# Internet of Medical Things (IOMT)-Based Epileptic Seizure Detection using EEG Signal Processing

*Dissertation submitted in fulfillment of the requirements for the Degree of*

**MASTER OF TECHNOLOGY**

**IN**

**ELECTRONICS AND COMMUNICATION ENGINEERING**

**WITH SPECIALIZATION IN INTERNET OF THINGS**

By

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**May, 2025**

# SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in the M.Tech thesis entitled **"Internet of Medical Things (IOMT)-Based Epileptic Seizure Detection using EEG Signal Processing"**, submitted by **RISHIKA GOEL** at **Jaypee University of Information Technology, Waknaghat, India,** is a bonafide record of her original work carried out under our supervision. This work has not been submitted elsewhere for any other degree or diploma.

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# DECLARATION BY THE SCHOLAR

I hereby declare that the work reported in the M-Tech thesis entitled **“Internet of Medical Things (IOMT)-Based Epileptic Seizure Detection using EEG Signal Processing”** submitted at **Jaypee University of Information Technology, Waknaghat India,** is an authentic record of my work carried out under the supervision of **Dr. HARSH SOHAL and LT. PRAGYA GUPTA.** I have not submitted this work elsewhere for any other degree or diploma.

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# LIST OF ACRONYMS & ABBREVIATIONS

| Abbreviation | Full Form |
|---|---|
| EEG | Electroencephalogram |
| DWT | Discrete Wavelet Transform |
| KNN | K-Nearest Neighbor |
| SVM | Support Vector Machine |
| LR | Logistic Regression |
| DT | Decision Tree |
| PSO | Particle Swarm Optimization |
| IoMT | Internet of Medical Things |
| ML | Machine Learning |
| CNN | Convolutional Neural Network |
| LSTM | Long Short-Term Memory |
| RNN | Recurrent Neural Network |
| BLSTM | Bidirectional Long Short-Term Memory |
| ANN | Artificial Neural Network |
| ROC-AUC | Receiver Operating Characteristic - Area Under Curve |
| CAD | Computer-Aided Detection |
| FFT | Fast Fourier Transform |
| STFT | Short-Time Fourier Transform |
| SE | Spectral Entropy |
| SampEn | Sample Entropy |

| Abbreviation | Full Form |
| --- | --- |
| TBI | Traumatic Brain Injury |
| CA | Classification Accuracy |
| AEDs | Anti-Epileptic Drugs |
| XAI | Explainable Artificial Intelligence |

# ABSTRACT

The challenge of tracking epileptic seizures lies in their unpredictable nature and the continuous monitoring required. This research introduces the Computer-Aided Detection (CAD) System, which is based on the Internet of Medical Things (IoMT) and classifies epileptic seizures using electroencephalogram (EEG) signals. Our approach entails the enhancement of the EEG signal using smoothing and sharpening techniques. Important features that need to be selected are extracted using statistical features and Hjorth parameters; selection is done via particle swarm optimization (PSO), a meta-heuristic algorithm. K-Nearest Neighbors (kNN), Decision Tree, Logistic Regression, and Support Vector Machine (SVM) are used to perform classification. From the analyses performed, it is clear that the PSO integration yields the best result, 99.5% accuracy with SVM and linear kernel. The work demonstrates the promise of IoMT-connected smart systems, which integrate signal processing and ML for more efficient and reliable seizure detection.

# CHAPTER-1

# INTRODUCTION

# CHAPTER 1

# INTRODUCTION

Epilepsy is a neurological condition characterized by recurrent seizures, which may temporarily affect consciousness, motor functions, or sensory perception. These seizures are primarily triggered by abnormal electrical discharges in the brain. To thoroughly understand epilepsy, it is essential to have a foundational knowledge of the human brain and various neurological disorders.

## 1.1 Human Brain

The human brain is the central organ of the nervous system and, along with the spinal cord, constitutes the central nervous system (CNS) [1]. It is structurally divided into three main parts: the cerebrum, cerebellum, and brainstem. The brain is responsible for regulating most of the body's vital functions by processing, integrating, and coordinating information received from the sensory system [1]. It plays a crucial role in interpreting sensory input and issuing motor commands that control the body's responses and actions.

### 1.1.1 Structure of Human Brain

Human Body has many differentiate organs specifically brain , specialized for discrete functions. It is generally separated into three primary regions: the cerebrum, the cerebellum, and the brainstem.

**I. Cerebrum**

i. The largest region of the brain, filling the highest position.

ii. It has two hemispheres (left hemisphere and right hemisphere), joined together by the corpus callosum, facilitating the exchange between the two hemispheres.

- Both hemisphere are each further divided into four lobes:

a) Frontal Lobe: Plays a role in decision-making, voluntary motor function, solving problems, planning, and speech.

b) Parietal Lobe: Processes sensory information like touch, temperature, and pain.

c) Temporal Lobe: Responsible for memory, auditory processing, and undertstanding language .
d) Occipital Lobe: Responsible mainly for visual perception and processing.

**II. Cerebellum**

i. Located under the cerebrum at the back of the head.
ii. Regulates balance, posture, coordination, and fine motor activities.
iii. Assists in smooth coordination of voluntary movements.

III. **Brainstem**

- The lowest structure of the brain, linking it to the spinal cord.
- Made up of three components: midbrain, pons, and medulla oblongata.
- Regulates essential functions of life, including heart rate, breathing, sleep patterns, and reflexes such as swallowing and coughing.

➢ **Other Key Components:**

a. Thalamus: Serves as a relay station for sensory signals message passing to the cerebral cortex.
b. Hypothalamus: Regulates hunger, thirst, temperature, and endocrine function to maintain homestasis.
c. Hippocampus: Central to the formation of new memories.
d. Amygdala: Filters emotions, particularly fear and aggression.
e. Basal Ganglia: Assists with voluntary motor actions and coordination.

These interlinked areas functions smoothly together seamlessly to deal with everything from basic survival instincts to complex thinking and behavior. Comprehensive of brain structure is crucial for diagnosing and treating neurological conditions such as epileptic seizures, which often originate in specific cortical or subcortical regions of the brain.

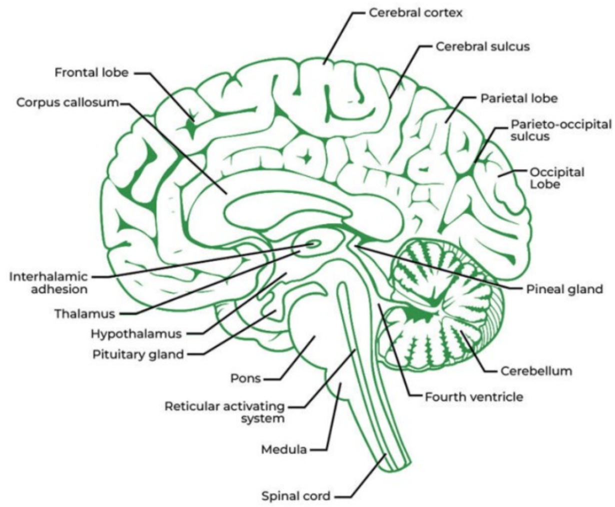


**Fig 1.1:** Structure of Human Brain [2]

## 1.2 Diseases related to Human Brain

The human brain, despite being protected by the skull and cerebrospinal fluid, is unsafe to a wide range of neurological disorders. These diseases can affect memory, movement, coordination, emotion, behavior, and basic bodily functions. Brain disorders may arise due to genetic factors, infections, traumatic injuries, autoimmune responses, tumors, or age-related degeneration.

Below are some of the major brain-related diseases:

### 1.2.1. Epilepsy

- A neurological condition characterized by recurrent, unprovoked seizures.
- Imployed by abnormal electrical discharges in the brain.
- Seizures can be focal (localized) or generalized (affecting the whole brain).
- Diagnosed primarily through EEG and managed using medications, surgery, or neurostimulation.

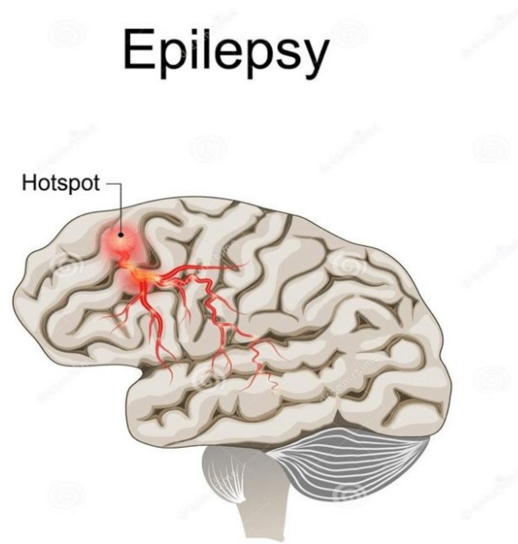


**Fig 1.2:-** Epilepsy hotspot in the brain [3]

### 1.2.2. Stroke

- It typically worsens when the blood supply to a specific region of the brain is restricted or reduced, depriving brain tissue of essential oxygen and nutrients.
- There can be ischemic (blockage) or hemorrhagic (bleeding).
- Symptoms include sudden weakness, paralysis, speech difficulties, and vision loss.
- Immediate treatment is critical to reduce brain damage.

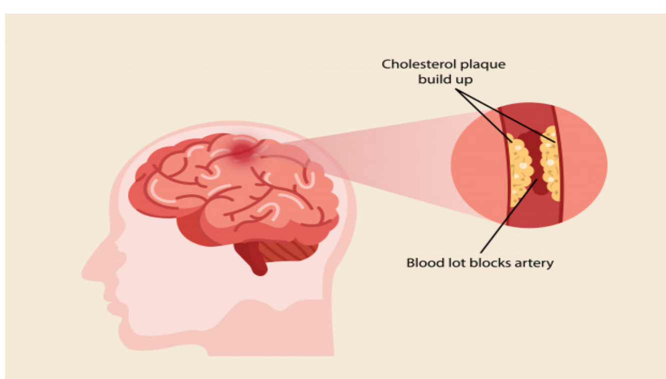


**Fig 1.3 :** Stroke [4]

### 1.2.3. Alzheimer's Disease

- A mentioned neurodegenerative condition that causes memory loss, confusion, and changes in behavior.
- Associated with the accumulation of beta-amyloid plaques and tau tangles in the brain.
- Commonly affects older adults and is the most common cause of dementia.

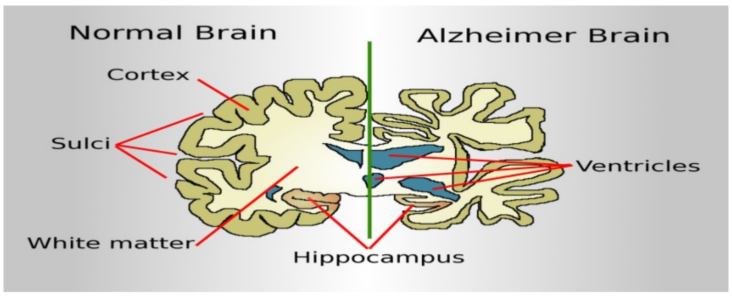


**Fig 1.4:** Normal Brain vs Alzheimer's Brain [5]

### 1.2.4. Parkinson's Disease

- A neurodegenerative movement condition resulting from the loss of dopaminergic neurons in the substantia nigra.
- Symptoms are rigidity, tremors, bradykinesia (slow movement), and postural instability.
- Treated with drugs such as levodopa and deep brain stimulation in advanced cases.

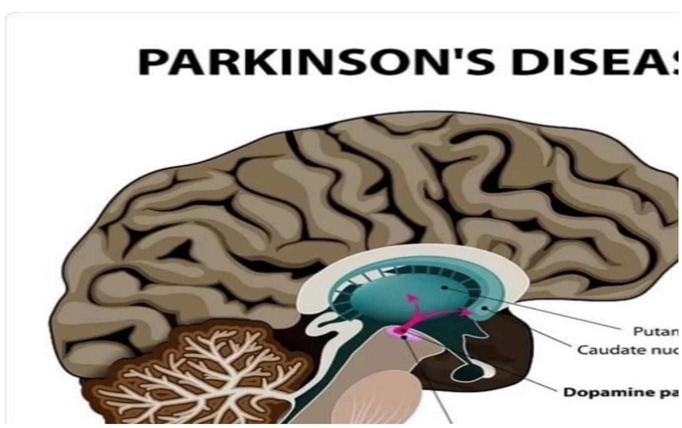

**Fig 1.5:** Parkinson's Disease [6]

### 1.2.5. Brain Tumors

- Unusual cell multiplications of cells in the brain; may be not-cancerous or  (cancerous).
- Symptoms rely on tumor location and size, including headaches, seizures, and cognitive changes.
- Diagnosed by  MRI or CT scans and treated by  surgery, radiation, and chemotherapy.

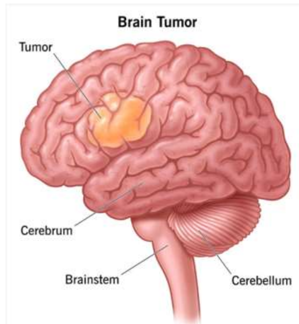


**Fig 1.6 :** Brain Tumor [7]

### 1.2.6. Traumatic Brain Injury (TBI)

- Conclusion from a blow or joint to the head causing temporary or permanent brain dysfunction.
- Common in accidents, falls, or sports injuries.
- Symptoms include confusion, headaches, memory loss, and changes in behavior.

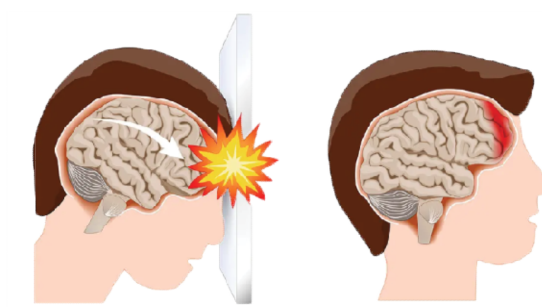

**Fig 1.7:** Traumatic Brain Injury (TBI) [8]

### 1.2.7. Migraine

- A neurological condition causing intense headaches, often on one side of the head.
- May be accompanied by nausea, vomiting, and visual disturbances (aura).
- Triggers include stress, hormonal changes, and certain foods.
- Managed with medication and lifestyle modifications.

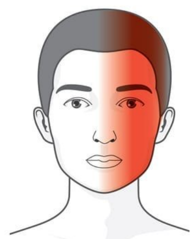

**Fig 1.8:** Migraine[9]

### 1.2.8. Cerebral Palsy

- A collection of disorders affecting movement, posture, and muscle tone.
- impacted by damage to the developing brain, often before feotus development.
- Indications of Cerebral Pasly vary from very low to severe and may include difficulty walking or speaking.
- Physical therapy and supportive treatments help improve function.

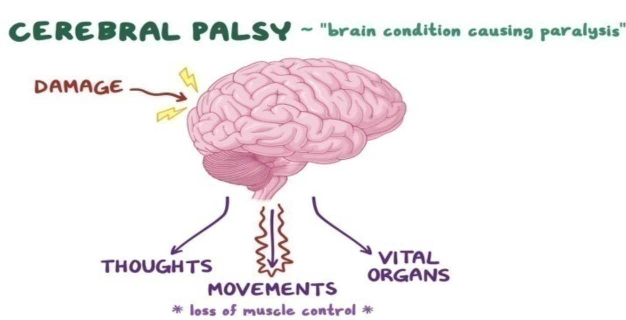


**Fig 1.9:** Celebral Palsy [10]

After the study of many diseases of the brain, I have selected Epilepsy in our thesis research. Epilepsy is one of the most prevalent and debilitating neurological diseases globally, frequently resulting in an extensive decline in quality of life. Individuals suffering from epilepsy may also be at risk of developing related conditions such as anxiety, depression, cognitive loss, sleep disorders, and in some cases, neurodegenerative illnesses like  Alzheimer’s and Parkinson’s disease.

## 1.3 Epilepsy:-

Epilepsy is a chronic neurological condition marked by recurrent and unprovoked seizures caused by abnormal electrical activity in the brain. While it can be develop at any age,  most often it is diagnosed during early childhood or among individuals older  than 60. According to the World Health Organization , approximately 50 million people arround the world  live with epilepsy, making it one of the most prevalent neurological diseases globally.

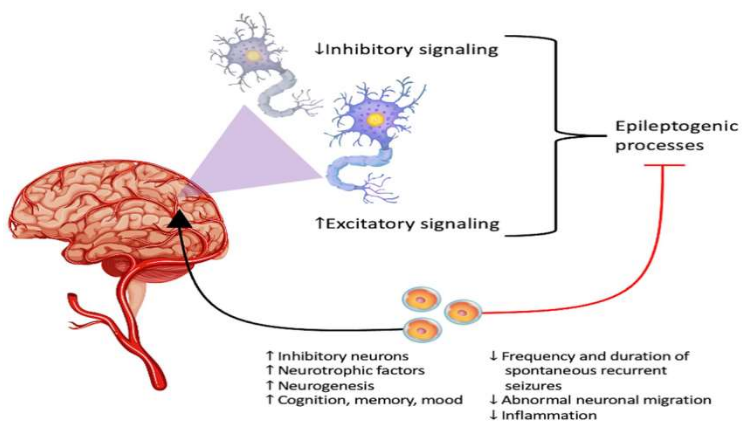


**Fig 1.10:-** Epileptogenic processes[11]

Epilepsy can derive due to various causes such as :-

a. Genetic mutations
b. Brain injury
c. Brain tumors
d. Neurodevelopmental disorders
e. Unknown(idiopathic) causes

## 1.4 Seizure:-

A seizure is sudden,uncontrolled burst of abnormal electrical activity in the brain. This disruption can lead to various symptoms such as altered awareness, involuntary muscle movements, behavioral changes and sensory disturbances. Seizures are possible for anyone at any age and there are many potential causes, ranging from an underlying medical condition to an injury or illness. There are treatments to assist you in controlling the number of times and how hard of seizure symptoms happen[12].

### 1.4.1 Types of seizures:-

Seizures are broadly categorized into two main types based on where the abnormal brain activity begins:

a. **Generalized Seizures (Generalized Onset Seizures):**
   The seizure originate simultaneously in both hemisphere of the brain. They can lead to symptoms such as body wide shaking, muscle jerk, or brief staring episodes that interrupt activity. Generalized seizures are more commonly observed in children and young adults but can affect individuals of any age.[12]

b. **Focal Seizures (Focal Onset Seizures):**
   Focal seizures begin in one specific area or "focus" of the brain. They typically cause symptoms on one side of the body and may or may not affect consciousness. In some cases, the person may be fully aware during the episode, while in others, awareness is impaired. Focal seizures can remain localized or evolve into generalized seizures affecting both brain hemispheres [12].

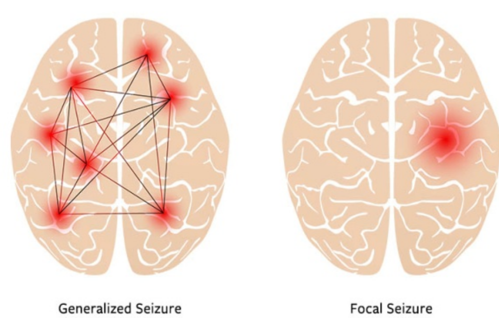


**Fig 1.11:-** Generalized Seizure and Focal Seizure[13]

## 1.5 Background of Disease

Influential physician Hippocrates disputed disease," thought to be a punishment from the gods. But the nature of the condition. In ancient Greece, epilepsy was known as the "sacred ancient Egypt, where medical texts contained descriptions of conditions resembling seizures but framed as spiritual or mystical. In fact the term epilepsy originates from the Greek word epilēpsis, which translates to "to be seized," a fitting description of the sudden and unpredictable an aetiological purpose and were considered possessed by demons and they received a punishment punishment after religious trials by an authority in the temples. Thoughts were similar in very first and oldest known neurological maladies, rooted in a history that has lasted over many millennia. The earliest reports about epilepsy are from ancient Mesopotamia dating back to 2000 BC, and people with epilepsy were the subject of engraving on clay in Epilepsy is one of the this belief around 400 BCE, suggesting that epilepsy was not a supernatural condition but a disorder of the brain that required medical treatment—an idea that was revolutionary for its time. Despite this early rational insight, the Middle Ages saw a return to spiritual and religious explanations, with epilepsy often associated with sin, witchcraft, or possession, leading to significant stigma and inhumane treatment of those affected.

in the mid-20th century provided hope to patients with more effective control of their seizures. would allow needed real-time observations of brain wave patterns that takes us closer to the cause of seizures. The development of AEDs medical specialty, and researchers such as John Hughlings Jackson contributed by establishing the association of seizures with abnormal electrical activity of the brain's cerebral cortex. It would be the invention of electroencephalography (EEG) by Hans Berger in the early 20th century that to classify seizures based on symptoms. In the 19th century, neurology became an established systematic study of epilepsy develop. The Enlightenment had arrived, and for the first time scientific inquiry was replacing authority of faith, with doctors beginning Only during the Renaissance and Enlightenment, did a more. from this condition worldwide. make strides, social stigma around epilepsy persists in much of the world. Despite this, the ongoing education, training, and technological advancement epilepsy is now transitioning towards more individualised, predictive, and preemptive treatments improving the quality of life for the millions who suffer sensors for seizures and the real-time use of Internet of Medical Things (IoMT) based paradigms. While we continue to including temporal lobe resections and vagus nerve stimulation were developed for refractory cases. The arrival of the 21st century saw developments in neuroimaging, genetics and machine learning adding new layers to our learning of epilepsy and also the growth of and wearables Surgical treatments

## 1.6 EEG and Epileptic Seizures:-

Electroencephalogram (EEG) is the most critical instrument for diagnosing and researching epileptic seizures. EEG monitors the electrical activity of the brain and can pick up:

- **Ictal activity**: Seizure-associated Abnormal rhythms.
- **Interictal activity**: Abnormal discharges between seizures, like interictal spikes, sharp waves, or spike-and-wave complexes.
- **Postictal changes**: Slow wave activity and decreased background rhythms following a seizure.

EEG is especially valuable in identifying:

a) Seizure focus (for focal seizures).
b) Epileptic syndromes (such as Lennox-Gastaut, Juvenile Myoclonic Epilepsy).

Epilepsy is abundant prevalent chronic neurologic disease worldwide. It is defined by unprovoked, seizure-induced attacks that not only impact an individual's health and quality-of-life, but also creates significant social and psychological effects. These attacks are the result of pathological, excessive, and synchronized electrical task in the brain and can change significantly in intensity and duration. In spite of the progress in clinical diagnosis and treatment, early detection of seizures is still the most difficult part for clinically treated patients with drug-resistant epilepsy or those with unusual seizure patterns.

Electroencephalography (EEG) has been identified as the most consistent way of measuring cerebral brain waves and is most widely used in monitoring and predicting seizures.

It captures electric activity of the brain via electrodes applied on the scalp and hence offers a realtime, unobstructive observation of the cerebral processes. Pre diagnostic of EEG signals manually, though, is vastly time-consuming, repetitive and prone to errors if carried out by one individual even on a unitelligent scale with tons of unbroken data. This is particularly so in the interpretation of EEG signals. This problem has motivated the growth of computer-based systems that automatically identify and classify this disease from EEG recordings.

The development of the IoMT has further changed the healthcare monitoring landscape. Integrating medical equipment with cloud, ML, and real-time data analytics, IoMT platforms facilitate remote, continuous, and automated patient treatment. For the case of epilepsy, IoMT-based diagnosis allow for the capture, processing, and analysis of EEG data in real time to provide timely warnings and information to healthcare professionals, patients, and caregivers.

This thesis suggests an IoMT-based computer-aided seizure detection system utilizing machine learning and signal processing methods for efficient and accurate classification of epileptic EEG signals.

# CHAPTER 2

# Literature Review

# CHAPTER 2

## Literature Review

1) A. Hassanpour *et al.*[14] proposed an EEG signal-dependent automatic seizure detection based on EEG signals and deep learning. They utilized real-time EEG feature extraction and classification using Convolutional Neural Networks (CNNs). The model achieved 92% high accuracy, proving the capability of deep learning in real-time and efficient seizure recognition for clinical applications.

2) S. Munirathinam *et al.*[15] developed an automatic EEG seizure detection system on the basis of entropy features. Seizure detection performance was enhanced by their algorithm, demonstrating the suitability of entropy-based features in automated EEG analysis.

3) T. Saneesh Cleatus *et al.*[16] employed spectral transformation and Convolutional Neural Networks (CNNs) to detect epileptic seizure. Their system achieved better classification accuracy,establishing the efficacy of integrated spectral features with deep learning in EEG analysis .

4) Kostas M. Tsiouris *et al.*[17] employed a three-dimensional CNN model for the automatic detection of seizures from multi-channel EEG data. They presented improved detection performance, which indicates the superiority of 3D CNNs in spatial-temporal feature extraction of EEG signals.

5) Seungjun Ryu *et al.*[18] conducted a pilot test of single-channel EEG seizure detection with machine learning. The findings indicated the feasibility of efficient seizure detection using low EEG channels, which motivated the development of cost-effective and portable diagnosis devices.

6) Hagar Gelbard-Sagiv *et al.*[19] wanted to improve wearable EEG seizure detection electrode configurations using machine learning. Their work was designed to make wearable seizure monitors more usable and accurate using intelligent electrode placement.

7) Meysam Golmohammadi *et al.*[20] investigated deep architectures for seizure detection from scalp EEGs automatically. Using CNNs and LSTM networks combined, they achieved enhanced detection performance, proving the efficiency of hybrid deep learning in EEG processing.

8) Umar Asif *et al.*[21] proposed SeizureNet, a multi-spectral deep feature learning model for seizure type classification. Their ensemble model efficiently classified multiple seizure types, with the capability of deep learning to identify subtle EEG pattern variations.

9) Y. Li *et al.*[22] proposed a unified temporal-spectral squeeze-and-excitation model for epileptic seizure detection from EEG signals. Their model efficiently extracted both temporal and spectral characteristics, which contributed to better detection performance.

10) Varsha Harpale *et al.*[23] proposed an adaptive method for feature extraction and selection for epileptic EEG signal classification. Their method improved classification performance by taking significant states of EEG data into consideration.

11) Y. Wu *et al.*[24] proposed a multi-channel long- and short-term memory-like spiking neural model as a method for detecting seizures in EEG signals. Their approach aimed to improve detection accuracy by mimicking biological neural processing.

12) Mariam K. Alharthi *et al.*[25] researches epileptic seizure disorder detection of seizures from EEG signals . Their research stressed the use of machine learning methods to identify seizure events from EEG data with high accuracy.

13) Chintalpudi S.L. Prasanna *et al.*[26] studied brain epileptic seizure detection using a joint CNN and exhaustive meta- heuristic approaches and an RNN-BLSTM classifier. Their hybrid model achieved high detection rates, emphasizing the complementarity between feature selection methods and deep learning methods.

14) Yatindra Kumar *et al.*[27] employed discrete wavelet transform-based approximate entropy and ANN to detect seizures of EEG. Their method was able to successfully extract EEG signal non-linear dynamics, leading to seizure recognition accuracy.

15) Y. Liu *et al.*[28] developed an automated seizure detection methods from CNN and LSTM networks. Their bidirectional recurrent neural network could classify epileptic EEG signals, thereby improving detection accuracy.

16) S. Savadkoohi et al. [29] proposed an explainable AI system detecting epileptic seizures in IOMT systems. Their method enhances seizure classification performance with EEG signals by employing explainable ML approaches in order to enhance transparency and trust in auto-diagnosis.

17) A. M. Al-Qurabat et al. [30] designed an IoMT-seizure detection model with an optimized algorithm. They employed the Flower Pollination Algorithm (FPA) coupled with a CNN classifier to enhance detection efficiency and accuracy for EEG signal analysis.

18) M. A. Sayeed et al. [31] introduced eSeiz 2.0, an IoMT based seizure detection platform that is accurate and low latency. The platform combines the PEM algorithm with machine learning techniques to remove false alarms and enhance real-time monitoring assistance.

19) A. S. Alickovic et al. [32] proposed a machine learning approach for the detection of epileptic seizure from EEG signals. Their work elucidates various ML classifiers employed with published EEG databases, describing how the performance of different algorithms differs in seizure detection.

20) H. Beeraka et al. [33] proposed a hybrid model of CNN, LSTM, and GRU for seizure detection in medical IoT applications. Their hybrid model effectively utilizes EEG data to provide accurate and automatic diagnosis of epileptic seizures.

**Table 2.1 :** Summary of Journal-Based Research Studies on EEG-Dependent Epileptic Seizure Detection Using MLand DL Techniques

| **S.No** | Authors | Methods | Features extracted | Classifiers | Results |
|---|---|---|---|---|---|
| 1) | A. Hassanpour *et al.* | CNN | Real-time EEG features | CNN | Detected seizures with 92% accuracy in real-time. |
| 2) | S.Munirathinam *et al.* | Entropy-based algorithm | Entropy features | Custom ML model | Improved seizure detection with entropy features. |
| 3) | T. saneesh Cleatus *et al.* | Spectral transformation and CNN | Spectral features | CNN | Improved classification accuracy. |
| 4) | Kostas M. Tsiouris *et al.* | 3D CNN | Spatial-temporal features | 3D CNN | Superior extraction of spatial-temporal features. |
| 5) | Seungjun Ryu *et al.* | ML on single-channel EEG | Single-channel features | ML model | Suitable for portable and cost-effective devices |
| 6) | Hagar Gelbard- | ML for electrode | Electrode configurati | ML-based optimizer | Improved usability and |

| | | | | | |
|---|---|---|---|---|---|
| | Sagiv *et al.* | placement | ons | | accuracy in wearable monitors. |
| 7) | Meysam Golmohammadi *et al.* | CNN and LSTM | EEG signal features | Hybrid CNN and LSTM | Improved seizure detection performance. |
| 8) | Umar Asif *et al.* | SeizureNet | Multi-spectral features | Ensemble DL | Efficient seizure classification. |
| 9) | Y. Li *et al.* | Squeeze-and-excitation model | Temporal-spectral features | SE-CNN | Improved performance in feature representation. |
| 10) | Varsha Harpale *et al.* | Adaptive feature extraction | Significant EEG states | Feature selection and classifier | Improved classification by incorporating relevant EEG states. |
| 11) | Y. Wu. *et al.* | Spiking neural model | Multi-channel features | Spiking neural network | Biological mimicry increased detection accuracy. |
| 12) | Mariam K. | ML model | EEG patterns | Machine Learning | Seizures were detected with |

| | | | | | |
|---|---|---|---|---|---|
| | Alharthi *et al.* | | | | high precision. |
| 13) | Chintalpudi S.L. Prasanna *et al.* | CNN with Feature Selection with RNN-BLSTM | Selected EEG features | Hybrid CNN and RNN-BLSTM | The deep hybrid architecture enables high detection rates. |
| 14) | Yatindra Kumar *et al.* | DWT with Approximate Entropy | Non-linear dynamics | ANN | Seizure patterns have been successfully recognized. |
| 15) | Y. Liu *et al.* | CNN with LSTM | EEG signal features | Bi-directional RNN | Enhanced accuracy in epileptic signal classification |
| 16) | S. Savadkoohi *et al.* | Explainable AI framework | Temporal-spatial EEG features | XAI with ML classifiers | Enhanced trust and performance in IoMT-based seizure detection. |
| 17) | A. M. Al-Qurabat *et al.* | Flower Pollination + CNN | Optimized EEG patterns | CNN | Improved detection accuracy and efficiency in IoMT |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | systems. |
| 18) | M. A. Sayeed *et al.* | PEM + Machine Learning | Low-latency EEG signal changes | ML-based classifiers | Real-time seizure detection with reduced false positives. |
| 19) | A. S. Alickovic *et al.* | Systematic ML analysis | Multi-dataset EEG features | Various ML classifiers | Reviewed multiple ML models to determine effective seizure detectors. |
| 20) | H. Beeraka *et al.* | CNN-LSTM-GRU Hybrid | Spatiotemporal EEG representations | CNN, LSTM, GRU | High-accuracy seizure detection in Medical IoT environments. |

This chapter discribes and compares various approaches available for epileptic seizure detection. In Chapter 3 general methodology utilized for the detection of epileptic seizure is explained in detail.

# CHAPTER 3

# METHODOLOGY

# CHAPTER 3

# METHODOLOGY

The general flow chart for the detection steps of epileptic seizure is showing in **Figure 3.1**. In this section, various process involved in the detection of epileptic seizure are discussed.

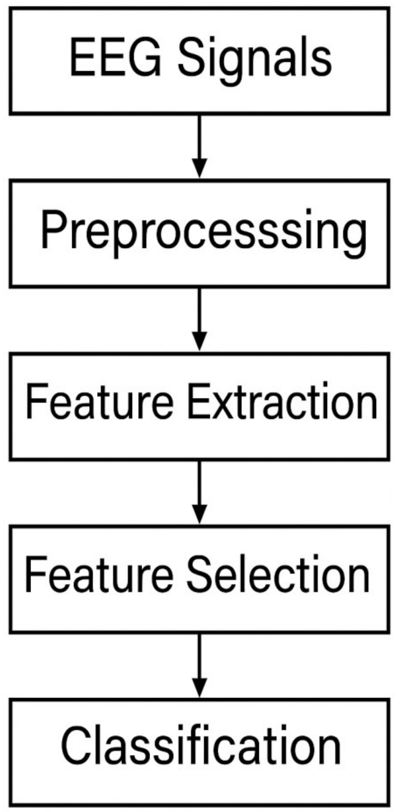


**Fig 3.1:** General flow methodology in the detection of Epileptic Seizure detection

## 3.1 Different databases Present

Various databases on the internet hold EEG signals captured from epilepsy patients and healthy subjects. These databases are essential in the development and testing of epileptic seizure detection and classification algorithms. Here is a list of some popularly used EEG datasets:

### 3.1.1. CHB-MIT Scalp EEG Database

This open-access dataset, collected at the Children's Hospital Boston, contains EEG redcordings from 23 pediatric patients diagnosed with drug – resistant epilepsy. The dataset comprises 846 hours of EEG recordings and 163 seizure events, recorded using a 23-channel EEG system. The recordings are annotated with the start and end time of each seizure, thus making it widely employed for both seizure detection and prediction studies.

### 3.1.2. Bonn University EEG Dataset :

This dataset have five subsets (A–E), each with 100 single-channel EEG segments with 23.6 seconds duration. Sets A and B are of healthy subjects with eyes open and closed, respectively, while sets C, D, and E represent interictal and ictal EEG from epilepsy patients. It is one of the popular datasets used datasets for binary and multi-class classification tasks in epilepsy studies.

### 3.1.3. Temple University Hospital (TUH) EEG Seizure Corpus :

TUH EEG is the largest publicly available EEG corpus in the world, created at Temple University. The seizure corpus comprises both training and evaluation datasets, with recordings collected from multiple patients of various ages. It has more than 3,000 seizure episodes from different seizure types including generalized and focal seizures. The dataset is ideal for training deep learning and real-time seizure detection models.

### 3.1.4. EPILEPSIAE Database :

This database contains patients' long-term continuous EEG recordings with drug-resistant epilepsy. It was developed under the EPILEPSIAE EU-funded project and includes multi-channel EEG data, clinical metadata, seizure annotations, and patient history. The recordings are taken in clinical conditions and are ideal for seizure forecasting research.

### 3.1.5. Seizure Prediction Project (Kaggle) :

Part of a competition on Kaggle, this dataset consists of intracranial EEG (iEEG) recordings from epilepsy patients with electrodes implanted. The data set comes labeled with preictal and interictal classified data segments, allowing researchers to practice seizure prediction tasks. It is particularly well suited for test deep learning and time-series models.

### 3.1.6. Swedish Epilepsy EEG Dataset :

Introduced by the University of Gothenburg, this information contains EEG recordings of neonates, children, and adults. Non-seizure and seizure events are covered with high-quality annotations. Can be beneficial for generalized model training across different age groups.

These data sets can be beneficial for the research, training, and testing of epileptic seizure detection systems based on signal processing and ML algorithms. They facilitate reproducible research and comparative studies on neuroinformatics and smart health monitoring.

**Table 3.1** shows the distinguish database used for detection of Epileptic seizure variety of available methods discussed in Chapter - 2.

**Table3.1:**Summary of different databases used for epileptic seizure detection

| S.NO. | Authors | Database |
|---|---|---|
| 1. | A. Hassanpour et al. [14] | CHB-MIT Scalp EEG Database |
| 2. | S. Munirathinam et al. [15] | Bonn University EEG Dataset |
| 3. | T. Saneesh Cleatus et al. [16] | CHB-MIT EEG Dataset |
| 4. | Kostas M. Tsiouris et al. [17] | CHB-MIT Scalp EEG Dataset |
| 5. | Seungjun Ryu et al. [18] | Custom Single-Channel |

| | | |
|---|---|---|
| | | Clinical EEG Dataset |
| 6. | Hagar Gelbard-Sagiv et al. [19] | Wearable EEG Device Dataset (Clinical Trials) |
| 7. | Meysam Golmohammadi et al. [20] | TUH EEG Seizure Corpus |
| 8. | Umar Asif et al. [21] | TUH EEG Corpus (SeizureNet Framework) |
| 9. | Y. Li et al. [22] | CHB-MIT EEG Dataset |
| 10. | Varsha Harpale et al. [23] | Bonn University EEG Dataset |
| 11. | Y. Wu et al. [24] | CHB-MIT Multi-channel EEG Data |
| 12. | Mariam K. Alharthi et al. [25] | CHB-MIT and Bonn Public EEG Databases |
| 13. | Chintalpudi S. L. Prasanna et al. [26] | Bonn EEG Dataset |
| 14. | Yatindra Kumar et al. [27] | Bonn University EEG Dataset |
| 15. | Y. Liu et al. [28] | TUH EEG Corpus (CNN + Bi-LSTM Experiments) |
| 16. | S. Savadkoohi *et al.* [29] | CHB-MIT Scalp EEG Database |
| 17. | A. M. Al-Qurabat *et al.* [30] | Bonn University EEG Dataset |
| 18. | M. A. Sayeed *et al.* [31] | CHB-MIT EEG Dataset |

| | | |
|---|---|---|
| 19. | A. S. Alickovic *et al.* [32] | CHB-MIT, Bonn, TUH EEG Databases |
| 20. | H. Beeraka *et al.* [33] | TUH EEG Seizure Corpus |

The components of the proposed system architecture are as follows:-

a) EEG Signal Acquisition: EEG signals are collected using wearable sensors capable of continuous monitoring. These sensors wirelessly transmit the data to a processing unit.
b) Preprocessing: Raw EEG signals often contain various artifacts and noise. Methods such as smoothing and sharpening filters are applied during preprocessing to enhance signal quality and identify critical features.
c) Feature Extraction: Important features are derived from the preprocessed signals of EEG to represent the underlying brain activity. These features include statistical parameters like mean, skewness, variance and Hjorth parameters include Activity, Mobility, and Complexity which provide insights into the temporal dynamics of the EEG signals.
d) Feature Selection: To reduce computational complexity and improve classification efficiency, PSO is employed for feature selection. PSO is a meta-heuristic optimization strategy inspired by the social behavior of bird flocks, which effectively identifies the most relevant features for seizure detection.
e) Classification: The selected features are input into various machine learning classifiers, Comparative analysis indicates that linear kernel of SVM classifier achieves the accuracy of 98.5% which is highest when paired with features selected by PSO.
f) IoMT Integration: The system is incorporated into an IoMT platform, facilitating real-time data transmission to healthcare providers. Alerts are activated upon seizure detection, enabling prompt medical intervention.

The contributions of this work are two-fold:

a. The integration of PSO for optimal feature selection from a union of time-domain and frequency-domain features.
b. The comparison of various classifiers for the purpose of EEG-based seizure detection on real-world datasets. This system not only improves detection performance but also has practical relevance to real-time seizure monitoring in wearable or implantable medical devices.

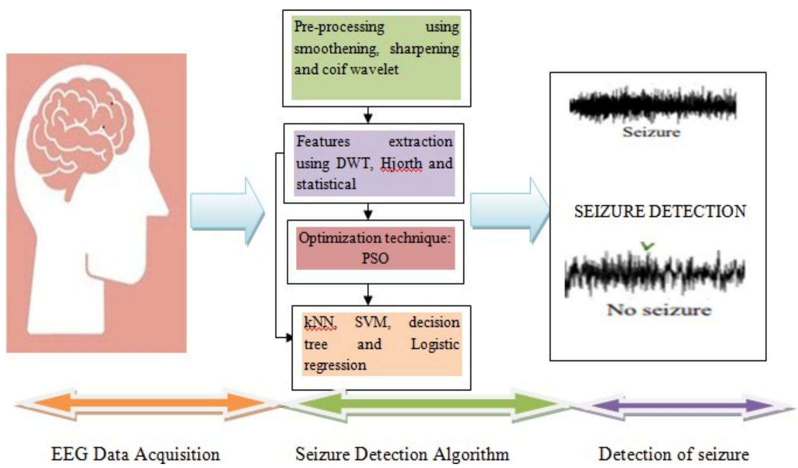


**Fig. 3.2 :**Proposed seizure detection algorithm[34]

## 3.2 Methodology

The project tries to classify EEG signals into normal type and ictal (seizure) types with high precision using sophisticated preprocessing, feature extraction, optimization, and classification. The entire methodology is broken into the following stages:

### 3.2.1. EEG Signal acquisition

EEG (Electroencephalography) signals are gathered from open datasets like the CHB-MIT and Bonn University EEG dataset, holding EEG recordings of both healthy and epilepsy patients. The signals are sampled at a particular frequency (e.g., 173.61 Hz or 256 Hz) and consist of segments of normal, interictal, and ictal states.

### 3.2.2.Preprocessing

Preprocessing is an important process in EEG signal analysis to enhance signal quality by eliminating noise and artifacts that can influence feature extraction accuracy and classification. Raw EEG signals always possess unwanted components like eye blinks, muscle activity (EMG), power line interference, and baseline drift. Successful preprocessing increases the dependability and intelligibility of the underlying brain activity pertaining to seizure detection.

**Common Preprocessing Techniques:**

**a) Filtering:**

Bandpass Filtering is utilized to maintain frequencies most pertinent to brain activity and normally in the range of 0.5 Hz and 60 Hz, removing DC offset and high frequency noise.

Sample: A 0.5–45 Hz Butterworth filter.

**b) Artifact Removal:**

Independent Component Analysis (ICA) or Regression Methods may be utilized to separate and eliminate artifacts due to eye movements, muscle contractions, or electrode movement.

**c) Normalization:**

EEG signals are normalized to a standardized range (Example [0,1] or -1 to 1) to provide consistency over all channels and subjects, particularly critical for machine learning routines

**d) Baseline Correction:**

Suppresses slow drifts or baseline fluctuations in the signal that may introduce bias into analysis.

**e) Segmentation:**

The EEG data is broken up into fixed-duration epochs (e.g., 2s or 5s segments) for standardized analysis and feature extraction.

Preprocessing guarantees that the most useful and clean EEG data are utilized in the later stages of feature extraction and classification so as to enhance the overall accuracy of the seizure detection system.

### 3.2.3. Feature Extraction

Two primary types of features are extracted from the preprocessed EEG signals:

#### A. Discrete Wavelet Transform (DWT)

DWT divides the EEG signal into different frequency sub-bands to capture both frequency and time domain characteristics.

- The EEG signal x(t) is passed through high pass (detail) and low pass (approximation) filters.
- The output is a set of wavelet coefficients:

$$A_{n(t)} = \sum_{k} x(k) \cdot \phi_{\{n,k\}(t)} \tag{1}$$

$$D_{n(t)} = \sum_{k} x(k) \cdot \psi_{\{n,k\}(t)} \tag{2}$$

The energy of each sub-band is calculated as:

$$E = \sum_{i=1}^{N} c_i^2 \tag{3}$$

#### B. Entropy Features

Entropy quantifies the irregularity or complexity of a signal. We use:

**i. Spectral Entropy (SE):**

It measures the disorder in the power spectral density (PSD):

$$SE = \sum_{\{i=1\}}^{\{N\}} P_i \, log_{\{2\}}(P_i) \tag{4}$$

**ii. Sample Entropy (SampEn):**

It measures the unpredictability in a time series.

$$SampEn(m, r, N) = -\ln\left(\frac{A}{B}\right) \tag{5}$$

**C. Statistical Parameters**

Statistical features are used to describe the issuance, shape, and spread of EEG signal values over the time. These features are time-domain descriptors that help in distinguishing seizure from non-seizure EEG segments.

Let the EEG signal be represented as:

$$x(t) = \{x_1, x_2, \dots, x_{N\}} \tag{6}$$

Then the commonly used **statistical parameters** are:

- **Mean** (average value):

$$\mu = \frac{1}{N} \sum_{\{i=1\}}^{\{N\}} x_i \tag{7}$$

- **Variance** (spread of signal values):

$$\sigma^2 = \frac{1}{N} \sum_{\{i=1\}}^{\{N\}} (x_i - \mu)^2 \tag{8}$$

- **Skewness** (asymmetry of the signal distribution):

$$Skewness = \frac{1}{N} \sum_{\{i=1\}}^{\{N\}} \left(\frac{x_i - \mu}{\sigma}\right)^3 \tag{9}$$

- **Kurtosis** (peakedness of the distribution):

$$kurtosis = \frac{1}{N} \sum_{\{i=1\}}^{\{N\}} \left(\frac{x_i - \mu}{\sigma}\right)^4 \tag{10}$$

These features help in understanding how the EEG signal deviates from normal behavior statistically.

**D. Hjorth Parameters**

Hjorth parameters are the time-domain measures that characterize the EEG signal's activity, mobility, and complexity, reflecting its dynamical behavior.

Let x(t) be the EEG signal of length NNN, and let dx(t) be its first derivative:

1. **Activity** – measures the signal power (variance):

$$Activity = var\big(x(t)\big) = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2 \tag{11}$$

2. **Mobility** – represents the mean frequency of the signal:

$$Mobility = \sqrt{\frac{Var\big(dx(t)\big)}{Var\big(x(t)\big)}} \tag{12}$$

3. **Complexity** – describes the similarity of the shape of the signal to a pure sine wave:

$$Complexity = \frac{Mobility\left(dx(t)\right)}{Mobility\left(x(t)\right)} \tag{13}$$

These Hjorth parameters effectively capture the **dynamic structure** of EEG signals and are useful in identifying seizure patterns.

### 3.2.4. Feature Selection

After feature extraction, a large numerous of features are obtained. To select only the most relevant ones and reduce computational complexity, **metaheuristic optimization algorithms** are used:

**Particle Swarm Optimization (PSO)**

Influence by bird flocking behavior, PSO optimizes feature selection using a swarm of particles.

- **Position update:**

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{14}$$

- **Velocity update:**

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot \left(pbest_i - x_i(t)\right) + c_2 . r_2 \left(gbest - x_i(t)\right) \tag{15}$$

### 3.2.5. Classification

The selected features are fed into machine learning classifiers to categorize EEG segments into **normal**, **interictal**, or **ictal** classes.

Popular classifiers used:

- **Support Vector Machine (SVM)**

$$f(x) = sign(w^T x + b) \tag{16}$$

- **K-Nearest Neighbor (KNN)**

Classification is based on the highest vote among the kkk closest data points in the feature space using Euclidean distance:

$$d(p,q) = \sqrt{}\{\sum_{i=1}^{n} (p_i - q_i)^2\} \tag{17}$$

- **Random Forest / Logistic Regression / Decision Tree /** may also be used for comparative evaluation.

### 3.2.6. Performance Metrics

The classifiers are evaluated using:

a. **Accuracy:**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

b. **Sensitivity (Recall):**

$$Sensitivity = \frac{TP}{TP + FN} \tag{19}$$

c. **Specificity:**

$$Specificity = \frac{TP}{TP + FP} \tag{20}$$

d. **Precision:**

$$Precision = \frac{TP}{TP + FN} \tag{21}$$

e. **F1-score:**

$$\mathrm{F1} = 2 \cdot \frac{\mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{22}$$

- **ROC-AUC:** Receiver Operating Characteristic curve – area under the curve for evaluating classifier performance.

# CHAPTER- 4

# Comparison of Feature-Based EEG Seizure Detection Models with and without PSO Optimization

# CHAPTER- 4

# Comparison of Feature-Based EEG Seizure Detection Models with and without PSO Optimization

Many transformation methods like Discrete Wavelet Transform (DWT), FFT, and STFT can be used as feature extraction techniques in EEG-based seizure detection. In the present work, DWT and entropy-based feature extraction techniques have been used due to their ability to capture both frequency and time domain characteristics from non-stationary EEG signals. DWT is more suitable for EEG signals compared to classical transforms like FFT, as it allows multi-resolution analysis and localized decomposition of the signal across frequency bands.

In this study, the feature extraction process is based on a combination of DWT coefficients, Hjorth parameters, and entropy measures (including spectral and sample entropy). These features are derived from the decomposed EEG signals and reflect important aspects such as signal power, complexity, regularity, and dynamic behavior. After feature extraction, the features are normalized and optimized using the Particle Swarm Optimization (PSO) technique to enhance classifier performance by eliminating redundant or less informative features.

For classification, ML models such as SVM, Logistic Regression, KNN, and Decision Tree are employed. In particular, SVM with a linear kernel showed the most promising performance. The classification process is evaluated using a 5  fold cross-validation approach, which ensures that the model's performance is validated across various partitions of the data and prevents overfitting.

These algorithmic steps and signal processing modules have already been discussed in detail in Chapter 3 (Methodology). This chapter focuses on presenting the results obtained, followed by a discussion of their significance, highlighting the impact of different feature combinations and optimization techniques on classification accuracy.

### 4.1: Data Collection

For the implementation of this method, EEG signal data is used instead of image data. These signals are collected from publicly available and widely used datasets such as the CHB-MIT Scalp EEG Database and the Bonn University EEG Dataset[14], as discussed in Chapter 3. For this study, a total of 100 EEG signal segments were selected—50 representing normal brain activity and 50 representing seizure (ictal) activity. The signals were preprocessed, segmented, and used for further feature extraction and classification.

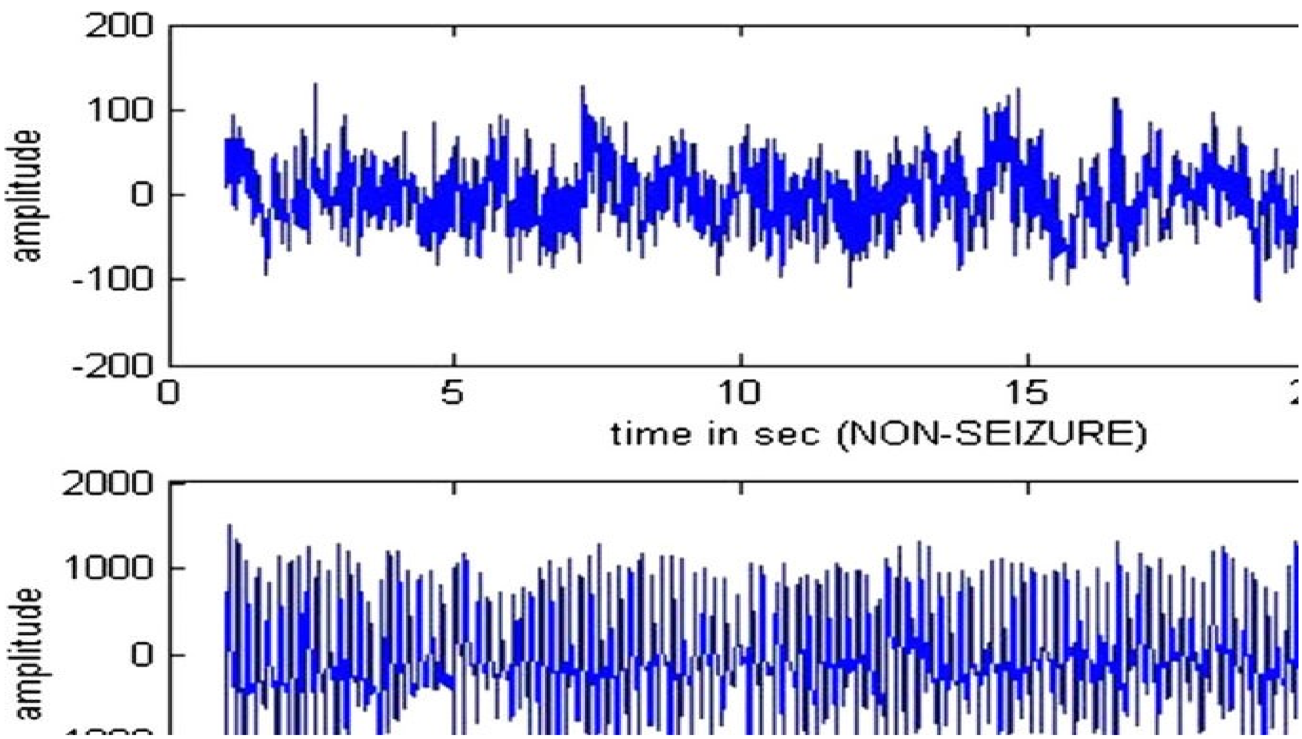


**Figure 4.1:** Sample of EEG signals for non-seizure and seizure traces [35]

## 4.2: Pre-Processing

The Pre-processing is a fundamental operation in the EEG-based seizure detection process. It aims to increase the quality of the raw EEG signals and reduce the presence of noise or irrelevant fluctuations. In this study, pre-processing involves converting raw EEG signals into a clean, analyzable form suitable for feature extraction.

Key pre-processing steps include:

- **Noise removal** using techniques like **smoothing and filtering** to eliminate artifacts caused by eye movement, muscle activity, or external electrical interference.
- **Signal sharpening** to emphasize significant transitions in brain activity.
- **Segmentation** of continuous EEG recordings into fixed-length time windows for uniform analysis.
- Conversion of these signal segments into **2D grayscale visual representations**, where appropriate, for edge detection or deep learning processing.

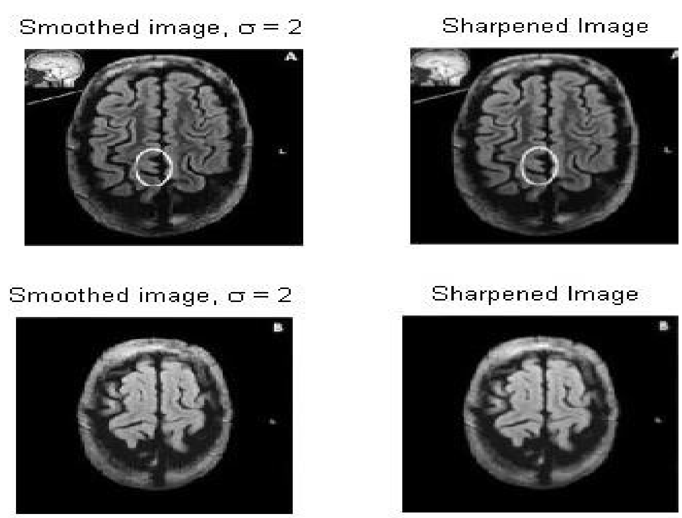


**Fig. 4.2 :**Smoothened and sharpened image[34]

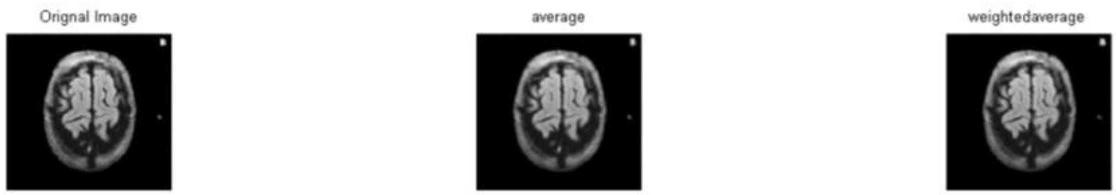


**Fig. 4.3:**Averageand weighted average filtering[34]


**Fig. 4.4:**Edge detection[34]

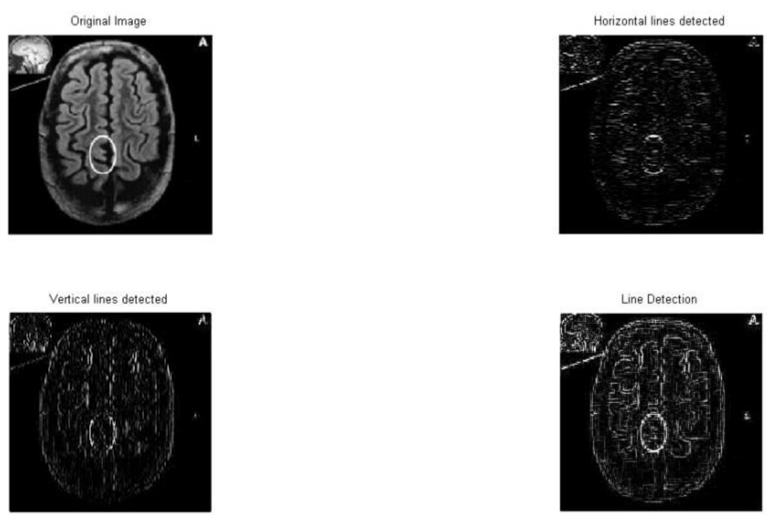


**Fig4.5:**Line detection [34]

This structured approach facilitates a clear comparison of the performance achieved using various feature combinations and classifiers. It helps the reader understand the context of the experiment, the techniques applied, and the resulting classification outcomes. **Table 4.1** summarizes the accuracy results obtained from different machine learning classifiers **without the use of any meta-heuristic optimization technique**.

## 4.3: Results

**Table 4.1 :** Accuracy without applying meta-heuristic approach.

| Accuracy | K-nearest neighbor | | | SVM | | | Decision Tree | Logistic regression | BEST (KNN, SVM, DT,LR) |
|---|---|---|---|---|---|---|---|---|---|
| | **3** | **4** | **5** | **linear** | **RBF** | **Poly** | | | |
| coif1(DWT)+Hjorth | 72.5 | 75 | 70 | **92.5** | 62.5 | 52.5 | **92.5** | **92.5** | 92.5 |
| coif2(DWT)+Hjorth | 72.5 | 70 | 72.5 | 92.5 | 62.5 | 52.5 | **95** | 90 | 95 |
| coif3(DWT)+Hjorth | 77.5 | 75 | 72.5 | **97.5** | 62.5 | 52.5 | 95 | 95 | 97.5 |
| Hjorthparameters | 77.5 | 75 | 72.5 | **97.5** | 62.5 | 52.5 | 95 | 95 | 97.5 |
| Statisticalparameters | 80 | 82.5 | 80 | **97.5** | 75 | 62.5 | 95 | 95 | 97.5 |
| Hjorth + Statistical parameters | 77.5 | 75 | 72.5 | **97.5** | 62.5 | 52.5 | 95 | 95 | 97.5 |
| DWT+statistical+hjorth | 70 | 72.5 | 72.5 | **97.5** | 62.5 | 52.5 | 95 | 95 | 97.5 |
| DWT+ Entropy | 83 | 80.5 | 80.5 | 98 | 96.65 | 98 | 98 | 95.5 | **98** |

To assess the performance of some of the feature extraction methods and classifiers in epileptic seizure detection, multiple machine learning models were trained and tested using combinations of DWT, entropy based, Hjorth parameters and statistical features. The classifiers employed in this study include SVM with linear, (RBF), and polynomial kernels , Decision Tree , K-Nearest Neighbor (KNN) for different numbers of k (3, 4, 5) and Logistic Regression.

**Figure 4.6** below shown an in-depth comparison of the classification accuracy achieved by each model on various feature sets. This figure facilitates determination of the best combinations of the feature extraction methods and classification algorithms for optimal detection of seizure performance.

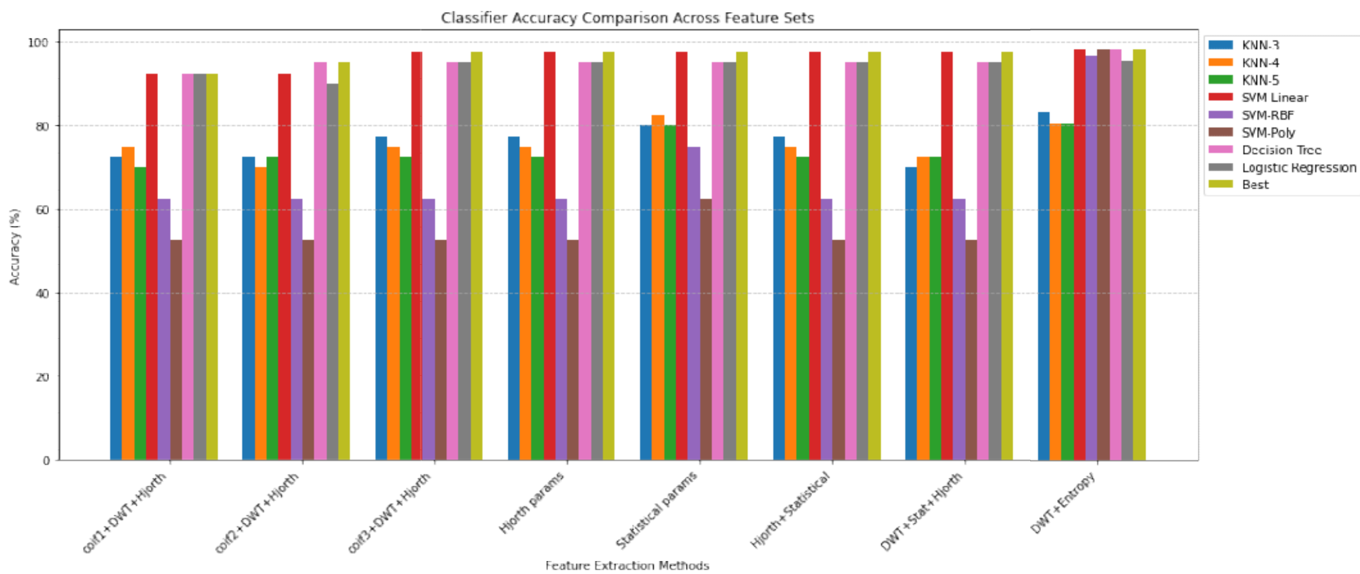


**Fig 4.6 :** Classification Accuracy without considering Meta-Heuristic Feature Selection Across Various Classifiers

Support Vector Machine (SVM) is a widely used supervised learning algorithm, particularly effective in binary classification tasks involving biomedical signals. Its primary objective is to identify the optimal hyperplane that distinguishes between two categories—in this context, seizure and non-seizure EEG recordings. Within an N-dimensional feature space, SVM constructs a hyperplane of dimension (N−1) to achieve accurate separation of the classes.

For SVM with linear kernel , the dot product is computed directly as $x_1 \cdot x_2$, referred to as a linear kernel, since it operates in the original input space. In contrast, kernel-based SVMs (e.g., polynomial or Gaussian) compute the dot product in a higher-dimensional space using a mapping $function\ \phi(x)$ where:

$$K(x_1, x_2) = \emptyset(x_1) \cdot \emptyset(x_2) \tag{23}$$

Kernel SVMs often require $O(n^2)$ time for training and O(nd) for classification, where nnn is the number of training samples and ddd is the number of input features. This becomes computationally expensive, especially with large datasets. On the other hand, linear SVMs are much more efficient—requiring only O(d) for classification and O(nd) for training—making them ideal for high-dimensional or sparse biomedical data such as EEG signals.

To enhance performance and minimize input feature dimensionally , meta – heuristic algorithms like PSO were employed. By identifying the more significant features, PSO contributes to improve classification accuracy and reduced computational complexity .

**Table 4.2** presents the accuracy results obtained using different classifiers after applying the PSO-based feature selection technique. The results demonstrate the effectiveness of optimization in improving model performance for epileptic seizure detection.

**Table 4.2:** Accuracy considering meta-heuristic approach.

| Accuracy | K-nearest neighbor | | | SVM | | | Decision Tree | Logistic regression | BEST (KNN, SVM, DT,LR) |
|---|---|---|---|---|---|---|---|---|---|
| | 3 | 4 | 5 | linear | RBF | Poly | | | |
| coif1 (DWT)+ Hjorth | 73 | 75.5 | 71 | 93.5 | 65.5 | 55 | 94.5 | 94.5 | 94.5 |
| coif2(DWT)+Hjorth | 73 | 70 | 73.5 | 93.5 | 65.5 | 55 | 97 | 92 | 97 |
| coif3(DWT)+Hjorth | 79.5 | 77 | 75.5 | 98.5 | 65.5 | 55 | 97 | 97 | 98.5 |
| Hjorthparameters | 79.5 | 77 | 75.5 | 98.5 | 65.5 | 55 | 97 | 97 | 98.5 |
| Statisticalparameters | 82 | 85.5 | 83 | 98.5 | 78 | 65.5 | 97 | 97 | 98.5 |
| Hjorth+Statistical parameters | 79.5 | 78 | 75.5 | 98.5 | 65.5 | 55.5 | 97 | 97 | 98.5 |
| DWT+statistical+ | 74 | 72.5 | 75.5 | 98.5 | 65.5 | 55.5 | 97 | 97 | 98.5 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| hjorth | | | | | | | | | |
| DWT+ Entropy | 96.50 | 98.5 | 94 | 99.5 | 97.33 | 98 | 96 | 99.5 | 99.5 |

To further boost the classification performance, a meta-heuristic approach was utilized for feature selection. Meta-heuristics are optimization algorithms based on natural phenomenun (e.g., genetic algorithms, particle swarm optimization) that helps in selecting the most informative subset of features. By Using this method , the number of dimensions in the feature space is minimized while preserving the most discriminative information, leading to improved classifier performance. The bar graph below illustrates the comparative accuracy of different classifiers— Logistic Regression, Decision Tree, KNN and SVM with linear, RBF, and polynomial kernels, —across various optimized feature sets. The results show a noticeable improvement in accuracy for most classifiers, especially when entropy and statistical features are used in conjuction with DWT.

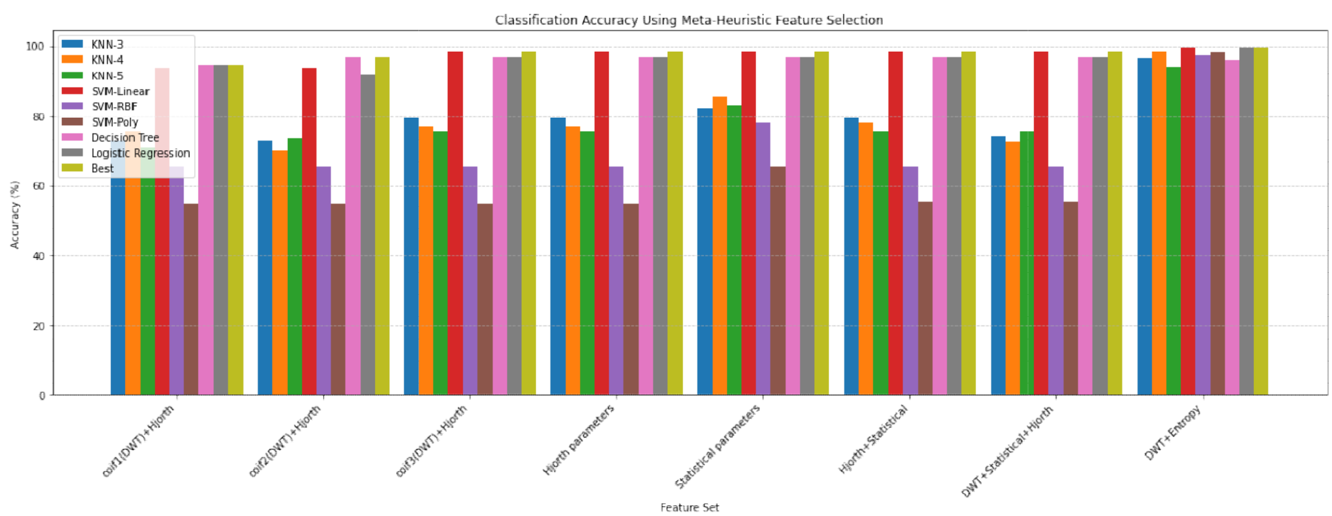


**Fig 4.7:** Classification Accuracy Using Meta-Heuristic Feature Selection Across Various Classifiers

The inclusion of **statistical parameters** provides valuable insights into the comprehensive distribution and variability of the signals used for this, effectively complementing the information captured by **Hjorth parameters**. The combination of both enhances the depth of feature representation, capturing diverse aspects of brain signal dynamics. Classifiers such as **SVM** and **kNN** contribute to robust decision-making by effectively modeling both local and global patterns within the feature space.

This integrated approach—merging Hjorth parameters with statistical features—lays a strong foundation for the proposed seizure detection system. In many EEG-based classification problems, multiple decision boundaries may seem appropriate; however, selecting the boundary that **maximizes the margin** is often preferred, as it increases separation between classes and enhances resilience to small variations in data.

The upcoming sections present the implementation approach, experimental results, and validation methods, offering a detailed assessment of how effectively the proposed model captures the intricate patterns found in epileptic EEG signals.

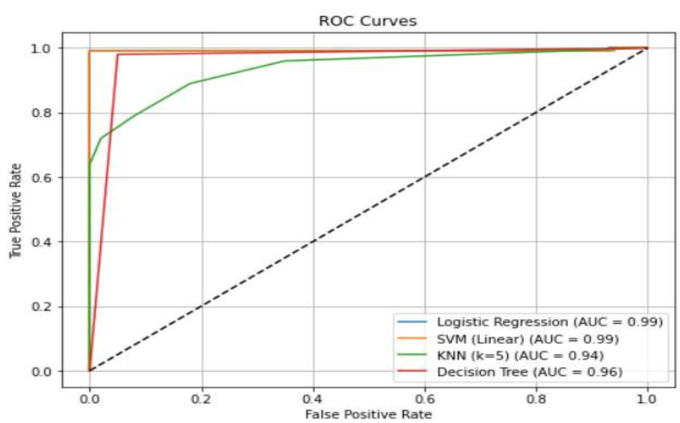


**Fig 4.8 :** ROC Curves

**TABLE 4.3:** Distinguishing to Seizure detection model

| Works | Methods | Cases | CA |
|---|---|---|---|
| Kumar *et al.*2014 [36] | DWT and neural network classifier | A-E<br>A,D-E | 100<br>95 |
| Tawfik *et al.* 2016[37] | Support vector machine and weight permutation unit | A-E<br>A,D-E | 98.5<br>96.5 |
| Yavaz *et al.* 2018[38] | generalized regression neural network and Cepstral analysis | A-E<br>A,D-E | 99<br>97.25 |
| Proposed model | DWT based Hjorth, statistical parameter considering SVMclassifier with linear kernelwithout optimization | A-D | 97.5 |
| Proposed model | DWT based Hjorth,statistical parameterwith linear kernel of SVM classifier and optimization technique | A-D | 98.5 |

| | | | |
|---|---|---|---|
| Proposed model | DWT based Entropy features with SVM classifier with linear kernel without considering optimization technique | A-D | 98 |
| Proposedmodel | DWT based Entropy features with SVM classifier with linear kernel and optimization technique | A-D | 99.5 |

An accuracy of 99.5% was achieved using the proposed model that integrates Discrete Wavelet Transform (DWT)-based entropy features with Support Vector Machine (SVM) using a linear kernel, optimized through Particle Swarm Optimization (PSO). This marks a 2% improvement in classification accuracy when compared to the same model without applying meta-heuristic optimization.

In the training phase, the SVM algorithm constructs an optimal a hyperplane that creates the widest possible separation between the closest data points of different classes, known as support vectors. from both classes—seizure and non-seizure—to ensure a more generalized and robust decision boundary. Despite its strong performance, SVM can be sensitive to assumptions such as linearity and normal distribution of data. Since EEG signals are typically non-linear and non-stationary, violating these assumptions can affect classification performance if not handled properly.

While KNN is non-parametric and easier to implement, it often involves higher computational cost during testing, especially for large datasets, and may not adapt as well to complex EEG patterns compared to SVM.

**Challenges Faced During Validation:**

i. High variability between subjects' EEG signals made it challenging to generalize the model across different individuals.
ii. The model showed initial signs of overfitting when using unfiltered, high-dimensional features.
iii.

EEG data included significant noise and artifacts (e.g., eye blinks, muscle activity), which impacted feature extraction quality.

**Solutions Applied:**

- PSO was employed for feature selection, reducing dimensionality and removing redundant or irrelevant features, which improved both performance and efficiency.
- A robust 5fold cross-validation approach was used to evaluate model consistency and minimize overfitting.
- Preprocessing techniques, including signal smoothing and segmentation, were applied to ensure cleaner, more uniform input for feature extraction.

In addition to traditional machine learning approaches, we also experimented with various deep learning architectures to evaluate their performance in classifying seizure and non-seizure EEG signals. Models such as DenseNet121, MobileNetV2, VGG16, VGG19, InceptionV3, and ResNet50 were implemented using image-like representations of EEG signal segments. While these models have shown promising results in many image-based biomedical applications, the performance in our case was comparatively lower than that of the optimized machine learning models. This may be attributed to the limited size and variability of the dataset, as well as the challenges in accurately converting EEG signals into a format suitable for deep learning models. The following table summarizes the classification accuracy achieved by each deep learning model.

**Table 4.4:** Accuracy after applying deep learning models

| Deep Learning Models | Accuracy |
| --- | --- |
| VGG16 | 92.5% |
| VGG19 | 82.5% |
| RESTNET50 | 72.5% |
| MOBILENETV2 | 95% |
| INTERSEPTV3 | 87.5% |
| DENSENET121 | 97.5% |

# CHAPTER-5

# CONCLUSION AND FUTURE SCOPE

# CHAPTER 5

## Conclusion and Future Scope

Epilepsy is a neurological condition that is attributed to unusual  electrical pursuit in the brain, usually directing to repeat attacks of seizures. Because seizure onset can be abrupt and unavoidable, early diagnosis and promt treatment are significant in preventing severe health complications and enhancing patient quality of life. In this study, we evaluated and compared the classification performance of various feature extraction techniques—including DWT-based Hjorth parameters, statistical measures, and entropy features—combined with PSO and SVM for feature selection.

The   model's performance was assessed using metrics  such as accuracy, sensitivity, specificity, and 5fold cross-validation accuracy. Among the approaches studied, the combination of DWT-based entropy features with SVM and PSO demonstrated the highest detection accuracy of 99.5%, along with strong sensitivity and cross-validation performance. In contrast, models without optimization or with alternative feature combinations performed slightly lower, highlighting the importance of both feature quality and selection strategy.

It can be concluded that the integration of wavelet-domain features with meta-heuristic optimization serves as an effecient and reliable procedure for EEG-based seizure detection. This work also compares and validates our proposed technique against several existing methods in literature, demonstrating superior performance.

However, the primary limitation of these methods lies in their computational complexity and sensitivity to EEG variability across subjects. In the future, this system can be enhanced for real-time implementation, integrated with IoT-based wearable devices, and expanded to detect other neurological diseases such as Parkinson's Disease, Alzheimer's, or sleep-related conditions, using bigger and longer EEG datasets.

# PUBLICATIONS

R. Goel and S. Jain, "Internet of Medical Things based EEG Epileptic Seizure Detection," in *Proceedings of the 2024 Eighth International Conference on Parallel, Distributed and Grid Computing (PDGC)*, Waknaghat, Solan, India, 2024, pp. 155–159, doi: 10.1109/PDGC64653.2024.10984265.

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# APPENDICES