected using timeseries analysis techniques that include both linear and nonlinear methods. However, since it takes neurologists a long time to review, the manual interpretation of EEG data derived from the recordings of EEG signals from a single patient is a very difficult and time-consuming process. The frequency, waveform, and amplitude data reflected from the EEG signals are examined and evaluated by the neurologists since the EEG signals during a seizure would display specific indicators such as spikes [11]. The accurate detection of ES, which relies on physicians' visual inspection, is a procedure that is typically time-consuming, demanding, and fraught with the danger of human mistakes.

The following is a list of the manual epilepsy diagnosis shortcomings in more detail:



Fig. 2 The illustration of seizure types and their sub-types

- It makes clinical diagnosis more arbitrary and susceptible to error because it necessitates the doctors to have extensive clinical diagnosis expertise and professional skills. Additionally, based on their individual experiences, various physicians may come to different judgments about the same EEG data.
- EEG signals possess just a low signal-to-noise ratio (SNR) because they are weak electrophysiological signals, which makes them susceptible to interference from noise. EEG signals surrounded by noise may exhibit waveform variations that make diagnosis challenging [12].
- Epilepsy is diagnosed using a substantial amount of EEG data. The EEG signals are typically captured simultaneously with video signals in the clinical setting to aid in diagnosis utilizing some behavioral indicators, which adds to the clinicians' workload. Making a diagnosis from patient EEG patterns requires clinicians to spend at least 16 h [13]. The clinician's evaluation of the EEG signals is greatly impacted in a clinical context by interruptions and a severe workload, which may result in incorrect diagnosis [10].

Several academics have suggested applying automated approaches to detect epileptic seizures to get over these limitations of the conventional process. So, it's important that epilepsy seizures can be found automatically in a therapeutic setting, and there should be more progress in automated classification methods that analyze and measure EEG patterns. ML systems are one of the most common methods used to identify epilepsy episodes. Useful conclusions can be drawn from the collected data with the help of these programs. Even though ML models can deliver high precision with proper training, doing so is typically challenging. The benefits of using ML-based tools are numerous. Through deductive reasoning, they can help clinical practice with risk assessment and therapy planning after being taught on big quantities of data, or training data. These automated systems are preferable to human labor because they perform routine tasks more quickly and with fewer mistakes. The ability of ML algorithms to handle large amounts of biological data and identify specific patterns and changes implicated in different illnesses has the potential to greatly expedite the development of new treatments [14].

The IoMT is having a significant impact on the healthcare industry by offering valuable solutions for a variety of applications in medicine and healthcare, including remote medical treatment, exercise programs, children's and elderly care, and the detection and prognosis of various historical illnesses like epilepsy, Alzheimer's, and schizophrenia. Utilizing wearable devices, IoMT technologies offer continuous and immediate personal medical monitoring [15, 16]. These technologies are also used to collect and send epileptic patients' EEG signals. In addition to such methods, machine learning techniques offer encouraging options for accurate seizure stage detection from incoming EEG signals.

Today, the IoMT, along with ML methods and the resources of cloud computing, have become powerful technologies that can help with a variety of issues in the healthcare sector [17, 18]. The limits of traditional methodologies have recently been overcome using ML techniques. It is a superb option for identifying epileptic episodes due to its capacity for obtaining pertinent information for identifying and categorizing them and its exceptional qualities [7]. The purpose of this study is to highlight the key developments in the application of ML techniques for the prediction of epileptic seizures based on the IoMT. We'll give a quick overview of neuroscience, the many technologies used to research the brain, and how they've been or might be applied to epilepsy prediction.

In summary, this article has the following contributions:

- 1. A review of many well-known ML/DL techniques has been given, with an emphasis on their application to IoMT-based epileptic seizure detection.
- 2. Describes several techniques for extracting features.
- 3. Provides an overview of the dominant methodology used in EEG data analysis.
- 4. Describes the various EEG signals that may be recorded.
- 5. An in-depth analysis of the most used EEG open-access datasets, along with detailed information on the participants who contributed to these datasets using a variety of methods.
- 6. Proposed an IoMT framework for automated epilepsy seizure detection and classification using ML. The proposed model is split into three layers: the device layer, which includes the Bluetooth-enabled EEG headset; the edge/fog layer, which includes the computational services; and the cloud layer, which includes cloud storage and other services. The critical health circumstances of an epileptic patient necessitate IoMT to respond quickly and with a reasonable amount of processing power. Latency is decreased when using the suggested edge/fog-IoT architecture instead of a cloud-based solution. In this framework, faster reaction times are achieved with less processing power and storage space, which is what edge/fog computing offers.
- 7. We provide an overview of the challenges that exist in creating autonomous models for detecting seizures by doing a comprehensive analysis of the available research.
- 8. Identifies the literature's shortcomings and offers opportunities and ideas for future study to aid researchers in having an effect.
- 9. This comprehensive study will help scientists find and use the best ML models using feature extraction approaches to further their work in detecting epileptic seizures.

Table 1 provides a comparison of this study with earlier survey studies.

This study is structured as follows: Sects. 2, 3, and 4 provide short overviews of the fields of neuroscience, brain-computer interface, and EEG signals, respectively. In Sect. 5, we explain the terms and give descriptions of some research datasets that are freely accessible to the public. In Sect. 6, we'll quickly go through how to analyze epileptic seizures from an EEG signal to better understand epilepsy. In Sect. 7, the requirements are laid out, along with a generic plan for finding seizures and an explanation of each step. Detection of epileptic seizures using several ML/DL classifiers is covered in Sect. 8, along with a thorough comparison of these methods. In Sect. 9, we give a quick overview of the IoMT and talk briefly about how it can be used in the healthcare field, especially in

Refs.	Year	Seizure detection	Seizure predic- tion	EEG analy- sis technique	Features	ML	DL	SP	IoT
Khansa et al. [11]	2019	X	1	1	1	1	Х	Х	X
Kuldeep et al. [17]	2019	1	Х	Х	1	\approx	1	Х	1
Supriya et al. [19]	2020	1	Х	1	Х	1	Х	Х	Х
Mohammad et al. [9]	2020	1	Х	Х	1	1	Х	Х	Х
Rasheed [20]	2020	Х	1	1	1	1	Х	1	Х
Athar et al. [21]	2021	1	Х	1	1	Х	Х	Х	Х
Bulusa et al. [22]	2021	Х	1	1	1	Х	1	Х	Х
Shoeibi [23]	2021	1	Х	1	1	Х	1	Х	Х
Banu et al. [6]	2022	Х	1	Х	Х	Х	1	Х	\approx
Ijaz et al. [24]	2022	1	Х	Х	1	1	Х	Х	Х
Milind et al. [25]	2022	Х	1	\approx	1	1	Х	Х	Х
Mohammed et al. [26]	2022	1	Х	1	1	1	Х	Х	Х
Souleyman et al. [27]	2022	1	Х	Х	Х	Х	Х	Х	1
This paper	2023	1	Х	1	1	1	✓	Х	1

Table 1 A comparison of this study with earlier survey studies

DL: deep learning, SP: signal processing, X: not discussed, \checkmark : discussed, \approx : partially discussed

ML-based epilepsy detection. At the end of Sects. 10, 11, and 12, we give a discussion and analyze the challenges encountered in the prior works, and we draw attention to the opportunities and future directions that exist as a result. Then, Sect. 13 concludes the paper.

2 Neuroscience

The comprehensive study of the brain is known as neuroscience. It combines a variety of disciplines, such as neurophysiology, which studies the brain's electrical characteristics, and neuropsychology (the branch of psychology that aims to study how the brain's neural networks contribute to our ability to think and reason); both neurochemistry (in which chemists study the brain's chemical characteristics of communication) and neuroanatomy (a domain dedicated to neuroanatomists' exploration of the human brain) [28]. There are many subfields within neuroscience, including but not limited to, cultural neuroscience, computational neuroscience [11], developmental neuroscience, clinical neuroscience, cognitive neuroscience [29], and molecular neuroscience, to mention a few.

Neuroimaging employs a variety of techniques to directly or indirectly picture the anatomy and operation of the central nervous system. Imaging techniques can be divided into two major categories: structural imaging, which deals with anatomy, injury or pathology; and functional imaging, concerning metabolic processes, cognition, or pharmacology. The following are examples of popular and prominent neuroimaging techniques: computed tomography (CT), which generates a sequence of cross-sectional images of the brain by computing the amount of X-rays that were absorbed; brain magnetic resonance imaging (MRI) scans that look at the structure of the brain to see whether there's anything wrong with it; in order to see larger structures in the brain, diffusion MRI tracks the movement of water molecules; cognitive neuroimaging, or functional MRI, which looks at how the brain works, positron emission tomography (PET) that produces a picture of the binding of active molecules, and magnetic resonance spectroscopy (MRS) imaging that studies metabolic changes in brain strokes, and seizures. Functional imaging techniques like EEG can be used to measure the electrical activity of the brain under various physiological conditions.

3 Brain-computer interface

A brain–computer interface (BCI) is a very effective method of transmitting mental processes to a digital device [30]. Since BCI encompasses aspects of both neuroscience and computer science as well as sophisticated signal processing, it is best approached as a multidisciplinary field of research. The medical and technical communities make extensive use of BCIs in a variety of settings.

For the purpose of studying neurological illnesses, neuroimaging methods are employed to capture brain activity. Many different types of BCIs, some invasive, some semi-invasive, and others completely noninvasive, are available for collecting brain signals. In invasive, microelectrodes are surgically placed to collect data from the brain's cortex. Semi-invasive techniques include the placement of electrodes on the brain's exposed surface rather than invading the skull to record electrical activity via the brain's arachnoid or dura. Electrodes placed on the scalp may assess the brain's electrical activity in a noninvasive manner. Neuroimaging modalities are shown in Fig. 3.

Although the signals obtained by invasive BCIs are of great quality, the act of implanting electrodes into the brain is both intrusive and costly. In the same way, as ECoG requires a craniotomy for electrode implantation, it can only be utilized in cases when brain surgery is clinically indicated. It is less affected by noise and artifacts and has a higher spatial resolution. Metabolically based positron emission tomography (PET), (fMRI) functional magnetic resonance imaging, and (fNIRS) functional near-infrared spectroscopy and electrophysiologically based EEG or MEG [30]. Table 2 provides a comparison of common types of noninvasive neuroimaging.



Fig. 3 Neuroimaging techniques

Technique	fMRI	fNIRS	PET	MEG	EEG
Category	Metabolic	Metabolic	Metabolic	Electrophysiological	Electrophysiological
Activity measured	Blood flow changes in the brain	Aggregation degree of Hb and deoxy-Hb	Chemical changes occur- ring in the brain	Electromagnetic changes from brain activity	Voltage fluctuations of neurons
Measurement	Indirect	Indirect	Indirect	Direct	Direct
Spatial resolution	High	Low	High	Low	Low
Temporal resolution	Low	Medium	Low	High	High
Portability	Low	High	Low	Low	High
Cost	High	Low	High	High	Low

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4 EEG signals

Identifying epileptic episodes in EEG recordings is a common use of electroencephalography (EEG). When compared to other neuroimaging modalities, it was popular because of its inexpensive cost and high portability. EEG is trustworthy for real-time applications due to its capacity to obtain readings every millisecond. Hans Berger created the EEG in 1923 as an imaging technique that is noninvasive for studying the brain. Electrodes placed on the scalp are a common implant used to gather data for electroencephalography, which records the patterns of brain waves [7]. Wired and wireless methods can be used to collect EEG signals, and these signals can be measured using electrode counts ranging from 1 to 256. Wet and dry electrodes are the two types of electrodes used to record brain impulses. If you're utilizing silver chloride or silver wet electrodes, the electrolyte gel will lower the impedance between the electrode and your skin, making the treatment more comfortable. If the impedance is low, it means the EEG signal is of good quality. Dry electrodes come in three varieties: insulating, non-contact, and contact [31].

EEG has a lower spatial resolution than functional MRI but offers a greater temporal understanding of brain activity. For analyzing EEG signals, five frequency bands-Delta (up to 4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–26 Hz), and Gamma-are typically examined (26–100 Hz). Table 3 summarizes various frequency ranges and how they relate to human behavior. The frequency range of EEG signals is from 1 to 100 Hz, while the EEG range is from 10 to 100 μ V. When using EEG data to identify a condition or decode brain activity, one must first extract features from the raw data or use its spectrum information by performing the wavelet transform (WT) or Fourier transform (FT). While deep learning techniques have been shown to be useful at automatically extracting features for training, an ML-based classifier is trained to utilize these derived features or adjusted raw data.

Depending on where the reference electrode is placed, there are two different ways to capture an EEG [11].

- 1. Bipolar montage: By placing electrodes on the scalp's electrically active areas, a voltage difference may be recorded during a bipolar montage.
- 2. Monopolar montage/unipolar montage: The referring electrode in a monopolar montage is positioned in a location that does not conduct electricity, while the

Frequency bands	Frequency range (Hz)	Relation to human behavior
Delta	1-4	Especially at the deepest stages of sleep, both in youngsters and in healthy adults
Theta	4-8	High-theta rhyme-waking adults show erratic cognitive activity
Alpha	8-12	Usually present in the posterior brain of healthy, calm people
Beta	12-26	Found in nervous, alert people's frontal lobes
Gamma	26-100	characteristic of persons who are worried, happy, or self-aware

Table 3 EEG frequency bands and associated research on how the brain works

other electrode is positioned in a region that is electrically active (e.g., an ear lobe).

Most often, electrodes are attached to the scalp, which is referred to as scalp EEG, in order to record EEG data. Due to the great distance between the electrodes and the neurons inside the skull, the recorded signals get distorted, which is the primary downside of scalp EEG. By inserting the electrodes on the brain's exposed surface, intracranial electroencephalography (iEEG) signals are captured with improved signal quality with respect to amplitude and distortion. The use of EEG for ES prediction study is highly recommended due to a number of its properties. The comparatively inexpensive price of the hardware is another important advantage, which enables it to be utilized for a lot more patients, and long-term storage of records is recommended. This feature, along with its capacity to monitor the many changes that epilepsy causes in the brain, is what makes it such a powerful tool. Numerous other methods, like fMRI or MEG, call for heavy, immovable equipment, driving up the price to a very high level. The My Seizure Gauge represents a good instance of a wearable sensor designed to serve like a specific advising device among the practical methods for forecasting epileptic seizures now available [32]. This machine can record scalp EEG, intracranial EEG, electromyography (EMG, which records the electrical activity of skeletal muscles), photoplethysmography (PPG), electrodermal activity (EDA), electrocardiography (ECG, which records the electrical activity of the heartbeat), and breathing.

5 Datasets publicly accessible

A dataset is essential for data scientists and academics to assess the effectiveness of their recommended models. Similar to this, we must record the brain's electrical activity to identify the seizures of epilepsy. The most commonly used technique for observing the neural activity of the brain is EEG recording. This EEG recording data are necessary for machine learning techniques to investigate novel seizure detection methods, such as seizure localization, monitoring patient seizures, and quick seizure detection. In order to evaluate and compare the outcomes, a standard reference point is required, and here is where open-source datasets shine. The most well-known datasets that are frequently utilized in epilepsy research be broken down into the subsections below. Figure 4 shows the proportion of different datasets utilized by academics and scholars.

5.1 CHB-MIT—EEG dataset

This data collection was compiled by researchers from the Massachusetts Institute of Technology and Children's Hospital Boston and is now hosted at the PhysioNet data repository [33, 34]. The PhysioNet server is communicated with through the Cygwin software, which makes collecting it easy. For each CHB patient, it lists the quantity of seizure and non-seizure EEG recording files [35]. The dataset is made up





of 23 patients: 5 men (3–22 years old) and 17 women (1.5–19 years old). The European Data Format (.edf) files for each patient's seizures and non-seizures clearly display the spikes with the beginning and ending times of seizures when viewed in a "EDFbrowser". EEG signals were recorded from a number of channels placed on the scalp in line with the 10–20 Worldwide System, although the primary datasets are all in 1-dimensional format. All of the signals in this dataset were captured at a frequency of 256 Hz.

5.2 Fribourg—EEG dataset

This dataset comprises invasive EEG recordings from 21 patients with refractory focal epilepsy before surgery at the University Hospital of Fribourg. The signals were gathered during epilepsy monitoring prior to surgery. In order to offer immediate recording from the focus region, eliminate distortions, and increase the signal-to-noise ratio (SNR), depth electrodes, strip, and intracortical grid were utilized [36].

5.3 Bonn University—EEG dataset

There are five distinct datasets in the overall dataset, which have been named (A–E), each with recordings of 100 single channels, each with a period of 23.6 s, and obtained using the typical 10–20 electrode insertion method. An identical 128-channel system for the amplifier is applied to each signal recording [37].

5.4 Bern Barcelona—EEG dataset

This dataset included 3750 focal and 3750 non-focal bivariate EEG files from EEG recordings made by five patients with a drug-resistant form of temporal lobe epilepsy. After surgery, three patients' seizures stopped entirely, while two patients continued to have just auras. Deep electrodes and an intracranial recording strip were used to capture the multichannel EEG data. By using 10-to-20 placement, the

electrodes were placed. Depending on whether more than 64 channels were used to record the EEG signals, they were either sampled at 512 Hz or 1024 Hz. They were able to determine the specific areas of the brain for each of the five patients' seizures based on the intracranial EEG recordings [38]. The seizure localization task can be accomplished with this dataset.

5.5 Kaggle—EEG dataset

The EEG dataset is part of a competition hosted by the American Epilepsy Society to identify seizures caused by epilepsy. It contains intracranial EEG data from two individuals and five dogs that experienced 48 seizures during a period of 627 h. Dog EEG waves were captured using 16 implanted electrodes, with 400 kHz samples. Comparatively, 15 deep electrodes and 24 subdural electrodes were used to record the EEG signals of patients 1 and 2, and the signals were sampled at 5 kHz [36].

5.6 Zenodo—EEG dataset

Helsinki University Hospital collected multichannel EEG data from 79 human babies for an average of 74 min. From the 460 seizures that were documented by three specialists [39], 39 newborns were diagnosed with epileptic seizures, whereas 22 were found to be seizure-free.

The further details for each dataset are included in Table 4.

6 Analyzing EEG signals for epilepsy

Analysis of EEG signals is the main way that ES activities are found in the brain. An essential clinical device for separating ES from non-ES is EEG recordings. Comparison of pre- and post-episode symptoms of epileptic seizure phases, as well as pre- and post-seizure times, may be distinguished using EEG data. A quick description of these phases is given in the following subsections [40, 41].

Dataset	Recording	Sampling frequency (Hz)	No. of patients	No. of seizure	Time (h)
CHB-MIT [33, 34]	Scalp EEG	256	22	163	844
Freiburg [36]	IEEG	256	21	87	708
Bonn [37]	Surface and IEEG	173.61	10	NA	39 m
Bern Barcelona [38]	IEEG	512	5	3750	83 m
Kaggle [36]	IEEG	400/5 KHz	5 dogs, 2 patients	48	627
Zenodo [39]	Scalp EEG	256	79 neonatal	460	74 m

 Table 4
 A comprehensive description of the publicly available EEG datasets used to identify seizures of epilepsy

Preictal states only appear during the time period prior to a seizure and do not occur at other times. It might not always be visible to the naked eye. However, it would be able to forecast seizures within a certain range of values and would reflect modifications that occur in the underlying signals. Preictal states must be detected early enough in a warning system for them to be therapeutically useful [42]. This reduces the amount of time that patients experience erroneous warnings.

6.2 Pro-ictal state

Seizures in those prone to epilepsy are more likely to occur here, although they still aren't assured.

6.3 Ictal and interictal state

The changes in EEG recording signals that take place during a seizure are known as the ictal state, while the interictal state is the period between two subsequent seizure onsets. The amount of epileptogenic neurons, cortical areas, and seizure duration can be altered for the same person.

6.4 Post-ictal state

Due to a seizure, this issue has manifested.

The wave pattern might contain insightful data regarding the activity of the brain. Neurologists with experience can identify diseases by looking at the EEG waves. However, because of the extensive spatial and temporal characteristics of the dynamic nonlinear EEG data, this approach requires a lot of work and is sensitive to incorrect identification. Therefore, automated methods, such as the extraction and analysis of EEG signal characteristics, can greatly aid in diagnosis [43]. You can see the differences between the normal, preictal, and ictal phases of epilepsy, in Fig. 5.

7 Methodology for identifying epileptic seizures

In this section, we show the methodology used to identify seizures in an EEG seizure dataset. Figure 6 provides a schematic of the system used to identify epileptic seizures.

7.1 Data collection

The dataset of brain signals must be gathered as a first step. A variety of monitoring technologies are used for this purpose. EEG and ECoG are frequently utilized because their channels or electrodes are adhered to the scalp as per the 10–20 International system at various lobes. Each of them is wired to the EEG equipment,



Fig. 5 EEG signal graphs for normal, preictal, and ictal stages



Fig.6 Schematic depicting how EEG readings and ML methods may be used to identify epileptic seizures

which it instantly sends temporal and geographical information as well as information about voltage changes [44, 45]. The subject's scalp receives the EEG channels from the EEG monitoring equipment and display on the screen the raw signals that result from reading electrical signals. Then, the analyst splits these unprocessed (raw) signals after carefully observing them into the "non-seizure" and "seizure" stages.

7.2 Data transformation

The significant following step after data collection is converting the data signal into a 2-D table format. This makes analysis easier and gives important data such as epileptic seizure detection. This raw data, therefore, won't be appropriate to provide important data. There are several feature selection methods that have been used for the processing task. The dataset is displayed as supervised in this stage, which indicates that it provides potential class values for the class attribute [9].

7.3 Data preprocessing

Preprocessing of the data comes before feature extraction or classification activities as a preliminary step. Designing algorithms for emotion categorization is difficult since, in general, EEG signals are frequently obtained in noisy environments. The environment may have an impact on EEG recording equipment. The noise may also be caused by eye movement and muscle activity. The noise-filtered signal ought to be the input signal used for emotion recognition. Additionally, redundant data with undesirable noise and artifacts are present in the obtained input EEG signals. To prepare the data for post-processing, it is crucial to remove these uncertainties. Preprocessing will make sure that EEG signals only contain pertinent signal-related information. Actual EEG recordings are contaminated by artifacts and outside noise, which is typically brought on by electrode movement. As a result, both the EEG signals' quality and classification accuracy are reduced. The supplied data is processed using several feature selection models [46]. Figure 7 depicts the most prominent physiological noises in an EEG signal.

Heart electrical activity causes artifacts to appear on an ECG. Eye blinking and eye movements cause EOG artifacts. When you clench your teeth to chew or swallow, you activate the temporalis and frontalis muscles, which causes an EMG artifact. The tongue's natural motions produce what are called glossokinetic artifacts. When electrodes are put above a beating vessel, pulse artifacts appear on the recording. Sweat from the body's sweat glands might alter the basis of the EEG sensors. The chest and head movement that occurs when breathing causes



Fig. 7 EEG signal anomalies caused by physiological noise

artifacts. Power cables, faulty electrodes, power line noise, and power line motion are common examples of environmental artifacts.

7.4 Data reduction and feature extraction

This stage involves reducing the feature values by taking out crucial features of a certain region regarding the input signal. A key component of classifying EEG signal data is the extraction of features. The primary goal of feature extraction is to gather trustworthy data for emotion recognition. In terms of technical terms, a feature denotes a distinguishing quality and a recognizable measurement derived from a section of a pattern. With the least amount of information loss possible, EEG data is transformed from its massive size into a manageable feature vector set using the feature extraction method. As a result, it facilitates analysis (classification) by facilitating easier and faster computational speed [47].

Fundamentally, there are two methods for extracting features from an EEG signal, namely manual and automatic extraction. In both the frequency and time domains, the manually created extraction characteristics are multivariate and univariate. The Horthy parameters, statistical moments, kurtosis, skewness, entropy, mean, and variance [48, 49] on the other hand, are examples of automated features. Figure 8 displays the linear and nonlinear measures for the multivariate and univariate characteristics that were used for ES prediction. Continuous wavelet transform (CWT), discrete wavelet transform (DWT), Fourier transform (FT), time–frequency domain (TFD), frequency domain (FD), and time domain (TD)-based features are some of the most common methods used to characterize an EEG signal [50]. Table 5 shows the EEG features that are most commonly used to detect epileptic activity.



Fig. 8 Channel-based feature categorization

Feature extraction method	Relevant features
Time-domain features	Standard deviation, approximate, sample entropy, Shannon entropy, power, energy, line length, zero crossings, min, max, variance, Hurst exponent, fuzzy entropy, entropy, mode, median, kurtosis, skewness, and mean
Frequency-domain features	Spectral entropy, spectral power, median frequency, peak frequency, and spectral energy
Time-frequency domain features	Root mean square, approximate entropy, Shannon entropy, median, energy, standard deviation, max, min, and line length
Discrete wavelet transformation	Standard deviation, variance, relatively bounded, entropy, energy, coefficients, relative scale energy, relative power, bounded variation, and Variation
Continuous wavelet transformation	Entropy, coefficient z-score, energy, and energy's standard deviation
Fourier transformation	Total spectral power, spectral edge frequency, spectral entropy power, peak frequency, power, and, median frequency
Nonlinear features	Higher-order spectra, Kolmogorov entropy, sample entropy, Hurst exponent, approximate entropy, largest Lyapunov Exponent

Table 5 EEG features that are most commonly used to detect epileptic activity

7.4.1 Time-domain techniques

EEG scans change over time and are not always the same. The outcome of a time-domain method called linear prediction is derived from the input and prior outputs. Independent component analysis (ICA), principal component analysis (PCA), and linear discriminant analysis (LDA) are widely used unsupervised time-domain summaries of EEG data. High-dimensional data (high-dimensional feature vectors in the case of epilepsy) may be transformed into low-dimensional data using principal component analysis (PCA), whereas high-dimensional data can be broken down into linear statistically independent components using ICA. The primary purpose of ICA in the analysis of EEG data is to eliminate artifacts, while LDA uses linear combinations of feature vectors to reduce the size of feature sets.

7.4.2 Frequency-domain techniques

When employing frequency-domain techniques such as the Fourier transform (FT), it is possible to measure the abrupt shift in frequency of EEG signals that occurs during an epileptic seizure. Parametric and nonparametric techniques may both be employed with FT to evaluate the power spectrum. PSD is typically estimated using the Welch (nonparametric) approach, an updated form of the standard periodogram technique. However, spectral leakage is a drawback that can be avoided by using parametric approaches. Taking the electroencephalogram data as a constant random variable, parametric approaches offer improved frequency resolution. Parametric approaches such as moving average (MA), auto-regression (AR), and auto-regressive moving average (ARMA) are frequently used.

7.4.3 Time-frequency domain techniques

The aforementioned frequency-domain and time-domain approaches have restrictions in that they can only give approximate frequencies involved at a given time instant or moment in time, respectively. Wavelet transform (WT), a time-frequency-based analytic approach, is frequently used to overcome these limitations and create multi-resolution deconstructed sub-band signals by running the EEG signal through filter banks in order to get over these restrictions.

7.4.4 Nonlinear techniques

Harmonic coupling in a signal's spectral content may be discovered using nonlinear analysis methods. Many other kinds of entropy, including the Kolmogorov entropy, the sample entropy, the Hurst exponent (H), and the approximation entropy (ApEn), are utilized in EEG analysis, as are nonlinear parameters with the largest Lyapunov exponent (LLE). LLE and entropy are frequently employed as characteristics for classifying epilepsy seizures. Entropy evaluates the unpredictability or uncertainty in the patterns of the data and gives hints about information encoded in the probability distribution of a signal. High levels of randomness in data patterns are indicated by higher entropy values. LLE reveals how dependent the system is on its starting conditions [3].

7.5 Classification

There are "non-class attributes" and "class attributes" in a dataset D used for classification. They are the foundational elements, and insight into them is crucial since they have a close relationship that may be used to categorize one another. As a 'class attribute,' C, the target property may have many values, such as seizure and non-seizure. In contrast, the qualities $A = [A_1, A_2, A_3, \dots, A_n]$ are classified as predictors or "non-class attributes." SVM, decision tree, random forest, and eXtreme Gradient Boosting are just a few of the classifiers that have found widespread usage in seizure detection [51].

7.6 Performance evaluation

Methods are compared and contrasted based on how accurately they provide outcomes. Tenfold cross-validation is widely used as a training method because in each fold, or a horizontal section of the dataset, one section is used as the testing dataset and the other nine are used as the training dataset. The classification performance is evaluated using a variety of performance measures, including accuracy, precision, recall, *F*1 score, and false-positive rate. These are derived from Table 6's breakdown of the four potential categorization results as false negative

Acronym	Detection type	Real-world scenario
ТР	True-positive	If a person suffers to 'seizure' and also correctly detected as a 'seizure'
TN	True-negative	The person is actually normal and the classifier also detected as a 'non-seizure'
FP	False-positive	Incorrect detection, when the classifier detects the normal patient as a 'sei- zure' case
FN	False-negative	Incorrect detection, when the classifier detects the person with 'seizure(s)' as a normal person. This is a severe problem in health informatics research

Table 6 Classification outcomes

(FN), false positive (FP), true negative (TN), and true positive (TP). Table 7 discusses several measures that may be used to evaluate the classifier's efficiency.

8 Machine learning techniques for epileptic seizure detection

In particular, this section offers a thorough analysis of the studies conducted on MLbased techniques for ES detection. At first, we focus on the promise of ML methods in the medical and biomedical fields.

8.1 An overview of ML in healthcare

Over the past few decades, ML has spread across a variety of academic fields by employing statistical techniques to find patterns in vast data sets. Large-scale biomedical data is now accessible, which is a significant development for medical researchers. The growth of ML techniques and data analysis methodologies is essential for the creation of efficient medical instruments [52]. For the purpose of illness diagnosis, ML has found widespread use in the healthcare industry, such as the classification of skin cancer [11], the detection of breast cancer [53], retinal image analysis for diabetic retinopathy detection [54], Alzheimer's disease diagnosis [55], and prediction of epilepsy [56]. This is because the complicated structure of medical data makes it a difficult challenge to manually discover representations.

8.2 ML for neuroscience

Neuroscientists have been primarily concentrating on what we've learned recently about the functional architecture and anatomical organization of the human brain. Technological developments have made it possible for neuroscientists to collect, process, and analyze neuroimaging data at a new level of detail; ML and DL are prime examples of the kinds of enabling technologies that might be utilized as a starting point for investigating fundamental questions regarding how the brain works [11]. In this part, we give a general overview of several machine learning (ML) approaches that have been applied to the study of neuroscience, including supervised learning, unsupervised learning, and reinforcement learning.

	Metrics	Formula
Accuracy	It is the number of correctly identified segments to the total number of segments	Accuracy = $\frac{\text{TP+TN}}{\text{TP+TN+PP+EN}}$
Sensitivity or Recall or true-posi- tive rate (TPR)	It is the number of segments correctly detected as seizures to the total number of segments with seizures	Recall = $\frac{TP}{TP+FN}$
Specificity	It is the number of segments correctly detected as non-seizure to the total number of segments with non-seizures	Specificity = $\frac{TN}{TN+FP}$
Precision	It is the ratio of true positives to the total number of cases	Precision = $\frac{TP}{TP_{ABP}}$
F-measure or F1-score	It is the weighted harmonic mean of precision and recall	$F1$ -score = 2 × $\frac{Precision \times Recall}{Precision + Recall}$
Matthew correlation co-efficient (MCOR)	It is a balanced measure of the quality of the classifier with a value between -1 and 1	$MCOR = \frac{TDP,TIN,FP,FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$

Table 7 Evaluation metrics

8.2.1 Supervised learning

In supervised learning, the learning algorithm receives training data together with labels applied by human specialists. This allows the algorithm to extract the relationship between the data and labels in order to accurately categorize the unknown data. For instance, a training dataset might contain photographs labeled with "home," "dog," or "cat," and we'd need a classifier that can foretell the label of a new image that the system hasn't seen before. One popular supervised learning method is the support vector machine (SVM) used for ES identification, which has numerous potential applications in theoretical and computational neuroscience. A supervised ML technique is used to analyze brain systems under stress [57].

8.2.2 Unsupervised learning

On a typical day, our brain is given the majority of the information on its own. As information is repeated, the brain creates a functional model and uses it to build perceptions. The patterns in the new knowledge are then found using this perception. The brain learns new things through perception, which is the inspiration for unsupervised learning algorithms. Unsupervised learning uses data that has not been tagged or classed to train algorithms. The diagnosis and categorization of disorders from neurophysiological data make substantial use of these algorithms.

8.2.3 Reinforcement learning

The study of animal behavior, or how animals interact with their environments and one another, contributed to the development of the field of reinforcement learning (RL). One of the most noteworthy technological advances that may be attributed to the merging of neuroscience and AI is RL. Reinforcement learning is the procedure of devising a plan to optimize an agent's performance in response to its interactions with its environment. The environment model, value function, reward signal, and policy form the backbone of every reinforcement learning system [11, 58].

8.3 Applications of ML on epilepsy-related EEG data

There are three main uses for ML techniques in the field of epilepsy: (1) detecting seizures; (2) predicting when they will occur; and (3) identifying where they will occur (the epileptogenic zone).

8.3.1 Automatic detection of seizures

A seizure might be detected either just before or just after it begins. EEG abnormalities are often identified and classified by neurologists by direct visual examination. Manually classifying EEG signals is possible, but it is time-consuming and prone to error. Numerous obstacles make it difficult to develop an automated system for detecting seizures that can be relied upon. Seizure EEG patterns, for instance, might vary widely across individuals and even within a single patient if the source of the seizure is located in a different part of the brain. Given that the primary goal of automated detection is to enable preventative steps in the case of a seizure, reducing the latency of detection is crucial; this calls for quick, efficient processing of the dynamic development of many EEG channels. Results from the majority of the early research are subpar, showing things like high false alarm rates and long lag times [59].

8.3.2 Localization of epileptogenic regions

The seizure onset zone (SOZ), also known as the epileptogenic zone, is the area of the brain where an abnormally high concentration of electrical activity at the start of a seizure occurs. The success rate of SOZ identification may be determined by comparing the number of electrodes correctly identified as the SOZ before and after resection in patients who attain seizure independence. In order to perform successful surgery for epilepsy, it is crucial to have a technique for identifying SOZs that is both reliable and accurate.

Because the electric activity of a seizure may burst suddenly and concurrently throughout a broad variety of cortical locations, identifying the core epileptogenic zone may be challenging. In order to best study the SOZ, it is recommended that signals be gathered via high-resolution intracranial electrodes. High-frequency oscillation (HFO) is one such biomarker since it is associated with the subthalamic zone (SZ) and may provide information that is not present in low-frequency discharges in epilepsy. Previous research employing intracranial electrodes, such as stereotactically implanted intracranial EEG (SEEG) and subdural electrocorticography (ECoG), has examined a number of shared characteristics or traits (rapid activity, signal flattening, delayed potential shift, etc.) [59].

8.3.3 Prediction of seizures

Predicting when a seizure will occur automatically is called "seizure prediction". The seizure prediction window might be several minutes long. Predicting when an epileptic seizure would occur would have far-reaching implications, including but not limited to reducing the likelihood of injury, easing worry, facilitating faster response times in cases of emergency, and allowing for more effective treatment (e.g., early medication, electric stimulation of the vagus nerve, deep brain stimulation). The research on seizure forecasting focuses on four primary stages. The first, "interictal," describes the time between seizures; the second, "preictal," describes the time right before a seizure; the third, "ictal," describes the time when a seizure actually occurs; and the fourth, "postictal," describes the time after a seizure but before the brain returns to its "normal" state. Most studies attempting to predict seizures have zeroed in on the preictal phase, which is characterized by the dynamic change of EEG data just before a seizure begins. The hypothesis of chaotic dynamics reportedly exhibits superior predictive capacity than linear data due to the dynamic character of preictal EEG. Univariate (e.g., spectral power) measurements have been

shown to have limitations, whereas bivariate and multivariate measures have been shown to have benefits [59].

8.4 ML classification techniques

In automated epilepsy detection systems, ML methods are the most common classifiers employed. Features are extracted, analyzed statistically, ranked, selected, and then fed into ML algorithm classifiers using traditional handcrafted feature extraction techniques. Various classification strategies as shown in Fig. 9, including support vector machines (SVMs), artificial neural networks (ANNs), random forest (RF), logistic regression (LR), naive Bayes (NB), decision tree (DT), and *k*-nearest neighbor (KNN) with a wide range of kernel functions, have been presented in the literature. Table 8 contrasts the results of several EEG detection methods from prior research with regard to the feature extraction method, classifier used, and detection accuracy [60]. A variety of classifiers are used in seizure detection, and we will go through the most well-known ones in the following subsections.

8.4.1 Support vector machine (SVM)

The support vector machine (SVM) algorithm is a two-stage method. It has several features, such as being able to handle a large number of predictors and variables even with a small sample size. In most cases, SVMs try to locate the optimal hyperplan for identifying and isolating instances of a given class from all other instances. Whichever hyper-plane produces the largest gap between the two groups is optimal. It is possible to formulate the problem of locating the best-separating hyperplanes as follows:

$$\min \frac{1}{2} \|w\|^2 \tag{1}$$

subject to

$$r^t(w^T x^t + w_0) \ge 1, \quad \forall t \tag{2}$$

where *w* are hyperplane parameters, x^t are training set instances, and r^t are the true labels.

The term "margin" refers to the largest distance between two adjacent data points on the hyperplane perpendicular to the slab. It is the linear decision surface's most pronounced gap among borderline patients that inspired its use in SVM as a means



Fig. 9 Machine learning classifiers

of classifying patients into distinct groups. It was excellent at handling nonlinear and high-dimensional data. It aids in predicting key features of unidentified testing data based on the structure of training data sets [61].

The linear kernel function, which is often used in SVM, is described by the following equation:

$$K(X,Y) = X^T Y \tag{3}$$

Alternatively, a polynomial of degree d may serve as a kernel function, as shown below.

$$K(X_i, X_j) = (X_i, X_j)^d \tag{4}$$

in which the total number of polynomials is denoted by $d(d \ge 1)$.

A function is said to be quadratic in its kernel if the degree of its polynomials is two or three.

8.4.2 Naive Bayes (NB) classifier

In the NB algorithm, characteristics and categories are the focus. One quick method under consideration analyzes all the data in the training sets while requiring less information for classification. NB is a probabilistic classifier that relies only on learning features independent of the class (as per Bayesian theory), such that any characteristic of a given class may be considered separately from the others. This idea of independence is typically a bad one. It is a Bayesian theorem-based algorithm. In order to determine a conditional probability, this classifier considers the association between each characteristic and the class for each occurrence [62].

Given a training set D with n classes and any attribute vector Y with class labels, it can be shown that the class to which attribute Y most likely belongs, based on the posterior probability, is:

$$P(C_i|Y) > P(C_j|Y) \text{ for } 1 \le j \le n, j \ne i,$$
(5)

where

$$P(C_i|Y) = \frac{P(Y|C_i)P(C_i)}{P(Y)},$$
(6)

by Bayes theorem.

To clarify, $P(C_i)$ stands for the probabilities of each class; the prior probability of *Y* is P(Y); the posterior probability of *Y* is $P(C_i|Y)$; and the posterior probability of *Y* conditioned on C_i is $P(Y|C_i)$.

8.4.3 K-nearest neighbors (KNN)

KNN is a simple, nonlinear, and nonparametric sample classification method [11, 63]. In practice, it performs well on big training datasets. Using this approach, a data item is assigned to the category with which its *k*-closest neighbors have the most familiarity

based on the results of a majority vote. Similarity metrics between the training and test data sets are the primary foundation of this approach. To determine which class a new sample belongs to, we look at the other samples in the same or neighboring k datasets used for training and use the results as our guide. In general, K should have a value between 3 and 10. In comparison with 1, those numbers are astronomically larger. A distance metric, such as the Manhattan distance, may be used to assess how close or similar two entities are to one another. For a p-dimensional space, the Manhattan distance is defined as:

$$d(i,j) = |x_{i_1} - x_{j_1}| + |x_{i_2} - x_{j_2}| + \dots + |x_{i_p} - x_{j_p}|$$
(7)

8.4.4 Artificial neural network (ANN)

ANNs are functions that are made up of neurons and weights. The input values are processed by the neurons, and the output is the outcome; the weights transport the information between the neurons. There are three primary layers of neurons: input, hidden, and output as shown in Fig. 10. Each piece of data that will be supplied into the network is represented by an input unit, and this layer comprises several such units. The hidden layers include the hidden units, which are based on two things: (a) the activities of the input units and (b) the weights that are based on the relationships between the input and the hidden units [62]. When given input, the ANN computes the weighted total of the inputs and incorporates a bias. A transfer function is used to visualize this calculation.

$$\sum_{i=1}^{n} W_i \times X_i + \text{bias} \tag{8}$$

$$\text{output} = \begin{cases} 1 & \text{if } \sum W_i \times X_i + \text{bias} \ge 0\\ 0 & \text{Otherwise} \end{cases}$$
(9)



Fig. 10 Artificial neural network layers

In order to create the result, it passes the weighted sum as an input to an activation function. A node's activation functions determine whether or not it should activate. The output tier is only accessible to those who are fired. Depending on the type of job we are completing, there are various activating functions that can be used.

8.4.5 Logistic regression (LR)

LR is a supervised technique for performing binary classification of events based on whether they occur or not. Given that it's a probability, the dependent variable can only take on values between zero and one. For use in LR, the probabilities are changed to logit form by dividing the chance of success by the chance of failure. This logistic function is also called the natural logarithm of chances or the log odds [21]. It is shown by the following expressions:

$$p(x) = \frac{1}{1 + e^{-(x-\mu)/s}} \tag{10}$$

where $p(\mu) = 1/2$ denotes the middle of the parabola μ , and *s* is the scale factor. Equation (10) can also be expressed as:

$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \tag{11}$$

Most of the time, maximum likelihood estimation (MLE) is used to figure out this model's beta parameter (or coefficient). The corresponding diagram of LR is shown in Fig. 11.

8.4.6 Decision tree (DT) classifier

The data are organized into a tree with each node indicating a test on one of the input variables, and the last node, the "leaf," reflecting the final decision. The testing and branching process is repeated by the classification algorithm. Learning from DTs uses a divide-and-conquer tactic by employing a greedy search to locate the best possible node splits within a tree. This partitioning is then iterated recursively from



Fig. 11 Logistic regression

Table 8	A synopsis of reviewed papers that	t evaluated the usage of comme	on feature extraction methods and	ML classifiers	
Ref. Ye	ar Dataset	ML classifier	Features	Performance metrics	Findings
[66] 20	17 Bonn	ANN	EMD	Accuracy	96.1%
[67] 20	17 Bonn	LS-SVM	Tunable Q-wavelet transform	Accuracy	100%
[68] 20	18 Freiburg, CHB-MIT	SVM, MLP, KNN, RF	EMD, DWT	Accuracy	100%
[69] 20	18 Toronto western hospital	RF	Cross-frequency coupling (CFC)	ROC, sensitivity, specificity	93.4%, 87.9%, 82.4%
[70] 20	18	ANN	DWT	Accuracy	95%
[71] 20	18 Bonn	RF	SVD	Accuracy	98.12%
[<mark>72</mark>] 20	18 Bonn	SVM, KNN, DT	Wavelet-based entropy	Accuracy	SVM = 98%, $KNN = 94%$
[73] 20	19 Publically available dataset	SVM	DWT	Accuracy	97.87%
[74] 20	19 Bonn, Freiburg	RF	Wavelet transform based features	Accuracy	95%
[75] 20	19 Bonn	SVM, KNN, DNN	Feature scaling loss function	Accuracy	SVM = 94%, $KNN = 74%$
[76] 20	19 CHB-MIT	RF	Wavelet packet decomposi- tion	Accuracy	84%
[77] 20	19 Bonn	SVM	DWT, Sigmoid entropy	Sensitivity, specificity, accuracy	100%, 100%, 100%
[78] 20	19 Bonn	SVM	Particle swarm optimization	Sensitivity, specificity, accuracy	99.5%, 99.25%, 99.38%
[79] 20	19 Bonn	Least-square SVM	DWT, Entropy	Sensitivity, specificity, accuracy	100%, 99.4%, 99.5%
[80] 20	20 Ramaiah College, CHB-MIT	SVM	Successive decomposition index	Sensitivity, F1-score	97.53%, 97.22%
[81] 20.	20 Bonn	NB, KNN, MLP, SVM	DWT	Accuracy	100%
[<mark>82</mark>] 20.	20 CAP sleep	ANN	DWT	Accuracy	91.1%
[83] 20.	20 CHB-MIT	RF, DT	DWT	Accuracy	99.81%
[84] 20	20 Kahib-Celebi school of medicine	SVM, KNN, NB, LR	EMD, DWT	Accuracy	SVM = 94.56%, KNN = 95.63%, NB = 96.8%

Table	·8 (coi	ntinued)				
Ref.	Year	Dataset	ML classifier	Features	Performance metrics	Findings
[85]	2020	CHB-MIT	DL, SVM, CNN	DFT, EMD, DWT	Sensitivity, specificity	92.7%, 90.8%
[86]	2020	Bonn	ANN, KNN, NB, SVM	DWT	Accuracy	97.82%
[87]	2021	CHB-MIT	Fuzzy classifier	Adaptive wavelet transform	Accuracy	96%
88	2021	CHB-MIT	SVM	DWT	Sensitivity, specificity	96.81%, 97.26%
[89]	2021	Bonn CHB-MIT	LR, NB, KNN, DL, RF, LSTM	Wavelet transform	Accuracy	RF = 97%, LSTM = 98%
[06]	2021	Bonn	SVM, KNN	DWT, Local binary pattern transition histogram	Accuracy	99.6%
[91]	2021	Bonn	Linear function	Correlation dimension	Accuracy	100%
[92]	2022	Bonn	SVM, ANN	DWT	Accuracy	SVM = 98.7%, $ANN = 98.7%$
[93]	2022	CHB-MIT	SVM/ RF	Tunable Q-wavelet transform	Accuracy	SVM = 90.4%, $RF = 93.5%$
[94]	2022	CHB-MIT	SVM	DWT, Eigenvalue	Accuracy, sensitivity	97%, 96.67%
[95]	2022	Bonn, Senthil Multispecialty Hospital	KNN, NB, SVM, DT	DWT	Accuracy	100%
[96]	2022	CHB-MIT	DT, RF, ANN, Ensemble Learning	DWT, DFT	Sensitivity, specificity, accuracy	91.9%, 89.7%, 91.9%

the top down until all or nearly all of the data have been assigned to their respective classes [64]. DT models often use either Gini impurity or information gain as a way to separate options. They are useful for judging how well a given set of test conditions can reliably classify test data.

The "information gain" is the change in entropy from before the separation to after the separation of a specific characteristic. The best split will come from the attribute with the most information gain because it does a better job of classifying the training data according to its target classification. Typically, the following formula is used to express information gain:

$$I_{\text{Gain}}(S, a) = \text{Entropy}(S) - \sum_{V \in \text{values}(a)} \frac{|S_V|}{|S|} \text{Entropy}(S_V)$$
(12)

where *a* is a specific class label or attribute.

Whereas the Gini impurity would indicate the likelihood that the classification would be wrong, if an arbitrary data point in the dataset were to be classified based on the distribution of classes. If a set, *S*, is pure (i.e., it only contains elements from one class), then its impurity is also zero. The following equation represents this:

Gini =
$$1 - \sum_{i=1}^{c} (p_i)^2$$
 (13)

where the probability of the occurrence of class i is denoted by p_i , and c is the total number of classes.

8.4.7 Random forest (RF)

RF is a classifier ensemble made up of several decision trees. Diverse components of the data collection are used to train the decision trees. Each DT receives a fresh sample as input, and the forest chooses the classification with the greatest votes [65].

8.5 Deep learning classification techniques

Deep learning (DL) is a subfield of ML that eliminates the need for human intervention in feature engineering by autonomously learning models from layered datasets. Layer upon layer of artificial neurons perform linear transformations on the incoming data in deep neural network models. The results of the transformations performed by each layer are fed into a nonlinear activation function. There are notable speed and precision gains when using DL with big datasets. In Fig. 12, we can see that there are four main groups of DL models [97].

8.5.1 Discriminative deep learning models

They can automatically acquire discriminative characteristics from incoming data and place it into predefined groups. Nonlinear modification is used to teach the characteristics that are distinctive, and probability projection is used



Fig. 12 Deep learning classification techniques

to determine categorization. Both feature extraction and categorization use cases are supported. Multi-layer perceptrons (MLPs), convolutional neural networks (CNNs), recurrent neural networks (RNNs) like gated recurrent units (GRUs) and long short-term memories (LSTMs), and RNNs like these are all examples of discriminative models [97].

- Multi-layer perceptrons (MLP) are multi-layer artificial neural networks. The synapses are taught by a learning method called backpropagation. Any continuous function can be approximated, and issues that are not linearly separable can be solved.
- Recurrent neural networks (RNNs) are a type of consecutive design in which an individual cell receives the input and the prior state and then passes on the output and the next state. They are useful for tasks like time-series prediction.
- Long short-term memory (LSTM) overcomes the diminishing gradient issue of the standard RNN by learning temporal characteristics with long-term relationships. In the LSTM framework, data are either stored in a memory block or deleted according to the decisions of its input gate, ignore gate, and output gate. Each LSTM block is replaced by two blocks in Bi-LSTM, which can handle a time series in both ways at once.
- Unlike other methods that rely on hidden state, GRU can operate with only past temporal data. There are two gates that make up this mechanism: a reset gate that chooses how data should be combined with stored information and a forget gate that determines how much information should be stored.
- In contrast to traditional methods, CNN does not require any preprocessing or human involvement in order to autonomously derive geographic characteristics from unprocessed data. The levels of a convolutional neural network (CNN) are convolutional, pooling, and fully connected (FC), respectively. Input pictures are used by the convolutional layer, which then uses what it has learned to create a feature map. The pooling layer can employ max, total, or average pooling procedures to the feature map, thereby reducing the map's area and thus the computational cost. A feature vector of a single dimension is created by the FC layer.

8.5.2 Representative deep learning models

These algorithms are capable of identifying typical characteristics in raw data. But they are limited to feature engineering applications only. Deep belief networks (DBN), restricted Boltzmann machine (RBM), deep convolutional auto encoder (DCAE), and autoencoder (AE) are typical methods used [97].

- The encoder of an AE gives a low-dimensional model of the incoming data, and the decoder of an AE can then reconstitute the original signal, making AEs an example of an unsupervised neural network learned on unlabeled data. Before beginning autoencoder training, hyperparameters like the number of layers, code size, number of nodes per layer, and loss functions must be determined. The two most popular loss functions are the binary cross entropy and the mean square error. Convolutional layers are used in DCAE instead of the basic AE's completely linked layers in the encoder and decoder.
- RBM is a two-layer artificial neural network with random connections between neurons in the buried layer. The input is reconstructed by translating both forward and backward. Nodes on the same stratum are unable to communicate with one another. Weights and prejudice are used to trigger the concealed layer. Due to the lack of an output layer, we must rely on the triggered buried neurons to recreate the input layer.
- DBN is a series of RBM designs that work together to form a probability generative model. Each RBM layer has the ability to talk to the levels around it. Unsupervised learning is used to teach the RBM components independently. The results of one section are fed into the next one. Finally, supervised learning is used to fine-tune the network and boost its categorization abilities.

8.5.3 Generative deep learning models

Using unsupervised learning, they figure out how to create new data points based on the actual distribution of the incoming data. Training generative models requires amassing a large quantity of data in the area so that the generated data can be used interchangeably with the training data. Reconstruction and signal-sample generation for improved data for learning are two common applications. Typically, generative adversarial networks (GAN) and variational auto encoder (VAE) are employed [97].

• A VAE can create new examples based on the chance distribution it learns from the training data. The hidden factors that are learned represent training data in a low-dimensional space. Points are chosen from a latent distribution that has been embedded with the input. To do this, we first decrypt the measured point to determine the error, and then, we backpropagate the error through the network. Since the latent spaces are continuous, they can sample at random and interpolate between values. VAE is capable of learning both generative and inferential models. VAE employs a loss function based on the negative log-likelihood of an outcome. • The "generator" and "discriminator" neural networks in a GAN are taught at the same time. The discriminator provides an approximation of the likelihood that a sample was drawn from the training data, while the generator records the spread of that data. The discriminator receives its feed from the generator's output. Backpropagation is used to incorporate the discriminators' results into the generator's weight changes.

Further reading on deep-learning models for epileptic seizure detection can be found in [6, 17, 22, 23, 98]. A synopsis of DL techniques used in epilepsy detection automation can be seen in Table 9.

9 An overview of the Internet of Medical Things

Initial research and development of remote patient monitoring systems sparked the application of IoT in healthcare. Since then, research on IoMT's uses has increased steadily, and current studies focus on finding ways to integrate IoT into many areas of healthcare, such as preventing the spread of illness and facilitating accurate automated diagnosis and treatment. Furthermore, there is a big demand right now for smart healthcare that is high-quality, affordable, and patient-centered. A huge need for real-time, intelligent, and remote healthcare services has been generated by the growth of IoMT and cloud technologies under the umbrella of smart cities [112, 113]. We provide a working definition of an IoMT system and a high-level overview of its architectural components in this section. Classifications of IoMT applications from the literature are shown in Fig. 13.

9.1 The IoMT definition

The Internet of Medical Things (IoMT) is a network of all possible healthcare resources that are interconnected to facilitate speedy data transmission via the Internet [1]. What this implies is that the whole healthcare system—doctors, hospitals, rehabilitation centers, medical equipment, sensors, and patients themselves—will be linked together for seamless, real-time data sharing. Many kinds of IoT devices are designed for the healthcare industry, such as smart wearable devices like portable insulin syringes, blood pressure monitors, stress monitors, weight trackers, hearing aids, fitness trackers, and EEG and ECG monitors. Previous research demonstrated that a smart city may offer real-time smart healthcare services when cloud technologies, IoT, and smart sensors are merged [114]. Therefore, in order to deliver high-quality healthcare services, an intelligent healthcare monitoring system ought to be capable of quickly processing multimedia signals and sensor data. However, the fundamental issue with epileptic patients is that they require prompt, high-quality care. For people suffering from seizures, any delay in receiving care or accessing medical facilities or hospitals could be catastrophic. As a result, people with epilepsy need

Table 9 /	A synopsis of Dl	L techniques used in e	epilepsy detection automation			
Ref.	Year	Dataset	DL network	Classifier	Performance metrics	Findings
[66]	2020	UCI	2D-CNN	Softmax	Accuracy	72.49%
[100]	2020	CHB-MIT	2D-CNN	SVM	Sensitivity, specificity	92.7%, 90.8%
[101]	2020	Bonn	AlexNet	Softmax	Accuracy, sensitivity, specificity	98.5%, 100%, 97.83%
[102]	2020	CHB-MIT	ResNet-50	Softmax	Accuracy	94.98%
[103]	2020	CHB-MIT	Bi-LSTM	Softmax	Sensitivity, specificity	93.61%, 91.85%
[104]	2021	Clinical	CNN-LSTM	Sigmoid	Sensitivity, specificity	88%, 92%
[105]	2021	CHB-MIT	Attention Bi-LSTM	Softmax	Accuracy, sensitivity, specificity	87.8%, 87.3%, 88.3%
[106]	2021	Bonn	CNN-AE	Softmax	Accuracy	99.53%
[107]	2021	Bonn	RNN	LR	Accuracy	98.5%
[108]	2022	Bonn	CNN, Bi-LSTM	STFT	Accuracy	93.9%, 97.2%
[109]	2022	CHB-MIT	CNN, RNN, stacked AE	Softmax	Accuracy, sensitivity, specificity	96.43%, 100%, 93.33%
[110]	2023	CHB-MIT	ID-CNN, CNN-LSTM	Softmax	Accuracy, sensitivity, specificity	94.83%, 90.18%, 99.48%
[111]	2023	CHB-MIT	DCAE + Bi-LSTM	Softmax	Accuracy, sensitivity, specificity	99.7%, 99.8%, 99.9%

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Fig. 13 IoMT applications

an intelligent healthcare monitoring system, which is essential and might typically solve this problem. There are three basic requirements [115] that must be met for a framework to develop and work well.

- *Interoperability* The wide range of devices being used in the framework should be able to cooperate among each other to enable the desired functionality.
- *Bounded latency and reliability* The network's entities need to be able to send and receive information quickly and accurately so that crises can be handled properly and the massive volume of data can be analyzed in unison.
- *Privacy and security* The IoMT architecture requires authentication and security mechanisms to ensure that only the appropriate organizations get the private data being exchanged. There are a number of methods, including encryption and physical unclonable functionalities, for verifying the identity of Internet of Things devices and ensuring their authenticity.

9.2 IoMT and ML-based epilepsy seizure detection

Everything from farms and smart homes to clinics and at-home health monitors is using loT and ML-powered monitoring devices to keep an eye on things. Over time, several practical uses for IoMT (Internet of Medical Things) have emerged. It's been tremendously helpful during the current COVID-19 epidemic. Today's health monitoring systems have come a long way beyond their basic data-gathering ancestors and often rely on Al to help them make intelligent judgements. Such sophisticated systems have the potential to foretell diseases like cardiovascular illnesses, seizures from epilepsy, and individual behavior [112, 116].

Improvements in loMT technology have opened several doors in the healthcare industry, particularly in areas like lowering service costs, facilitating monitoring outside of hospitals, and spotting anomalies as soon as they occur in real time. Acute disorder treatment and monitoring are also a part of these cutting-edge methods. An epilepsy disorder is a neurological condition characterized by repeated seizures that are caused by an abrupt electrical disruption in the brain. Consequently, prompt detection and prediction are of the utmost importance so that the patient may get the best possible care and therapy [112, 117].

In [118], the authors suggested an IoMT-based system that uses an individual's EEG signal to foresee the commencement of a seizure. An EEG sensor's readings are continually analyzed and processed by the system to isolate the brain's hyper-synchronous pulses. The onset of a seizure may then be detected using this collection of features. It was implemented by means of a voltage level detector and a signal rejection algorithm (SRA) for filtering out noise and other undesired signal distortions. Using a predetermined threshold for hyper-synchronous pulses over a certain interval, an oncoming seizure may be identified. The device sends out an alert to the appropriate caregivers or physicians as soon as a seizure is detected. Figure 16 provides a simple diagrammatic representation of the whole system. 96% sensitivity and 97.5% specificity were reported in the experiments using the seizure detector.

In [119], the authors explore how discrete wavelet transform (DWT) may be used for detecting epileptic seizures. The IoMT architecture is used in the suggested system. IoT nodes capture the EEG signal and use DWT to analyze it. After the signal is broken down into its component bands, features like standard deviations, signal complexity, and activity may be extracted from them. A deep neural network (DNN) classifier is then trained on these extracted characteristics to make the diagnosis of normal, interictal, or ictal EEG activity. In the experiments, the accuracy for two classes (ictal and normal) was reported at 100%, while the accuracy for all three classes (ictal, normal, and interictal) was 98.6%. This dataset employed a novel ensemble methodology, compiling data from many publicly available EEG dataset including 100 EEG segments and each segment containing 4097 data points. By sending immediate notifications to medical professionals and caregivers, this method facilitates remote monitoring.

Another recent paper [120] proposed a deep learning-enabled Internet of Thingsbased platform for continuously monitoring and predicting epileptic episodes. The raw data from the EEG headset is sent wirelessly to an FPGA, where it undergoes preprocessing to extract critical spatiotemporal properties before being input into the integrated deep convolutional neural network (DCNN). When a seizure is identified, the EEG data and the outcome of the CNN model's prediction are sent to a Raspberry Pi, which then incorporates real-time alerts. A cloud is used to store the EEG signal for later review by a medical professional. The suggested approach achieves an experimental prediction accuracy of 96.1%.

Specifically, "Grand mal epilepsy Tonic-Clonic (GTC) seizure," which is a kind of generalized epilepsy, is the topic of [121]. The study's primary objective is to detect early warning signs of epileptic behavior in people in the hopes of preventing the onset of the disorder. They employed EMGs, ECGs, accelerometers on all three axes for fall detection, and Dallas temperature sensors to monitor bodily temperature signals in order to bring the IoT system up to date and accomplish this goal. Seizures may be classified according to a wide variety of criteria, including muscular spasms, body temperature, heart rate, and falls, thanks to a fuzzy logic algorithm applied to a defined data set of patients with various diseases. These are sent into a system to determine the kind of seizure, with the result displayed graphically on the loT platform's (ThinkSpeak) dashboard. Abnormal circumstances trigger an "If This Then That" (IFTTT)-based SMS notification to medical staff. An epilepsy monitoring system prototype has been developed and proven effective. In terms of monitoring core bodily functions including temperature, heart rate, muscular spasms, and falls, they reported 98.90%, 95.49%, 83.0%, and 87.21% as average accuracy, respectively.

In contrast to the majority of previously published research, which relies on EEGbased monitoring to assess and forecast the start of seizures, a different method is proposed in [122]. They suggest an Internet of Things-based system for monitoring heart rate in order to identify seizures, with heart-rate variability being the primary metric for analysis. Children with neurological problems, aged 15 and younger, are the focus of this research. The authors accomplished their goal by developing a prototype wearable device to track heart rate and uploading the results to a cloud-based database for further study. The outcomes of this study, however, have not yet been recorded, since the research is still ongoing.

9.3 The proposed IoMT/ML-based automated epileptic seizure detection system

Figure 14 depicts the primary components of the suggested model for an IoMT/MLbased automated epileptic seizure detection system. The suggested model is split into three layers: the device layer, which includes the Bluetooth-enabled EEG headset; the edge/fog layer, which includes the computational services; and the cloud layer, which includes cloud storage and other services.

To begin processing at the device layer, an EEG collection module, in the form of a head-mounted EEG headset, is used to collect raw EEG data. An EEG headset is used to record electrical brain activity by placing electrodes on the head. These electrodes can measure small changes in voltage caused by current waves travelling through neurons in various regions of the brain. When an EEG headset is used, the raw EEG signals are sent over Bluetooth to the subsequent layer. An edge/fog-based



Fig. 14 An outline of the suggested IoMT/ML-based automated epileptic seizure detection system

application collects these signals digitally and then sends them to a cloud-based server at the cloud layer through a wireless or cellular network.

There are six layers in the suggested method for layered automatic epileptic seizure detection, specifically, the data collection layer (DCL), data transmission layer (DTL), information analysis layer (IAL), seizure classification layer (SCL), decision making layer (DML), and cloud storage layer (CSL). In Fig. 15, we can see the technologies [11] that make it possible to create these layers. Figure 16 depicts the layered design of the suggested system.

9.3.1 Data collection layer

The epilepsy patient's scalp EEG data samples are collected by the data collecting layer (DCL) through a wearable EEG headset. This EEG recording device can be used in real-time because it collects patient data every second, enabling it to successfully serve as a lifesaver for epileptic patients. EEG headsets come in a wide variety of styles and functions, including the NeuroSky Mindwave EEG headset and the Emotiv EPOC headset (both released in 2018). For straightforward transmission and use on edge/fog, this layer additionally transforms detected data into textual representation. In this architecture, this layer serves as a sublayer of the device layer and is known as the frontend.

9.3.2 Data transmission layer

The DTL, which is a part of the device layer in this paradigm, is responsible for sending the data of EEG that has been detected by the EEG headset to the fog server. Low-energy Bluetooth technology is used to send the digitally stored EEG data samples that the EEG headset senses to the edge/fog layer. Then, these data samples are







Fig. 16 The suggested IoMT/ML-based automated epileptic seizure detection system's layered design

sent from edge/fog layer to the cloud server by using the 4G network or Wi-Fi to connect to the Internet.

9.3.3 Information analysis layer

The main task of the IAL is to carry out the preprocessing, the extraction of features, and feature selection for the dimensionality reduction of raw samples of EEG. EEG signals are preprocessed by changing their time domain to the frequency domain. Due to the increasing number of patients using this service, there is an issue with enormous data of EEG signals. Dimensionality reduction is used to eliminate duplicate features and choose just the appropriate information.

9.3.4 Seizure classification layer

Samples of an epileptic patient's scalp EEG are categorized into different phases of the seizure by the SCL layer, like normal, preictal, and ictal, or normal and abnormal. Machine learning models are used to categorize EEG signals based on several selected properties derived from IML. This layer is crucial for accurately forecasting the preictal stage with the greatest accuracy and the shortest time of classification in order to provide real-time services as quickly as possible.

9.3.5 Decision-making layer

The DML is in charge of deciding whether or not a patient is in a safe state. In the event that SCL identifies the preictal stage as the result, the DML will decide whether to send an alert message to the patient, his or her family, and any local hospitals or ambulance services in case the patient has a seizure. This way, the right steps can be taken to save the patient's life before the seizure happens.

9.3.6 Cloud storage layer

This layer is crucial for the daily collection and processing of sensed EEG data samples from epileptic patients. In order to uniquely identify the raw EEG signals received for a specific patient, the raw EEG signals gathered from an epileptic patient are saved on this layer together with the patient's personal data. The patient's information consists of their social security number, also known as their Unique ID (UID), as well as their name, age, gender, home address, family members' names, phone numbers, etc. This layer gives DML-specific details it needs to handle emergency circumstances, such as the location and phone numbers of a nearby hospital and registered family members. Many hospitals, healthcare institutions, and research and development companies also receive summarized EEG data samples for use in creating new drugs or vaccines and conducting additional studies on the subject of early epileptic seizure detection.

10 Discussion

The results of an investigation into the detection of epileptic seizures are discussed here. Addressing the difficulty in identifying epileptic seizures and the impact this has on people's lives was a primary focus of this discussion. As a neurological illness, it is crucial to catch it early and get treatment so you don't suffer permanent damage or possibly die from it. This research has covered the different feature extraction techniques, classifiers, and datasets used to identify epileptic seizures. The greatest evidence we have is that KNN, ANN, RF, and SVM are often employed in conjunction with feature extraction approaches to make it easier to detect EEG signals across a variety of datasets. Also, most properties are studied in the time-frequency, frequency, and time domains, and all three of these domains give satisfactory results. In addition, the majority-used datasets and their explanations are provided. Many outcomes have been shown to change depending on which datasets are used to solve the issue. Studies that employed signal decomposition techniques on brain signals, such as those based on wavelets or similar approaches, were selected for this analysis because they shed light on the different types of epileptic seizures and ways of preventing them. In Table 7, we describe in detail the most important methods that have already been used.

The results of this study show that there is no best ML model for identifying epileptic seizures, even though different models are used. When deciding on the best model, you should think carefully about the dataset and issue characteristics, such as the need for real-time detection, the minimum acceptable accuracy, and the use of pre-trained models. It is possible to find a variety of model databases online. Due to the fact that each one was built with a unique combination of inputs and criteria, making direct comparisons between them is problematic. In general, the high performance of ML algorithms is a major benefit. As a result, many other fields have found a use for these types of models. However, additional data are required for training, and training itself is time-consuming. Building a reliable model takes a lot of effort and needs a massive amount of information.

11 Challenges

According to the extensive assessment of relevant literature, it was found that despite recent advancements in the detection and categorization of epileptic seizures, numerous challenges remain prevent researchers from making progress. These challenges comprise, among other things, the following:

- 1. First, there is a lack of publicly accessible big epileptic seizure datasets, which would be useful for thoroughly validating the suggested ML-based epilepsy detection and classification algorithms.
- 2. Real-world applications need to detect EEG signals from continuous EEG signals, but most datasets only contain predetermined subsets of these signals.

- 3. Many attempts have been undertaken to merge existing EEG datasets in order to validate ML models for epilepsy detection and classification, since this requires a vast quantity of data. Even with this progress, it is still hard to combine these datasets because they have different properties (including sampling rate, electrode count, and other variables) and were collected in different ways.
- 4. In order to create a feasible epileptic seizure detection and classification system that meets the demands of mobile health and IoMT, it is absolutely essential to have some understanding concerning how to improve the models' performance. This is because, in real-world situations, ML models usually need a lot of computational resources to be built, which can sometimes be hard to get.
- 5. Sensitive and confidential medical information is gathered in healthcare monitoring systems. Any loss of sensitive information is seen as extremely immoral. HIPAA, the Health Insurance Portability and Accountability Act, has therefore concluded that public clouds are inappropriate for use with healthcare data. Private clouds are preferred over public ones for telehealthcare services due to their higher levels of HIPAA compliance, security, and confidentiality.
- 6. In the last few years, academics have paid a lot of attention to another important issue in seizure diagnosis: class imbalance caused by EEG data that takes an hour or more to analyze. In data mining, medical datasets are one of the most common places where unbalanced classification happens. Prior studies concentrated on developing methods for identifying seizures. Researchers ignored the fact that the EEG data set is extremely skewed due to the imbalance between the lengthy hour of EEG readings and the short epilepsy interval (seconds to minutes). Researchers in the past did not elaborate on how to address class differences in seizure detection. Despite the fact that this problem was discussed and supervised learning models were used by a few authors, no reasonable answer was proposed for giving the minority class (seizures) more consideration. In addition, it seems like a reasonable strategy, though they did not specify a cutoff number for favoring a minority group [123].

12 Opportunities and future directions

Researchers can learn a lot about how to predict epileptic seizures using feature extraction methods by learning more about nonlinear features and understanding the results of different classifiers, especially SVM and its many hybrid versions. In addition, this research was undertaken to comprehend the rationale behind the use of epileptic seizure detection algorithms in the field of ML. In addition, future research can focus on petit mal, also known as an absence seizure, and its detection, which is somewhat difficult due to its short duration and lack of visual symptoms. However, the incidence of these seizures is higher and can have a psychological impact on a child's life, as it only affects children between the ages of 4 and 14. There does not seem to be a large body of literature dedicated to the use of ML methods for the identification of absence seizures. The development of a child-friendly EEG alternative based on IoMT that may be used in a home setting is a potentially promising area of research. Due to the fact that children with absence seizures typically exhibit

only modest indications or symptoms of absence seizures or abnormal behavior, like looking blankly at the wall or not comprehending what is being said, a device should be made after testing the algorithms for the detection process with a lower chance of false positives so that the seizures can be detected and monitored at home.

As aforementioned, this study presents an in-depth analysis of current methods for detecting and classifying epileptic seizures. From more conventional methods to the cutting-edge ML applications of today, enormous advancements have been made throughout the years. However, several difficulties have been highlighted, posing important research concerns that have yet to be answered but are crucial for the effective implementation and improvement of these proposed models. A few ways in which future studies might be improved are outlined below:

- 1. Due to the large size and high dimensionality of epileptic seizure datasets, it is recommended that research be done on dimensionality reduction methods that could lower the dimensionality of the dataset while keeping the key signal information.
- 2. When designing a classifier, it is important to take into account qualities that minimize computational complexity and runtime.
- 3. Methods must be developed to detect the beginning of a seizure and quantify its intensity in models that include invasive recordings.
- 4. The most important thing for researchers is to select a classifier that does not leave out any of the important EEG channels or electrodes.
- 5. Real-time, online, and offline detection are all needed, so it is important to use the right ML algorithms and include the right datasets.
- 6. There has to be substantial research into hybrid ML approaches.

13 Conclusion

This research analyzed the articles chosen for this study on the subject of epileptic seizure detection techniques by conducting a thorough literature review. The research extensively describes the data source, performs an analysis of the MI classifiers used in the study, and details the feature extraction techniques used. Views were provided of a variety of publicly accessible datasets, as well as examples of how these datasets were utilized in the majority of the studies included in this review. For epileptic seizure identification, feature extraction methods are mostly concentrated on the time domain, frequency domain, time-frequency domain, wavelet transform, and signal decomposition methods. Good findings from comparative research with the feature extraction approaches were the primary reason for studying SVM, RF, KNN, LR, DT, NB, and ANN as classifiers. Future researchers are encouraged to focus on the absence of epilepsy in children and to generate a distinct dataset for this form of epilepsy; it is also advised that the most relevant prediction models be studied so that the direction for quality research can be identified. Based on this study, it is clear that the areas of ML and cloud computing within IoT-based smart healthcare have the most potential for impact and development. Researchers of the future are advised to enhance these components for the sake of the expanding human population. Finally, it is clear that loMT improves the quality of life for patients and the elderly by enhancing wellness programs and allowing for more timely diagnosis and treatment of chronic conditions at a reduced cost.

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