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Electrical and Computer Engineering

EPILEPSY DISEASE DETECTION BY EEG SIGNAL RECOGNITION USING AI TECHNIQUE AND IOTS

Ali Mohammed Hussein AL-SHAREEFI

Master's Thesis

Supervisor

Asst. Prof. Dr Abdullahi Abdu IBRAHIM

İstanbul, 2024

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DEDICATION

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Ali Mohammed Hussein AL-SHAREEFI

Signature

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ABSTRACT

EPILEPSY DISEASE DETECTION BY EEG SIGNAL RECOGNITION USING AI TECHNIQUE AND IOTS

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This research introduces a novel approach for detecting epileptic seizures, leveraging advancements in IoT, moderate signal strength, and advanced deep learning autoencoders. The core aim is to synergize signal function performance with enhanced feature extraction capabilities of a deep learning autoencoder, thereby enabling the technology to identify optimal characteristics more efficiently and swiftly than existing traditional methods. This new method will undergo comparative analysis against various existing computational tools in the same domain. Additionally, it will be benchmarked against established studies in this field. The efficacy of this framework is underscored by its impressive 99.00% accuracy, positioning it favorably among leading research in epilepsy detection and EEG signal classification.

Keywords: EEG Signal, Auto-Encoder, Epilepsy Detection, Deep Learning, NIRS, MEG, EKG .

ÖZET

AI TEKNİĞİ VE IOTS KULLANILARAK EEG SİNYAL TANIMA İLE EPİLEPSİ HASTALIĞININ TESPİTİ

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Bu araştırma, epileptik nöbetleri tespit etmek, IoT'deki gelişmelerden, orta düzeyde sinyal gücünden ve gelişmiş derin öğrenme otomatik kodlayıcılarından yararlanmak için yeni bir yaklaşım sunuyor. Temel amaç, derin öğrenme otomatik kodlayıcının gelişmiş özellik çıkarma yetenekleriyle sinyal işlevi performansını sinerjiye kavuşturmak, böylece teknolojinin en uygun özellikleri mevcut geleneksel yöntemlere göre daha verimli ve hızlı bir şekilde tanımlamasını sağlamaktır. Bu yeni yöntem, aynı alandaki mevcut çeşitli hesaplama araçlarıyla karşılaştırmalı analize tabi tutulacaktır. Ayrıca bu alanda yapılan çalışmalarla karşılaştırılacaktır. Bu çerçevenin etkinliği, onu epilepsi tespiti ve EEG sinyal sınıflandırmasında önde gelen araştırmalar arasında avantajlı bir konuma getiren etkileyici %99,00 doğruluğuyla vurgulanmaktadır.

Anahtar Kelimeler: EEG Sinyali, Otomatik Kodlayıcı, Epilepsi Tespiti, Derin Öğrenme, NIRS, MEG, EKG.

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ABBREVIATIONS

SVM	:	Support Vector Machine
IoTs	:	Internet of Things
NN	:	Neural Network
WSN	:	Wireless Sensor Network
SSAE	:	Stacked Sparse Autoencoders
DT	:	Decision Tree

1. INTRODUCTION

This study establishes a crucial link between the human brain and computer systems, facilitating the transmission of brain-generated electrical signals [9]. These signals are captured either externally through electrodes placed on the skull or internally for more direct measurement. This computer-brain interface enables users to transmit commands to the computer through mental processes. Conversely, the brain-computer interaction involves sending stimulatory electrical signals to the brain. Two primary types of brain-computer interfaces exist: the invasive and the non-invasive. The process encompasses four main stages: signal acquisition, signal preprocessing, classification of brain signals, and the application interface for computer interaction [1]. The collection of brain signals employs various non-invasive techniques like brain waves (EEG), functional magnetic resonance imaging (fMRI), near-infrared spectroscopy (NIRS), and Meg (MEG), while invasive methods include cortical imaging (EKG) for a more direct assessment of brain activity.

In 1875, Richard Caton first documented the recording of brain electrical activity in animals. Later, in 1929, Hans Berger achieved the milestone of recording the first human EEG [2]. Primarily, EEGs have been instrumental in diagnosing epilepsy [3]. Additionally, they are employed for assessing conditions such as insomnia, comas, various brain diseases, and brain death. Initially, EEGs were pivotal in identifying tumors, strokes, and localized brain disorders. Their widespread use in signal acquisition is attributed to their superior temporal resolution, reliability, and user-friendliness, despite some limitations in spatial resolution. The standard practice for EEG signal acquisition typically involves the (10-20) system for electrode placement.

Shifting focus to the evolution of internet communication, Jeremy Rifkin's highlights its significant development. Marking over a quarter-century since the World Wide Web's inception, the traditional telecommunications-based internet is evolving into a new, digitized form, encompassing renewable energies. Nowadays, the internet's scope extends to a vast array of sectors including railways, roadways, maritime vessels, automobiles, GPS, and unmanned aerial vehicles. In the United States, three prominent internet domains have emerged, focusing on transportation and logistics, and an automated internet for renewable energy.

Figure 1.1: Test Steps [2].

Figure 1.2: Small EEG Test Machine [3].

1.1 CONTRIBUTIONS

a. Develop an innovative technique for classifying EEG signals, designed to automatically diagnose epilepsy seizures. This method relies on processing EEG signals acquired from EEG testing equipment and transmitted via IoT devices to a central processing unit.
b. This novel application significantly advances medical diagnostics by integrating cutting-edge technologies like IoT, deep learning, and signal processing, thereby yielding unprecedented results in the field.
c. As a new development, this application's outcomes have been benchmarked against a range of existing studies in the same domain, showcasing its comparative effectiveness and innovation.

1.2 LIMITATION OF STUDY

A primary constraint lies in the nascent nature of deep learning research, which necessitates considerable time for thorough exploration, especially in the context of a master's thesis. Furthermore, certain technologies, like CNN and LSTM, demand specialized and often costly equipment, with CUDA being a notable example. However, by utilizing the capabilities of CNN and LSTM functions, viable solutions can be identified, leading to favorable results when addressing such challenges.

2. OVERVIEW

2.1 EPILEPSY

Epilepsy, a common neurological disorder, affects individuals of all ages and genders, resulting in seizures and unusual behaviors such as altered sensations and loss of consciousness. It has a global impact, affecting over 50 million people, and ranks as the third most prevalent neurological ailment in the US, following stroke. Epileptic seizures originate from excessive rhythmic excitation of brain cells, creating an electrical disturbance in the brain. The nature of a seizure depends on the location and extent of this electrical disruption, with seizures stemming from overactivity in specific neuron groups. The progression of epileptic seizures comprises three main phases: the preictal phase or baseline activity before the seizure, the ictal phase during the seizure, and the postictal phase following the seizure's end. Epilepsy's recurrent seizures can be attributed to inherited syndromes or other conditions; for example, inheriting a mutation affecting neuronal behavior and organization. Additionally, brain injuries, such as infections or strokes, are known to trigger epileptic seizures [4,5]. Symptoms of epileptic conditions vary, including temporary confusion, staring spells, sensory hallucinations, brief blackouts, or impaired memory. Figure 2.1 displays EEG signals from both typical and anomalous cases.

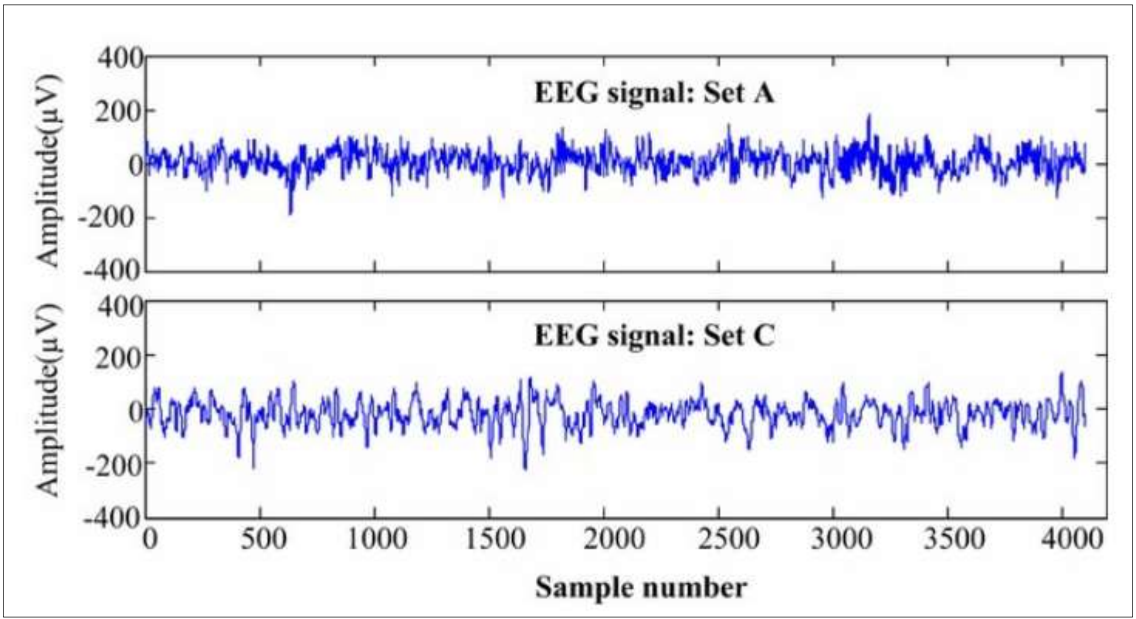

Figure 2.1: Normal and Abnormal EEG [5].

2.1.1 Electroencephalography

The EEG captures the electrical signal potential originating from the human brain. Its analysis, particularly in clinical settings, holds significant importance for evaluating epilepsy-related conditions. Neurophysiologists frequently rely on EEG interpretations for their assessments. Advancements in EEG technology have led to the deployment of multiple electrodes on the scalp, offering indirect insights into the brain's physiological functions. The integration of artificial intelligence with EEG technology enhances the capabilities of Brain-Computer Interface (BCI) devices. These devices are designed to acquire, process, and analyze EEG signals, facilitating efficient identification and analysis of patterns in brain activity. EEG technology classification primarily revolves around recognizing distinctive numerical features [6].

a. Electroencephalogram signals are inherently non-stationary, necessitating feature computations that adapt to their time-varying nature.
b. The analysis involves dealing with a substantial number of Electroencephalogram channels.

2.1.2 Epilepsy and EEG

Epilepsy is defined as a condition that impacts brain function and the broader nervous system, encompassing characteristics of both a disorder and an illness. In typical circumstances, the brain's electrical energy, generated by its cells, is effectively transmitted through the nervous system to facilitate muscle movements. However, in the context of epilepsy, the brain encounters difficulties in regulating this electrical energy, giving rise to abrupt and intense impulses, which can potentially lead to seizures.

The distinction between epileptic seizures and other forms of seizure activity is crucial: not all seizures indicate epilepsy. Anyone can experience a seizure under specific conditions such as high fever, dehydration, severe head injury, or oxygen deprivation. However, recurrent seizures without apparent causes suggest the diagnosis of epilepsy.

The origins of epilepsy are diverse, stemming from disruptions in normal brain activity. These disruptions could be due to diseases, brain damage, or abnormal brain growth, with the exact causes often remaining unidentified [7, 8]. Epilepsy can be attributed to various factors, such as brain chemistry, genetics, concurrent disorders, environmental influences, injuries, and complications during pregnancy or childbirth. Seizures that impact both hemispheres of the brain fall into the category of generalized seizures, with several subtypes including:

a. Absence seizure
b. Clonic seizures
c. Atonic seizures
d. Tonic seizure

Studies conducted to assess the prevalence of epilepsy in Western regions have revealed that roughly 0.5% of the population is afflicted by this condition. Furthermore, a significant proportion, about 2-5% of individuals, encounter seizure episodes at least once during their lifetime. It is worth highlighting that the occurrence of epilepsy tends to be lower in industrialized nations as compared to developing countries.

2.2 BRAIN COMPUTER INTERFACE (BCI)

BCI technology represents a rapidly growing research field with diverse applications, particularly in the medical sector. It spans a significant range from preventive measures to rehabilitation processes for patients with neuronal injuries. This technology plays a crucial role in analyzing brain signals and their impacts.

BCI devices are particularly beneficial for individuals with disabilities who are unable to physically respond or communicate. These devices interpret brain activity into digital commands that the user can employ to interact with computers. Feature extraction systems in BCI technology are essential for isolating specific attributes from cerebral signal patterns. Historically, EEG analysis was predominantly based on visual inspection. However, such visual assessments are highly subjective and do not lend themselves well to standardization or statistical analysis of the signals. Consequently, various methods have been developed to more objectively evaluate brain signal data. These include a range of linear and non-linear techniques for feature extraction [9].

2.2.1 Compoants of BCI

The primary objective of Brain-Computer Interface (BCI) technology is to detect and quantify specific brain signal characteristics that reflect the user's intentions. These characteristics are then converted into actionable commands in real time, enabling control over a user's device (as illustrated in Figure 2.2). The BCI system functions through four sequential components:

a. Signal acquisition,

b. Feature extraction,

c. Feature transformation and

d. Device output.

Each of these components operates under a structured protocol that outlines the startup time, signal processing details, device control mechanisms, and types of performance monitoring. An effective operational protocol provides the flexibility necessary for the BCI system to cater to the unique requirements of individual users.

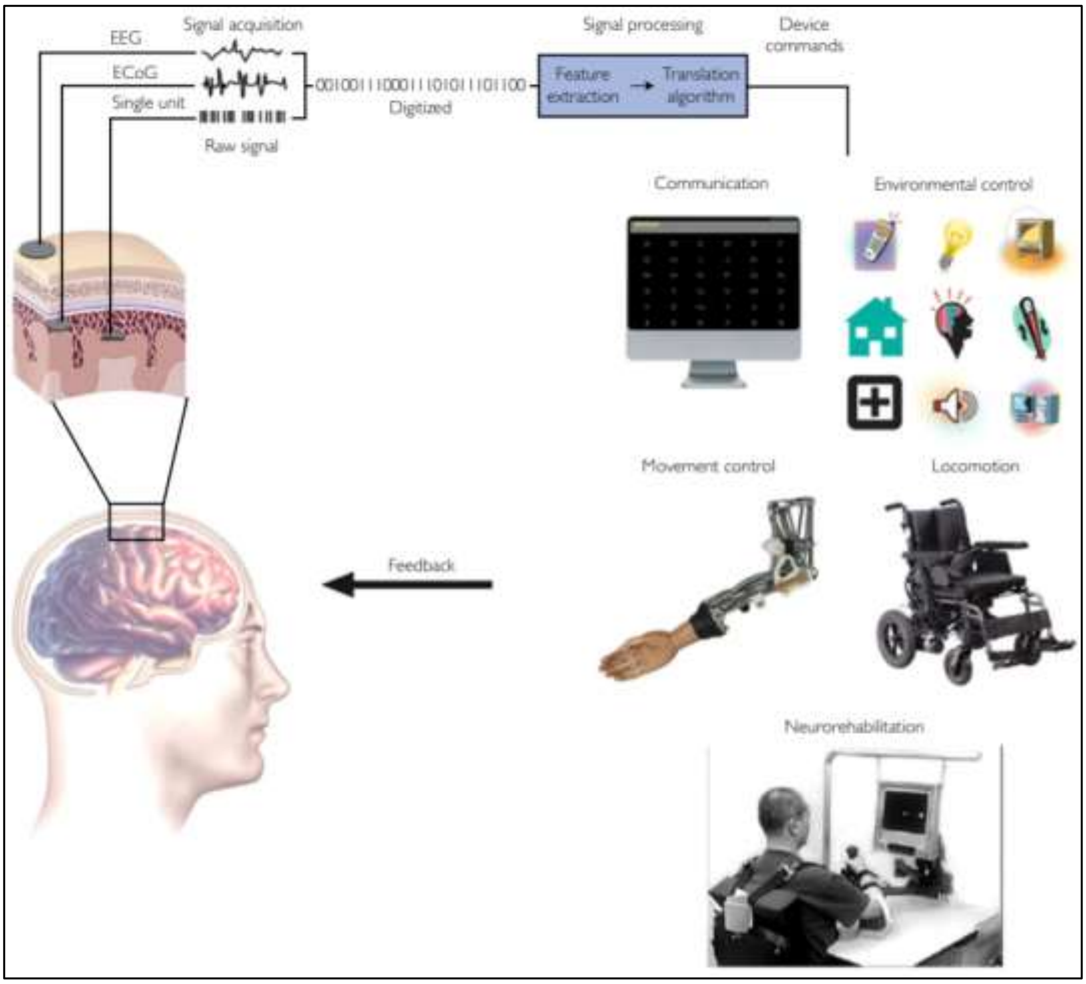

Figure 2.2: BCI System [10].

2.2.1.1 Feature extraction

a. Density-based Optimal Clustering (DOC) represents a distinctive approach that combines elements from both bottom-up and top-down methodologies. At its essence, DOC centers on the concept of a projective cluster and strives to establish this cluster optimally using a mathematical framework. This entails recognizing a robust clustering tendency within a specific set of instances denoted as C towards a designated set of dimensions represented as D, forming a pair (C, D). The primary objective of the DOC method is to identify the most suitable pairs (C, D) to effectively carry out the clustering process.

   This identification involves creating a smaller subset S through any legitimate method, such as random sampling. The approach entails comparing elements in both C and S, ensuring that the absolute difference between them does not exceed a predefined subspace length, denoted by ω, which is determined by the user. This step is repeated multiple times, with C and S being continuously sourced either through random sampling or other methods, until the optimal combination is found.

For DOC's functionality, another critical parameter is the minimum number of instances, α, required to form a class. The minimum acceptable density of a cluster is then calculated based on the values of α and ω. Moreover, DOC proposes a balance between the number of dimensions and subspaces, a process governed by another parameter, typically denoted as β. This balancing act is crucial for DOC, as the time complexity of the process increases exponentially with the number of dimensions and linearly with the number of cells [11].

b. MAFIA, similar to ENCLUS, is another adaptation of the CLIQUE algorithm. Unlike CLIQUE, MAFIA enhances result performance by introducing an adaptive grid size that takes into account the data distribution specific to the dataset. MAFIA follows the fundamental steps of bottom-up methods, initially dividing the entire space into various subspaces. To determine the minimum number of intervals required, MAFIA employs a histogram. This approach aligns with CLIQUE's approach of merging neighboring dense cells into broader regions, eventually shaping clusters. Nevertheless, a notable distinction in MAFIA lies in its spatial partitioning strategy, which is grounded in data distribution. This adaptive approach notably enhances result accuracy. MAFIA establishes thresholds for both area density and adjacency merging, permitting the consolidation of neighboring regions within these predefined limits to create clusters. It's important to recognize the sensitivity of MAFIA to these threshold values.

   Typically, MAFIA starts with a default grid as a base, and then adapts this grid according to the data. Similar to CLIQUE and ENCLUS, MAFIA can handle various input scenarios, including large datasets and different sizes and shapes of subspaces, and is capable of generating overlapping clusters. While MAFIA surpasses both CLIQUE and ENCLUS in terms of time efficiency, it's essential to recognize that MAFIA's time complexity also increases exponentially with the growth in the number of intervals [12].

c. FINDIT, short for Fast and Intelligent Subspace Clustering Algorithm using Dimension Voting, employs a top-down methodology that integrates the concept of voting. This algorithm relies on a particular distance metric called Feature-Oriented Distance (FOD). FINDIT's core objective is to identify instances that exhibit agreement on features surpassing a specified threshold value, denoted as ϵ. In situations involving high-dimensional data, instances may align closely on multiple features, although not necessarily on all of them.

The initial step of FINDIT involves selecting two small, randomly generated sets to serve as the nuclei of clusters, a phase termed the sampling stage. Subsequently, FINDIT employs these medoids to calculate FOD, enabling it to ascertain correlations and facilitate the formation of clusters. The threshold value is incrementally adjusted until the clusters achieve a stable configuration, a process known as the cluster-forming stage. Finally, FINDIT assigns the dataset instances to these established medoids across the identified subspaces.

Two key parameters guide FINDIT's operation: the minimum number of instances permissible per cluster and the minimum allowable distance between any two clusters. A notable limitation of FINDIT is its iterative approach in identifying the optimal arrangement, which tends to escalate the algorithm's time complexity. In various applications utilizing FINDIT, integrating an effective sampling technique with the algorithm is often proposed to enhance its efficiency and operational speed [23].

d. ORCLUS is an algorithm that leverages inter-attribute correlations present within a given dataset. It begins by arbitrarily defining clusters and then, through an iterative process, assigns data points to the nearest cluster, a phase known as clustering assignment. Subsequently, ORCLUS moves to the next phase, where it identifies subspaces linked to these established clusters. This identification is mathematically achieved by selecting eigenvectors corresponding to the smallest eigenvalues, derived from the covariance matrix of each cluster. This process often results in the formation of clusters that are proximate and can be merged.

   The algorithm's mathematical intricacies result in significant complexity, prompting the use of sampling techniques to improve its efficiency. However, a drawback of this approach is the potential oversight of smaller clusters, which might be missed due to the sampling process [24].

e. The Projected Clustering (PROCLUS) algorithm is recognized as one of the earliest top-down approaches in clustering. It shares several principles with the ORCLUS algorithm, particularly in the method of dataset sampling, the establishment of medoids, and the iterative refinement of the clustering process. In PROCLUS, a suitable greedy algorithm is employed to select an optimal number of mediods, ensuring that these mediods are not in close proximity to one another. This phase, known as clustering initialization, ensures that each cluster is represented by at least one class.

Upon completing the initialization process, PROCLUS proceeds with a set number of predetermined randomly chosen medoids, denoted as k, to traverse a compacted dataset while evaluating the effectiveness of clustering improvements. The clustering quality is maintained by monitoring a specific parameter known as the average subspace dimensionality, denoted as l. Each medoid is associated with k l features. The subsequent step involves identifying suitable subspaces for each medoid and assigning data points based on Manhattan segmental distance. The iteration phase culminates with the removal of any medoid holding a minimal number of data points. The final phase in PROCLUS, known as the refinement phase, entails reassigning data points to enhance cluster quality. PROCLUS necessitates equally partitioned subspaces and a specific average feature count, with an essential consideration being overlapping, as data points are ultimately linked to a single cluster. Compared to CLIQUE and ENCLUS, PROCLUS often exhibits slightly faster performance, especially with large datasets. However, like other iterative approaches, PROCLUS's efficiency is influenced by input parameters, impacting the clustering quality. Additionally, the elimination of medoids can result in the loss of potentially significant clusters [15].

f. The δ-Clusters algorithm is based on the coherence between subsets of instances and attributes. It calculates this coherence, utilizing it as a distance metric for clustering. This algorithm identifies clusters by exploring the relationships within coherent data samples, enabling the discovery of instances based on their coherence. Various coherence measures can be employed, with some researchers opting for PearsonR for this purpose [16].

   In its initial phase, δ-Clusters establishes cluster seeds. The algorithm then enters an iterative stage aimed at enhancing these clusters through a random shuffling technique. This technique involves experimenting with different data samples and attributes to elevate the quality of clustering. The iteration continues until further improvements are no longer attainable. The operation of δ-Clusters is notably influenced by two critical parameters: the size of each cluster and the total number of clusters considered. The time complexity of δ-Clusters is directly impacted by these parameters. Additionally, when implementing the δ-Clusters method, possessing prior knowledge or an estimate of the cluster size proves advantageous, especially in the context of large datasets. Notably, δ-Clusters differentiates itself from other top-down approaches by utilizing coherence as its primary measure, rendering it a valuable technique across various applications, particularly within the medical field [17].

g. The field of clustering faces the recurring challenge of unsatisfactory results, particularly when dealing with extremely dense or sparse datasets. In the current era, the complexity of datasets has escalated significantly due to the widespread use of sophisticated systems, making it impractical to avoid high-dimensional data. Therefore, any proposed improvement in clustering techniques must account for the prevalence of high-dimensional datasets, as they are commonly generated by many contemporary systems.

   In response to these challenges, advancements in computing have facilitated the adoption of 'soft methods', which are generally more cost-effective to implement and yield more efficient clustering results. Recognizing this need, researchers over the past two decades have introduced various soft clustering enhancement strategies. Soft subspace clustering, a recent development in the field, addresses the ongoing issue of high dimensionality. This approach incorporates various algorithms that focus on reducing dimensionality to achieve better clustering outcomes.

2.2.1.2 Classification

In Machine Learning (ML), classification is a fundamental concept that involves teaching machines to group data according to specific criteria. It encompasses the process where computers organize data based on predetermined characteristics, a process known as supervised learning. In contrast, there's also an unsupervised approach to classification, referred to as clustering, where computers identify common characteristics to group data without predefined categories.

A common example of classification is seen in the identification of spam emails. Developers can train a ML model with sets of emails labeled as spam and not-spam. The goal is to develop a system that can recognize spam characteristics from this training set and filter out spam in new emails [18].

Classification plays a crucial role in today's world, where vast amounts of data are utilized for various decisions in sectors like government, finance, and medicine. Researchers access extensive data sets, and classification helps them make sense of the data, uncovering patterns. While classification in ML involves applying complex algorithms, it's a natural process for humans, who categorize things based on similar features daily. For example, at a grocery store, one might instinctively group items by food type (fruits, vegetables, meat, etc.). In ML, classification is about teaching computers to perform similar grouping tasks [19].

a. Neural Network (NN)

Artificial Neural Networks (ANNs), inspired by human brain functionality, comprise artificial neurons as their fundamental components. These neurons are strategically distributed across multiple layers, with each layer's neuron arrangement dictating its operations and its position within the network determining its type. Neurons receive inputs from the preceding layer, which are essentially the outputs of neurons in that layer. As illustrated in Figure 2.3, a neuron's output is derived by multiplying each input with a corresponding weight, then summing these values and applying an activation function. The nonlinearity introduced by the activation function enables the detection of complex features, accommodating nonlinear margins in feature values. Additionally, a bias value is incorporated into the neuron's input to fine-tune the positioning of these feature margins, with the neural network adjusting the bias based on the feature detection needs [20].

ANNs perform two primary types of computations: forward and backward passes. Both are essential during training to update the weights and biases. However, only the forward pass is necessary for making predictions. In the forward pass, computations start at the input layer, progressing layer by layer until the network's output is calculated. Training the neural network involves adjusting weights and biases to attain optimal output. This adjustment is facilitated by various optimizers, mainly derived from the gradient descent algorithm. These optimizers fine-tune the values based on the difference between the network's actual output and the desired output, utilizing the rate of change in the output for each parameter as a guide for optimization.

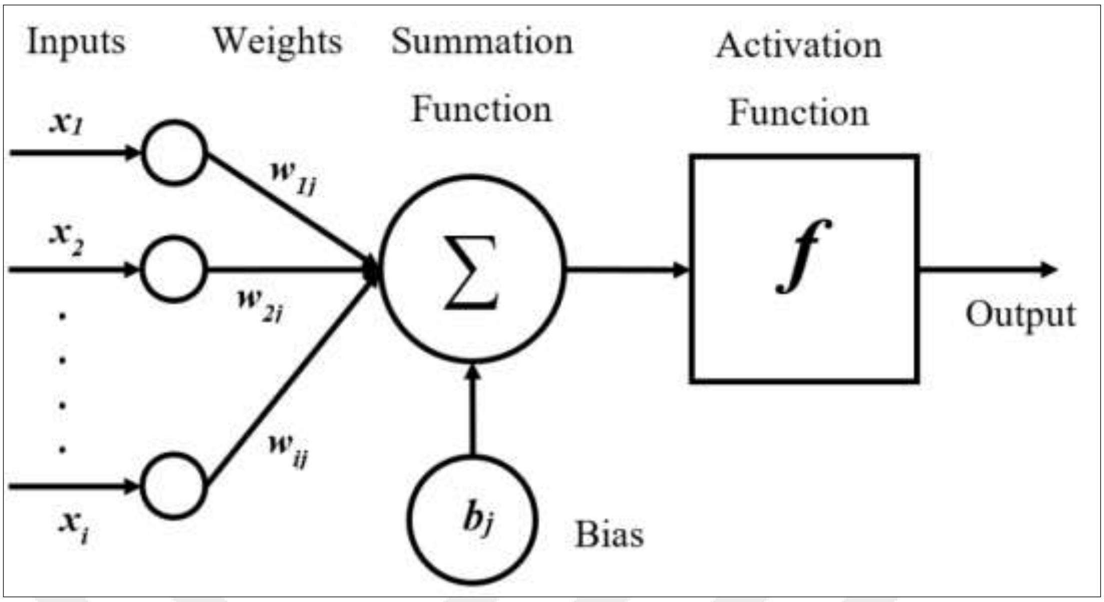

Figure 2.3: Neural Network Structure [21].

The equation (2.1) represents the mathematical model of the neural network.

$$Y = \sum(Weight * input) + bias \tag{2.1}$$

The input is represented the data features which will be analysed by the network and y is the predication of the network model.

b. Naive Bayes (NB)

The NB algorithm operates as a probabilistic classifier, calculating a set of probabilities through assessing combinations and frequencies of values. It fundamentally relies on Bayes' theorem, employing the assumption of conditional independence. This implies that, within this framework, the value of a particular feature in a given class is considered independent of the values of other features [22]. As a statistical classifier, NB falls under the category of supervised learning. The process of NB, as depicted in Figure 2.4, includes reading the data, dividing it into a training set, and then applying the NB algorithm for classification.

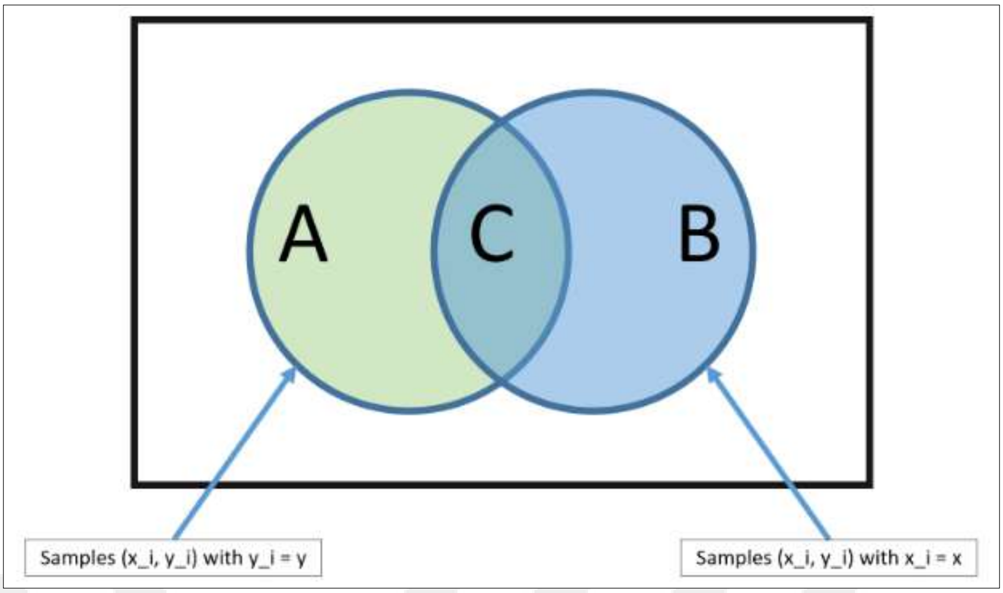

Figure 2.4: Naïve Bayes Classifier [22].

The NB algorithm utilizes a straightforward mathematical model, enabling it to process and learn data with remarkable speed. The mathematical formulation of the NB algorithm is depicted in equation (2.2).

$$P(A \backslash B) = \frac{P(B \backslash A) X \, P(B \backslash A)}{P(B)} \tag{2.2}$$

Where P(A|B) represents the posterior probability (with A being the class, such as Normal/Abnormal, and B the predictor), P(B|A) is the likelihood of the predictor given the class, P(A) is the prior.

c. J48 classifier

The J48 classifier is a straightforward implementation of the C4.5 DT algorithm, primarily used for classification tasks. This process is highly effective in solving classification problems. In this algorithm, a tree is constructed in a binary format to facilitate the classification process [23]. Figure 2.5 demonstrates the construction of this tree.

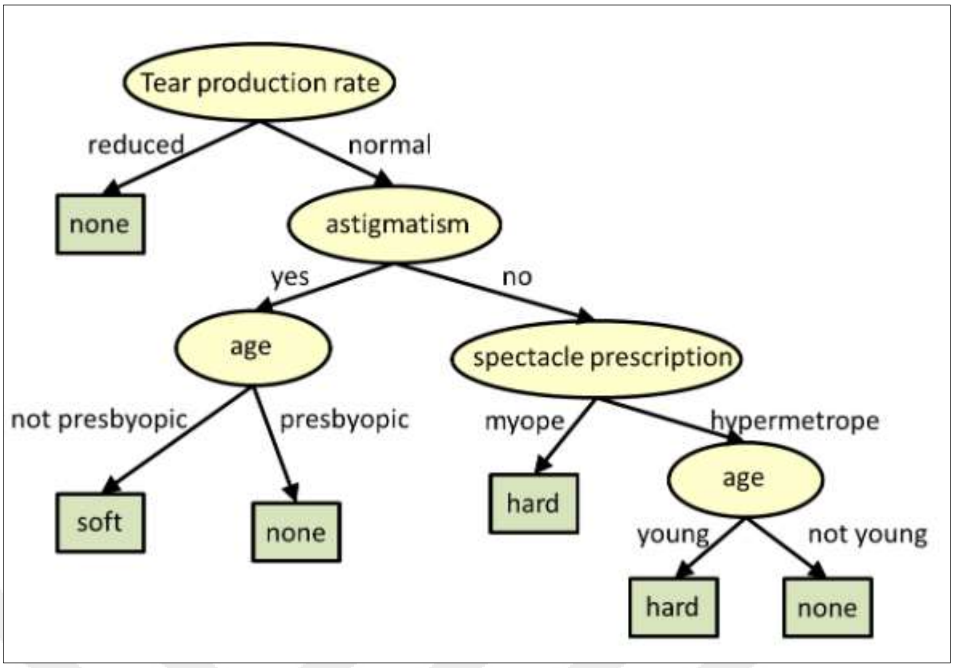

Figure 2.5: Decisions Tree [23].

d. Support Vector Machine (SVM)

Support Vector Machines (SVM) are distinct classifiers characterized by a separating hyperplane. Utilizing labeled training data in a supervised learning context, SVM algorithms develop an optimal hyperplane to classify new data points. In a two-dimensional space, this hyperplane manifests as a line that bifurcates the plane, creating two distinct regions [24]. Mathematically, the SVM is depicted as in equation (2.3), where the hyperplane effectively segregates data points into two classes (red & green), as illustrated in Figure 2.6. This separation is further detailed in equations 2.3 and 2.4.

$$y = a * x + b \tag{2.3}$$

$$a * x + A = \pi r^2 b - y = 0 \tag{2.4}$$

$$W.X + b = 0 \tag{2.5}$$

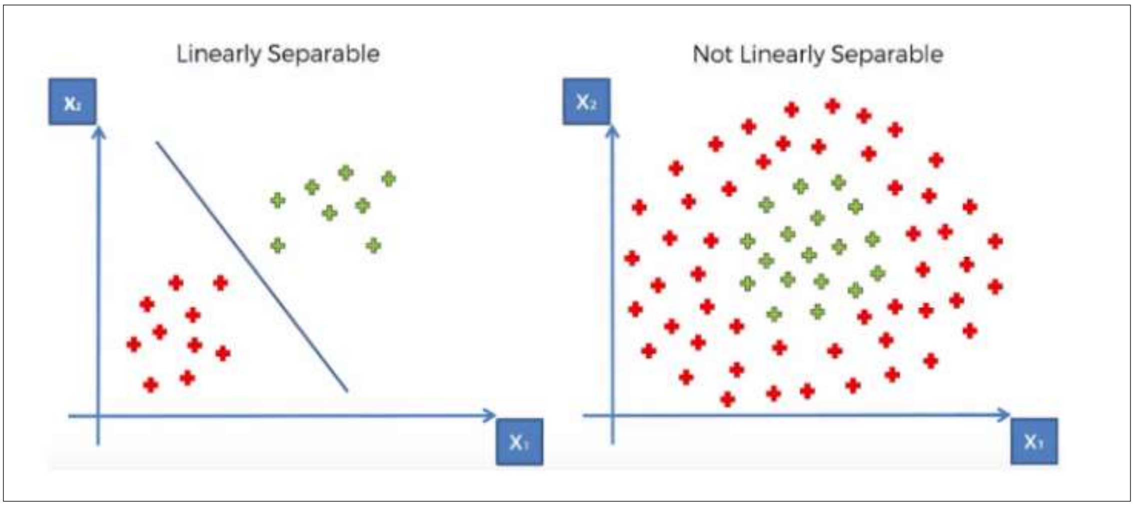

Figure 2.6: SVM [24].

e. Multi-Layer Perceptron

An examination of existing literature indicates a consistent usage of Feed Forward Neural Networks (NN) among various types of connections for 'artificial neurons'. Within this realm, one specific approach is the Multilayer Perceptron Neural Network (MLPNN). The structure of MLPNN is depicted in Figure 2.7.

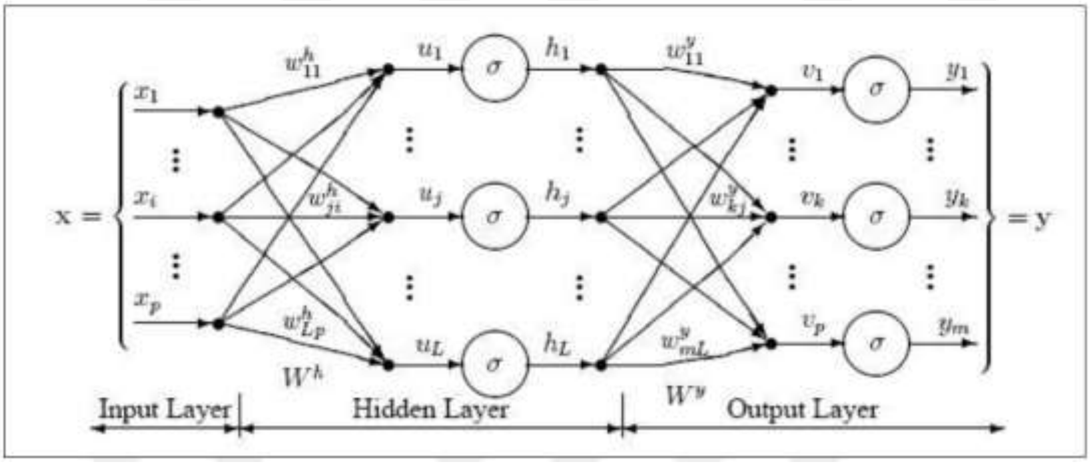

Figure 2.7: Multi-Layer Perceptron [25].

The MLPNN is a renowned model in the field of ANN. It is characterized by three distinct types of layers: the input layer, the hidden layers, and the output layer, each containing several nodes. Information flows sequentially from one node to another, starting from the external nodes that transmit signals to the input layer. The output from the first layer is relayed to the subsequent layer through weighted connections, where it undergoes processing before being sent to the final output layer via similar weighted links. The processed output of the second layer is then transmitted to the last layer to produce the final result [25].

The operational steps of MLPNN are as follows:

a. The first layer receives input data, processes it, and generates a preliminary output.
b. The discrepancy between the predicted and actual outputs is computed to determine the error.
c. The Back-Propagation (BP) algorithm is employed to adjust the weights of the connections.
d. Weight adjustments commence with the connections between the nodes of the last layer and the preceding hidden layer, progressively moving backwards through the network.
e. Once BP is complete, the process is initiated again.
f. This iterative procedure continues until the error between the actual and predicted outputs is minimized to the lowest possible difference.

2.3 LITRETURE REVIEW

Since the 1970s, various methodologies have been developed and are still in use for identifying epilepsy activity in the brain. Initially, two primary techniques, Fourier transform and parametric transform, were employed for seizure detection [26]. However, given the non-stationary nature of EEG signals, time-frequency domain techniques, such as the wavelet transform (WT), have been deemed more suitable [27]. The application of wavelet decomposition is contingent on the sample count, ideally being a power of 2 (2^(N)).
In research, different combinations of methods have been explored for EEG signal analysis. For instance, one study utilized Discrete Wavelet Transform (DWT) combined with Principal Component Analysis (PCA) and Support Vector Machine (SVM) for emotion recognition in EEG signals [27]. Another approach involved the use of DWT along with Maximal Overlap Discrete Wavelet Transform (MODWT) and Feed Forward Artificial Neural Networks (FFANN) for seizure detection [28]. Subasi and others have classified EEG signals using a combination of DWT, PCA, Independent Component Analysis (ICA),

Canonical Discriminant Analysis (CDA) with SVM, and DWT with Approximate Entropy (AnEn) and ANN. Furthermore, a neuro-fuzzy interface system in conjunction with ANN was employed for EEG signal classification in various studies [7], [14], [29]. This paper specifically discusses the use of MODWT with SVM, and MODWT combined with PCA and SVM for classifying EEG signals in the context of seizure detection.
Srinivasan and colleagues developed a novel system operating in the frequency-time domain for feature extraction, utilizing Recurrent Neural Networks (RNN) for classification, achieving a notable accuracy of 99.60% [30]. Subasi and Erchelebi introduced an Artificial Neural Network (ANN) approach, incorporating Wavelet Transformation (WT), and reported an efficiency of 92% [31]. Subashi's individual approach involved Wavelet Transforms combined with expert model systems, yielding an efficiency of 94.5% [32]. Kannathal and team proposed an Adaptive Neural Fuzzy Inference System (ANFIS) based on entropy measures, achieving 95% efficiency [33].

Tsallas and associates introduced a method centered on time-frequency analysis combined with ANN, reaching an impressive accuracy rate of 100% [34]. Polat and colleagues suggested using Fast Fourier Transform in conjunction with a Decision Tree (DT), resulting in a 98.72% yield [35]. Acharya et al. employed Wavelet Packet Decomposition (WPD) for segment decomposition and Principal Component Analysis (PCA) for extracting distinctive features from wavelet coefficients. They then used a Gaussian Mixture Model (GMM) classifier to categorize these extracted features, attaining an accuracy of 99% [36].

2.4 EVALUATION PARAMETERS

This section focuses on computing four key parameters to assess the effectiveness of the proposed method for face recognition. These statistical parameters include:

Accuracy, which measures the closeness of the obtained value to the actual (true) value.

Additionally, the evaluation employs a confusion matrix to determine various metrics associated with the method's performance, including True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

2.5 VALIDATION USING RANDOM SUBSAMPLING

In the process of collecting data from the general population, a commonly employed and straightforward method is random sampling. This technique permits the selection of specific subsets from the population under consideration. For instance, in an organization with 300 employees, a subgroup of 30 individuals might be selected for a study. In this context, the general population encompasses the entire employee pool of the company, while the sample comprises the 30 selected individuals. Typically, the selection of each employee is carried out through a random distribution from the total pool of employees chosen for the survey. However, it's important to acknowledge that there is a possibility of certain groups or instances not being adequately represented, resulting in what is termed a sampling error. To further assess this method, K-safe iterations are employed to validate random subsamples. In each iteration, a subset is extracted from the random sample, subjected to a series of tests, and then instances from the safe subset S are excluded from the initial learning phase. Subsequently, test statistics are applied across all iterations.

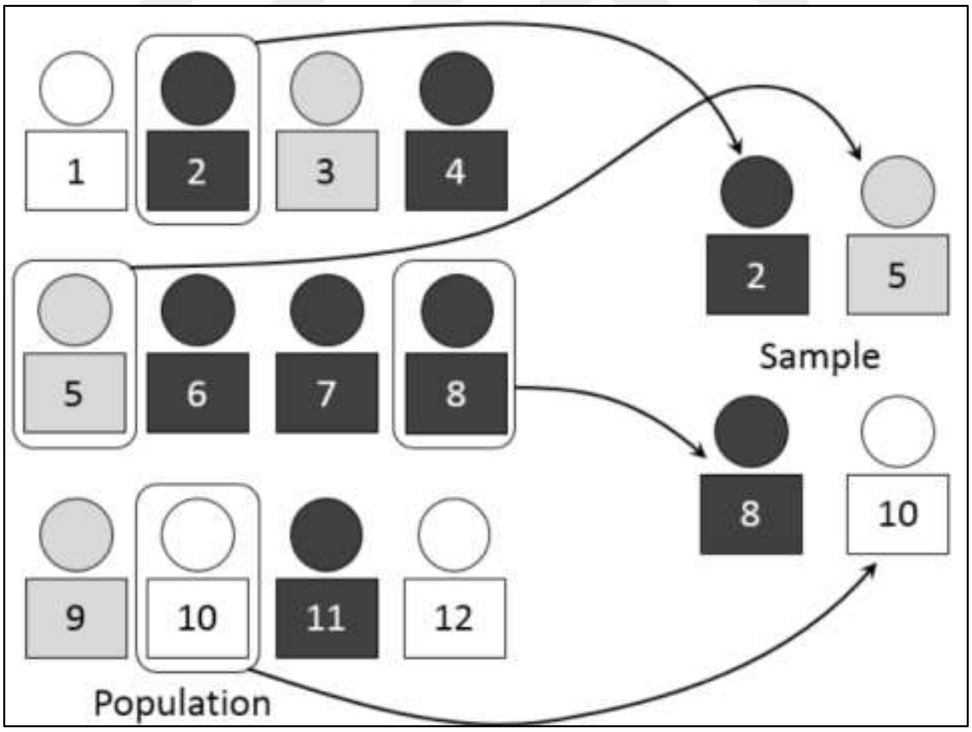

Figure 2.8: Random Subsampling.

3. MATERIAL AND METHODS

3.1 WIRELESS SENSOR NETWORK (WSN)

The advent of wireless sensor networks has inspired extensive research in many ways. However, the possible applications that can be implemented in KAA have been discussed for a long time. Used for various types of earthquakes, automobiles, thermal, visual, infrared, acoustic, etc., KAA monitors various environmental conditions such as temperature, humidity, pressure, speed, direction and temperature. sensor. There are ways to increase the number of KAA plants. By monitoring the existence of the Earth for possible structural threats to humans from space, studying the structure of soil and water, collecting information for protection, environmental monitoring, meteorological and climate analysis, we can continue the war and increase the number of examples, such as monitoring the solar system and beyond, seismic acceleration, voltage, temperature, wind speed and GPS data. Using the knowledge of the sensor nodes of the neighboring node, the nodes have a balanced power consumption. The region's activity management layer maintains a balance between synchronization and search operations. In addition, the sensor should not simultaneously perform detection actions in the area of the node. Therefore, at a given power level, some nodes may see other powers in addition to the node. These layers of control can move the data that the sensor can send over the network, share resources between nodes, and efficiently use the power consumption of the sensor node. The application layer required to get the job done is responsible for traffic management. The received data is a software application that converts it to the format. It is a layer of the sensor network found in various applications in various fields such as agriculture, military, environment and medicine [37].

a. Star Topology

If the base station can send messages to multiple remote locations, or is this a communications topology to be received? Remote nodes from a base station can send or receive messages. The exchange of messages is not permitted. The advantage of this type of network to a wireless network is that it can be easy to remotely operate. Nodes in these networks are designed to reduce energy consumption and facilitate low-latency communication between remote sites and base stations. A limitation, however, is that the base stations must be within the radio transmission range of each node, which can lead to unreliability. This is because network management hinges on the connectivity of a single node. Refer to Figure 3.1 for a visual representation of this setup.

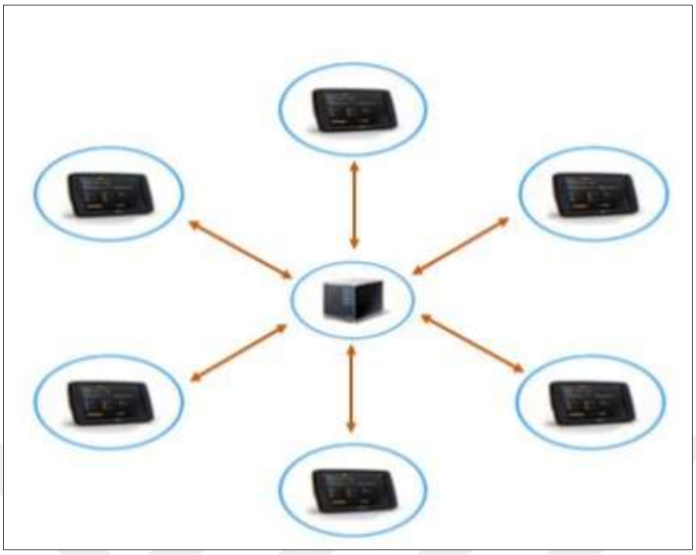

Figure 3.1: Star Topology [37].

b. Mesh Topology

The network topology exhibits a tiered link structure. An intermediary node serves the purpose of dispatching messages to a designated node in instances where a node endeavors to communicate with nodes beyond the radio range. In case a node becomes inactive, distant nodes maintain the ability to establish connections with other nodes within proximity and receive messages. Messages can be directed to the intended destination. However, the drawback of such network configurations lies in their propensity to drain power when incorporating multiple communication nodes, often leading to a reduction in battery life. As the number of communication networks increases for a particular destination, the number of nodes diminishes. This results in an extended message transmission duration, particularly when electrical work becomes necessary.

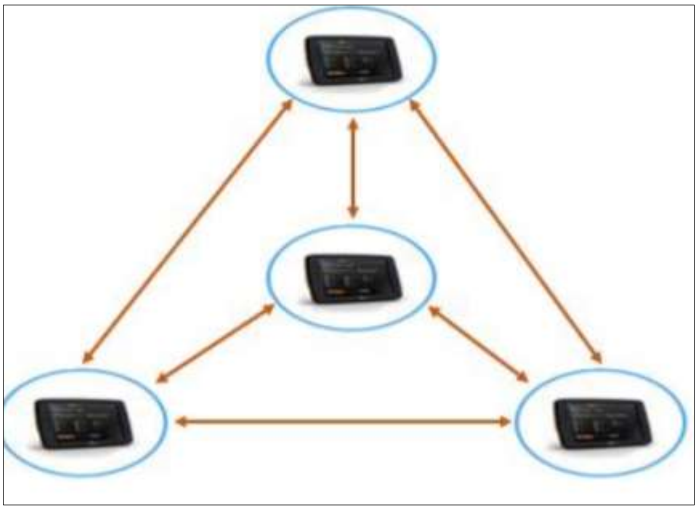

Figure 3.2: Mesh Topology [37].

3.1.1 Applications of WSNs

The rapid development of sensor technology has resulted in compact and intelligent sensors that enable WSNs to be used in a wide variety of applications. WSN jobs can be divided into two types. Monitoring and monitoring shown in Figure 3.3.

WSN is used in many areas. Current predictions suggest that most objects used in everyday life have a sensor that can interact with people and similar objects or learn more about their surroundings. WSN traces are traceable, but there are two types. As shown in Figure 1.3 above, there are many types of WSN applications, including military, medical, agricultural, industrial, and environmental applications. It focuses on supporting armed forces such as bases of operations built with advanced sensors using WSNs. Other military examples: information on injuries and health, self-regulation and surveillance of the bodies of soldiers on mines connected to self-regulation networks. WSN is under National Security Watch, which monitors airports, ports and other high-traffic areas for crisis management and border security. In the health sector, the BAN (Body Wireless Network) consists of intelligent sensors that can be used to adjust the patient's state of health [38].

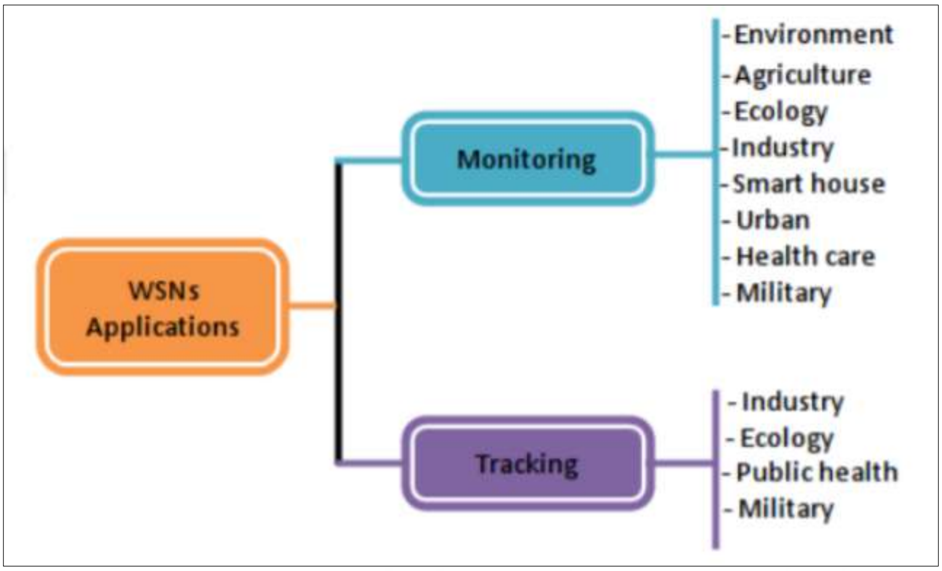

Figure 3.3: WSNs Application Areas [38].

3.1.2 Advantages of Wireless Sensor Network

a. Can be installed on a floating network.

b. Reach a bad environment (sea, forests, farmland).

c. Very flexible (like adding workstations)

d. Economical operation

e. Restrictions on excessive use of electrical cables.

f. Applicable to various types of activities

g. Monitoring from the center.

3.1.3 Limitations of Wireless Sensor Network

a. Limited memory (hundreds of kilobytes)

b. Average processing power (8 MHz)

c. Short communication distance

d. The energy consumption is high.

e. Minimum Performance Required: Limits the protocol.

f. Time-limited battery

3.2 INTERNET OF THINGS (IOTS)

When defining the IoT, a consensus is elusive, with most researchers and articles asserting that a definitive definition remains elusive, subject to philosophical debate. Consequently, various interpretations of IoT emerge, encompassing a range of technologies and associated products, such as environmental technologies, sensor networks, wireless sensor networks (WSN), object naming systems (ONS), and RFID. Furthermore, these interpretations can be influenced by geographic or national boundaries. For example, in China and Europe, it is commonly referred to as the IoT, whereas in the United States, alternative terms like Smart Grid, Smart Object, Cloud Computing, or Data Grid are frequently employed.

The origin of the term "IoT" can be traced back to Kevin Ashton, who introduced it during his presentations at Procter & Gamble in 1999. Subsequently, thanks to the Auto ID Center, this term gained widespread usage globally in 2001. The core concept underlying the IoT is the interconnection of everything in our surroundings with the internet. This includes devices and objects in close proximity to individuals, enabling interactions within the digital realm.

The IoT facilitates seamless communication between people and objects, irrespective of time, location, or the entities involved. This entails the utilization of various services, networks, or pathways, revealing essential components such as computing, convergence, content, connectivity, collections, and communication. These components create a framework where interactions between people and things, as well as between things themselves, occur in a fluid and unrestricted manner [39].

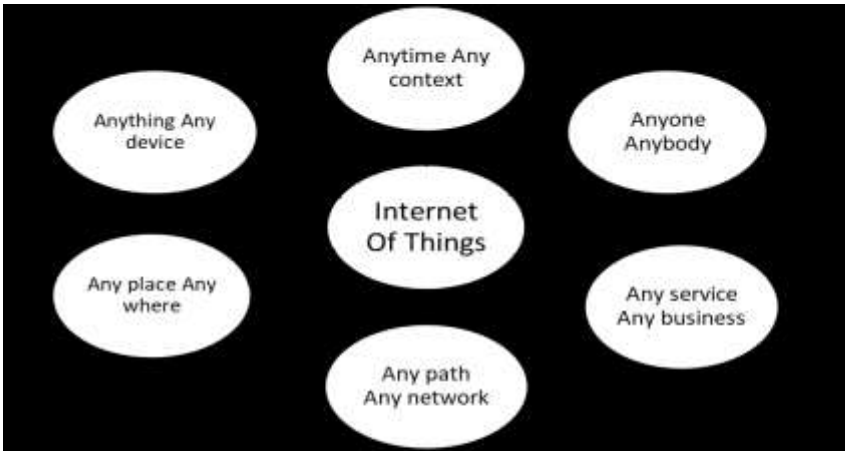

Figure 3.4: Internet of Things Adapted Scheme [39].

3.2.1 Sensors and Actuators

Discussing the conversion of physical signals into electrical ones brings us to the realm of detection devices. In this context, the sensor assumes the role of an integral component within the interface connecting electrical devices to the physical world. Another vital component of this interface is the drive unit, responsible for converting electrical signals into physical signals. Smart sensors possess the capability to establish communication with their counterparts, facilitating tasks such as monitoring temperature, humidity, and motion detection.

In a broader perspective, Wireless Sensor Networks (WSN) consist of sensors that collaborate and engage in communication. Within the realm of industrial electronics, there is a growing demand for sensors that can interface with microcontrollers. Smart sensor developers and researchers are primarily focused on revolutionizing control and measurement systems by incorporating memory elements into these devices.

As previously mentioned, sensors are engineered to capture information about the objects and environment surrounding them. On the other hand, actuators are responsible for carrying out actions that impact the environment or objects. These actions may include emitting radio waves, light, sound, or odor. In the IoT landscape, objects leverage their capabilities to establish communication with humans.

Typically, sensors are combined with actuators to form a sensory-executive network. For instance, in scenarios where gas spreads through a room, sensors are deployed to detect the presence of carbon monoxide in the environment. When a dangerous gas leak is detected, the actuator triggers an alarm, alerting individuals in the affected areas. The ultimate aim of this combination is to facilitate interactions between people and their surroundings, aligning with the overarching purpose of the IoT [40].

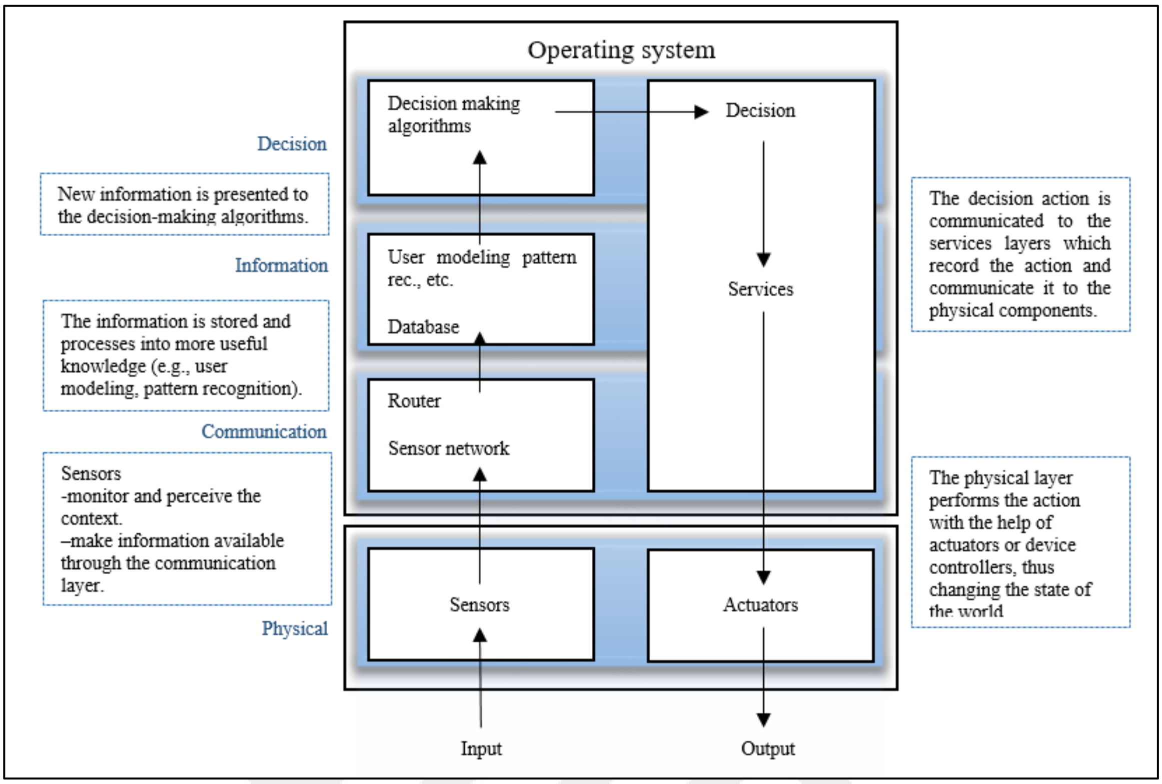

Figure 3.5: The Physical and Software İnterface of the Smart Home Products [40].

The wireless sensor network (WSN) is seen as a different base Hardware technology for the IoT. Smart A network of environmental sensors is required to collect the information. It is necessary because it is easy to install and maintain. The role of the sensor network is to monitor the environment or other objects. Movement, volume, humidity, temperature, pressure, sound level, amps when you have a number of sensors that interact with each other in terms of properties like orientation, speed, object size, etc. This is known as a Wireless Sensor Network (WSN). WSN is a group of sensors and It can contain a gateway that collects and transmits data from the sensor. Server. WSN can be used for condition monitoring, industrial monitoring, environmental monitoring and traffic monitoring surveillance etc. See Figure 3.6.

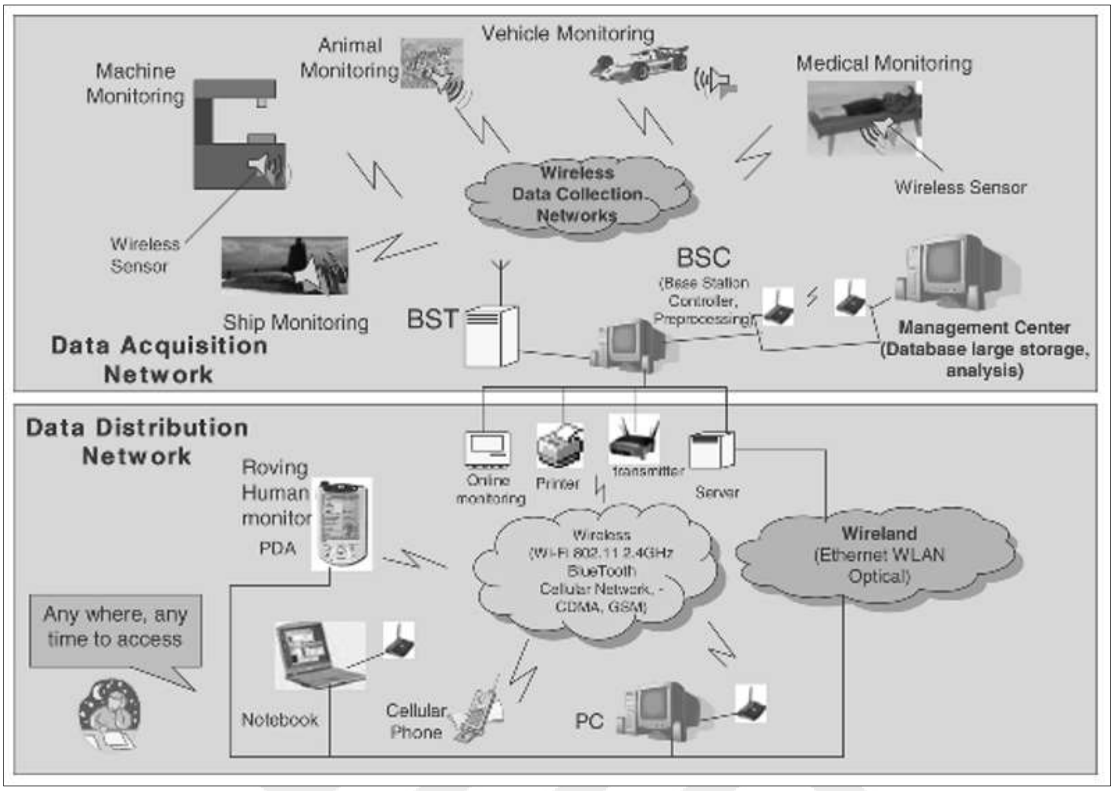

Figure 3.6: Wireless Sensor Networks [41].

3.2.2 RFID

RFID technology holds a pivotal role within the IoT landscape, serving as a foundational component of the network infrastructure. Its primary function lies in the identification, tracking, and tracing of assets. In brief communications, it is often referred to simply as RFID.

RFID tags utilize electromagnetic fields generated by RFID readers. A typical RFID system comprises RFID tags, RFID readers, antennas, access control, software, and a server. Through the RFID reader, users gain the capability to identify, track, and manage all devices systematically linked to RFID tags. Consequently, RFID systems find increasing utilization across various industries, ranging from supply chain management to product tracking, medical surveillance, and logistics optimization [41].

RFID tags commonly feature small radio antennas responsible for transmitting data over short distances. RFID technology can employ both powered and unpowered mechanisms to activate electronic tags. Powered devices rely on batteries to actively transmit data to remote receivers, exemplified by electronic road toll systems utilizing active RFID tags. In contrast, passive RFID devices leverage inductive coupling with an active reader for both powering the tag and transmitting data.

Notable advantages of RFID systems include streamlined business processes, heightened accuracy in inventory information, cost-effective labor, improved operational efficiency, and the provision of real-time data pertaining to involved devices. These advantages drive adoption across manufacturing, distribution, and retail sectors in numerous industries. The tracking capabilities inherent to RFID are commonly heralded as a pioneering facet of the IoT.

3.2.3 Middleware

With the increasing use of sensor technology in mobile devices, sensors are being used to overlap multiple software applications offering different customized services, creating a system architecture and modifying the required architecture. It can effectively respond to the use of various sensors and receive sensations on a large scale. Heterogeneity requiring increasingly scalable application requirements, context management software libraries, mobile device constraints, modularity and scalability, and the availability of various resources in the physical world. Compatibility with other physical equipment is required [42]. Existing middleware provides a higher level of abstraction built into network operating systems, provides resilient shared resources, and consists of session and view layers to hide problems (see Figure 3.7). "

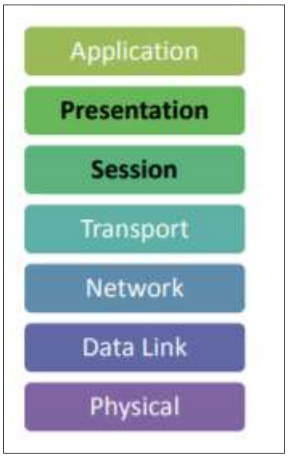

Figure 3.7: OSI Reference Model [42].

Promote distributed systems within the ISO / OSI Reference Model, ensuring heterogeneity, reliability and efficiency. On the other hand, context middleware (see Figure 3.8) defines the level of abstraction between operating system execution and software system applications.

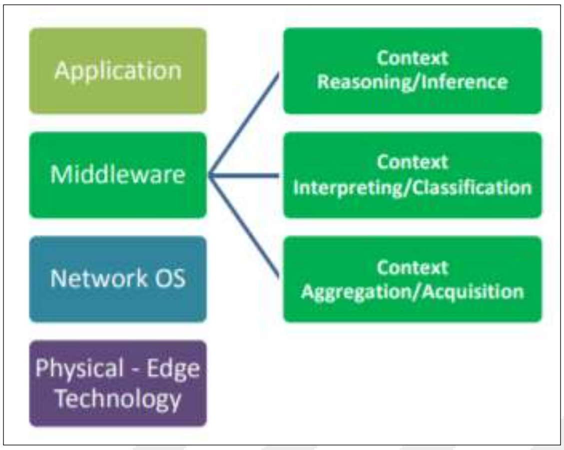

Figure 3.8: Context-Aware Middleware

The goal is to address the heterogeneity inherent in the physical world by leveraging advanced technological connectivity that introduces specialized mechanisms and services beyond those offered by the operating system. Customization of physical devices, such as sensor networks, embedded systems, and advanced technologies like RFID and NFC tags, enables control of these devices, facilitates communication between them, and facilitates data reception. Applications and services undergo thorough analysis and transparent delivery.

Through this transparency, the application layer remains isolated from the internal middleware components, avoiding direct interaction with the underlying implementation of the secondary layer. Consequently, the application receives contextual information without knowledge of its source. This middleware, in turn, extends support for abstractions tailored to the application's requirements, creating a protective interface that conceals operations between the sublayer and the physical layer, including hardware components, beneath the application level.

Middleware empowers application developers to offload the computational burden associated with managing application contexts onto the middleware itself, as it exclusively supports logical middleware implementations. Applications can effectively manage created objects, encompassing characteristics and context, based on context management principles.

Furthermore, the middleware offers robust optimization capabilities guided by system constraints, such as relative processing costs linked to object activities, limited battery power, and insufficient information storage.

Notably, middleware mapping encompasses object management across all contexts and provides comprehensive global access to shared resources, a fundamental requirement for all applications operating on the same host [43].

3.2.4 Architecture

The ever-expanding concept of the IoT presents a challenge in defining a singular architecture. The IoT concept encompasses various elements, including networks, communications, information technology, and sensors, among others. As previously mentioned, researchers engage in ongoing discussions regarding the architecture of the IoT, with no one-size-fits-all solution emerging as the definitive choice. Several articles propose alternative options for realizing the IoT concept. One suggested conceptual architecture prioritizes meeting the requirements of smart objects while considering other architectural parameters. The architecture of the IoT is generally structured into three layers: the awareness layer, the network layer, and the application layer. The awareness layer essentially functions as the sensory apparatus responsible for object recognition and data collection. This involves the use of technologies like RFID tags and readers, sensors, cameras, GPS, labels, and barcode readers.

The network layer, akin to a cognitive center, handles data transmission and processing in network control centers, intelligent processing centers, data centers, and converged networks, including the internet.

The application layer serves as the intermediary between the IoT and users, facilitating the deployment of intelligent IoT applications to meet industrial requirements. This layer extensively utilizes various data processing software, such as middleware, for tasks like data warehousing, data mining, and decision-making across a wide range of applications.

Middleware, positioned between the network and application layers, is a hierarchical component that manages communications, controls, and positioning, ensuring seamless coordination.

Beyond this perception level, data collected at various levels undergoes modification to extract pertinent information for analysis while minimizing data processing overhead and preventing information loss or damage. This enhances transmission efficiency.

Beneath these layers lies another tier known as the transport and processing layer, which assumes a role analogous to the network layer. Its functions encompass classification, storage, retrieval, and data loading. Instead of transmitting entire data packets, this layer selectively forwards user data from the application level to restore meaningful information at the application level.

Additionally, there exists an application layer responsible for aggregating, exchanging, and analyzing the most recent data collected. This layer may provide a user interface (UI) for IoT applications, serving users, user devices (such as mobile phones and PCs), clients, and more. It also encompasses cloud computing capabilities, including data centers and IoT control centers [44], which harness the network's capacity to intelligently process vast amounts of information.

3.3 DEEP SPARSE AUTO-ENCODER

The Sparse Auto-encoder (SAE) is essentially a neural network composed of multiple encoding algorithms, with each algorithm represented as a distinct layer. These layers are independently trained to encode unlabeled data. Notably, the input to each encoding algorithm is the output from the preceding one [45]. The training process of an encoding algorithm involves the computation of essential variables through various techniques that optimize the similarity between the input 'x' and the reconstruction ('x'.) $^{\cdot}$ The encoding process, which transforms the input 'x' into ('x'.)$^{\cdot}$, can be illustrated by the following equations:

$$\dot{x} = f(x) \tag{3.1}$$

$$n_1^{(1)} = M_f(w_{11}^{(1)}x_1 + \cdots\ w_{15}^{(1)}x_{5+} + b_1^{(1)}) \tag{3.2}$$

$$n_i^{(1)} = M_f(w_{i1}^{(1)}x_1 + \cdots\ w_{i5}^{(1)}x_{5+} + b_i^{(1)}) \tag{3.3}$$

The last mathematical equation can be exemplified in model (3.5):

$$n_{w,b}(x) = M_f(w_{11}^{(2)}n_1^{(2)} + \cdots\ w_{15}^2 n_5 + \cdots + b_1^{(2)}) \tag{3.4}$$

To address the inconsistency between the input 'x' and the yielded output ('x'.) ̇, an objective function is applied. Various techniques are employed to determine the optimal parameters for the network, with the mathematical details provided in [46].

The Deep Encoding Autoencoder (DEA) comprises multiple advisors, each tasked with extracting significant features from the input dataset 'X'. The inclusion of multiple advisors serves the purpose of progressively reducing the dimensionality of the dataset and swiftly minimizing its size for efficient computation of the loss function. The fitness function of the Autoencoder is represented as Equation (3.5).

$$E = \frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{k}(x_{kn}\ -\ \hat{x}_{kn})^2 + \lambda * \frac{1}{2}\sum_{l}^{L}\sum_{j}^{n}\sum_{i}^{k} w_{ji}^{(l)^2}\ + \beta * \sum_{i=1}^{D(1)} \rho\ \log(\rho||\hat{\rho}_i) + (1-\rho)\log\left(\frac{1-\rho}{1-\hat{\rho}_i}\right) \tag{3.5}$$

In this context, the error relation is denoted by the parameter E, where 'x' signifies the input features, 'x̂' represents the reconstructed data produced by the Autoencoder (AE). Additionally, λ stands as a constant, as does β. The variable 'L' signifies the number of hidden layers, 'n' denotes the amount of explanations, and 'k' represents the number of hidden layers. Lastly, the preferred cost is indicated as ρ, and ρ̂_i signifies the typical activation level of a neuron 'i'.

3.4 PROPOSED METHOD

In this study, the EEG test done in the home or sub-central EEG test stations which the test complete and the EEG signal sent by using IoTs to the center of the data that used to diagnosis the epilepsy diseases. The EEG data transferred by using gatway to the center which the center machine contain the AI based technique to diagnosis epilepsy disease. The AI technique consists from number of stages to present remarkable resuts.

The average power of signal calculated to reduce the size of the EEG signal and extracted the suitable features. The average power function calculate the average power for each period selected by the user assume we selected 4 elements then the average power of the 4 elemets calculated and produce one element (value).

Furthermore, the calculated average powers are wired to the deep learning technique which in this study we applied deep sparse auto-encoders. The first auto-encoder reduce the size of input features and extracted high level features from input features.
Furthermore, the output of the first auto-encoder is connected to the second auto-encoder. The primary objective of the second auto-encoder is to reduce the input dimensionality and extract high-level features from the output of the first auto-encoder. It's important to note that auto-encoders are trained using unsupervised learning techniques, without the reliance on labeled data. Their purpose lies in reducing input features and eliminating redundant ones.

Conversely, the features extracted by the auto-encoders are fed into the softmax layer. The primary role of the softmax function is to transform class scores into probabilities. The softmax loss, often referred to as cross-entropy loss, is commonly employed in multi-class classification problems. The first step in this process involves the computation of non-normalized log probabilities using the softmax function. Following this, the non-normalized log probabilities undergo a transformation into non-normalized probabilities using an exponential operation. Ultimately, each value is normalized by dividing it by the total value, resulting in the ultimate probabilities. Furthermore, incorporating label information and probabilities, the magnitude of loss is computed at the conclusion of this procedure.

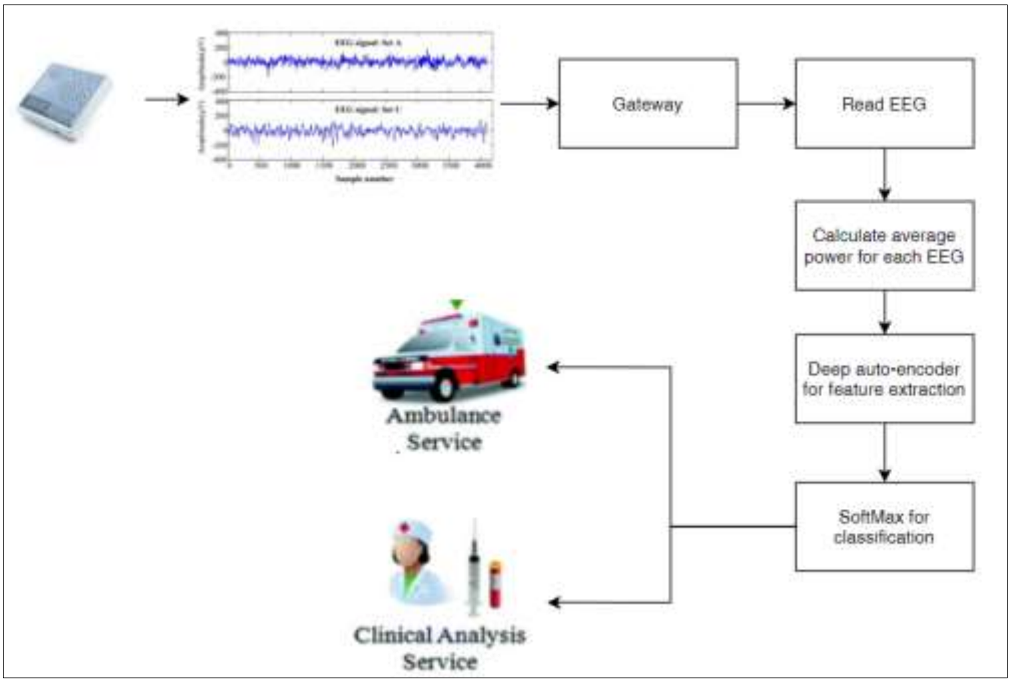

Figure 3.9: Proposed Method.

4. EXPERIMENTS AND DISSCUSION

Multiple experiments were conducted in diverse scenarios, and the outcomes were evaluated through various metrics. Comparisons were made among the outcomes of different experiments, with specific findings emphasized.

The experiments were implemented using MATLAB 2018 as the primary tool. The dataset features, as elucidated in Chapter 3, were employed as input for the proposed system, which was developed using MATLAB 2020.

The proposed method initially underwent adaptation to detect epileptic seizures, yielding satisfactory results in comparison to previous findings obtained through different detection methods. The dataset comprises two distinct groups: "A" signifies healthy cases, while "E" represents Hatenkan's activity cases. For each case (patient), the proposed framework processes 4096 data instances and calculates spectral energy density with a running time parameter set to 4. Subsequently, the data is consistently reduced to 1024 functions, resulting in a more precise data analysis.

The specific collection period for functional variables may vary across different datasets. An illustration of a data instance (patient) is presented in Figure 4.1, while the extracted properties from the spectral energy density passage for this case are depicted in Figure 4.8. The output from this process is then fed into the first autoencoder, which reduces the input size from 1024 to 500. Subsequently, the second autoencoder further reduces the data size, converting it from 500 to 100. Table 4.1 outlines the configuration options for the autoencoders.

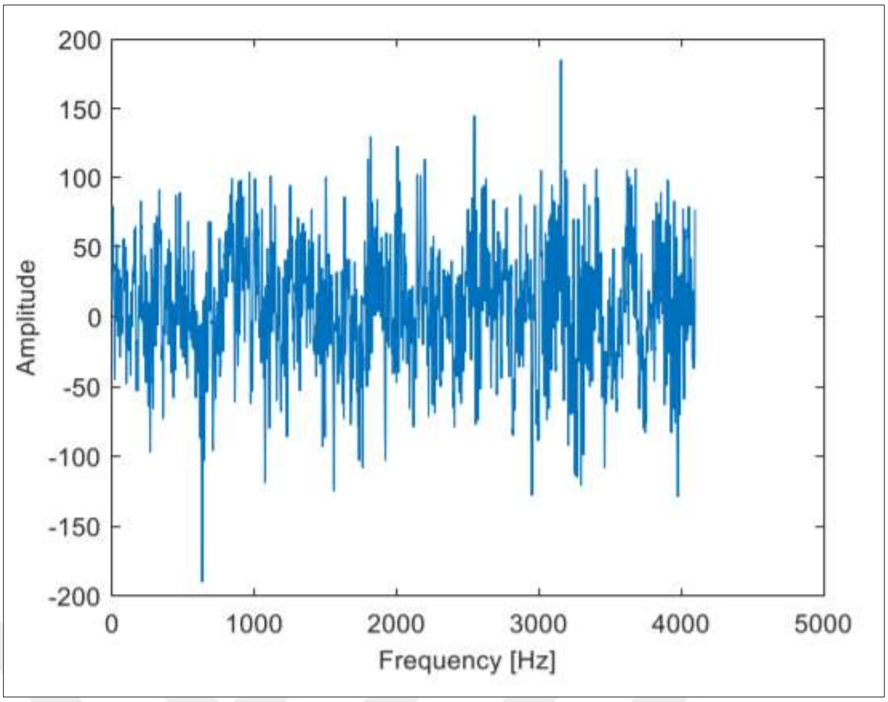

Figure 4.1: An instance (Patient Data) From Epilepsy Dataset.

The SoftMax algorithm was employed to classify the extracted features obtained at the conclusion of the process. Essentially, an autoencoder was utilized for patient identification, distinguishing between those with and without epileptic seizures. This utilization of autoencoders and SoftMax levels was preconfigured to achieve greater expressiveness and facilitate hierarchical grouping.

A total of 200 patients were considered in this study. Only 50% of the data was used for the training phase, with data selection for training and testing carried out randomly. This process was repeated five times, and the results were averaged, as presented in Table 4.1.

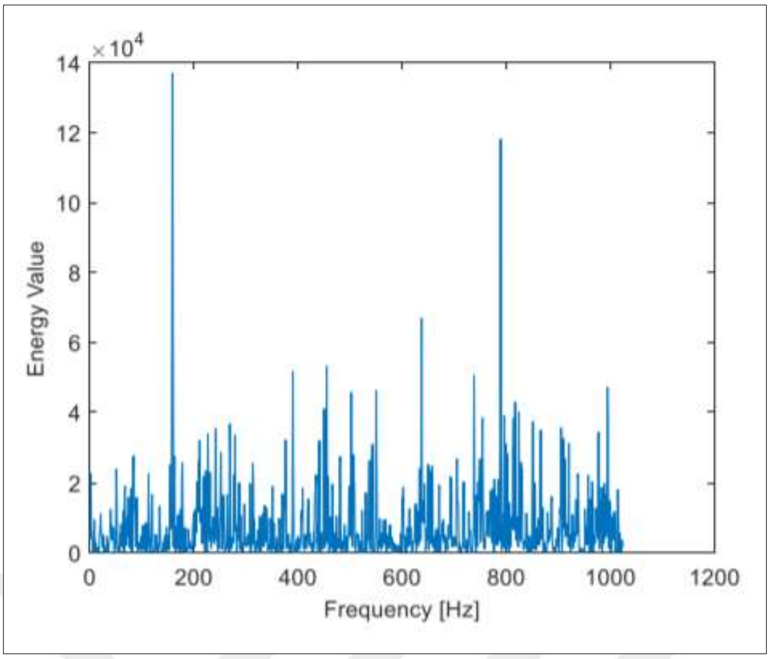

Figure 4.2: Features Epilepsy Dataset.

Table 4.1: The Auto-Encoders Parameters Values.

Factors	Auto-encoder 1	Auto-encoder 2
Hidden Size (HS)	500	100
Max Epochs (ME)	380	80
L2Weight Regularization (L2)	0.004	0.002
Sparsity Regularization (SR)	3	2
Sparsity Proportion (SP)	0.13	0.1

Table 4.2: The System Evaluation Parameters.

Results	DSAEs Based ESD
Sensitivity	100
Specificity	100
Precision	100
Negative Predictive Value	100
False Positive Rate	0
False Discovery Rate	0
False Negative Rate	0
Accuracy	100
F1 Score	1
Matthews Correlation Coefficient	1

In this framework, an average of power-based feature extraction techniques is combined with the intricate structure of the autoencoder, as demonstrated by previous studies in Table 4.2. These studies represent the primary methods for character identification and classification. However, it is worth noting that these methods are time-consuming in addressing the issue of epilepsy detection.

Furthermore, in previous studies, it was observed that utilizing 60% of the data for the learning phase yields optimal results, which aligns with the outcomes achieved by the proposed framework utilizing only 50% of the training data.

Table 4.3: Comparison of Methods.

Reference	Methods	Data Selection	ACC%
Srinivasan et al. [47]	Time–frequency domain feature-Recurrent neural network	50% Train-50% Test	94.60
Subasi and Ercelebi [48]	WT+ANN	60% Train-40% Test	92.00
Subasi [49]	Discrete WT-Mixture of expert model	60% Train-40% Test	94.5
Kannathal et al [50]	Entropy measures-ANFIS	58% Train-42% Test	92.22
Tzallas et al. [51]	Time–frequency analysis—ANN	60% Train-40% Test	93
Polat et al. [52]	Fast Fourier transform-DT	Tenfold cross validation	98.72
Acharya et al. [53]	WPD-PCA-GMM	60% Train-40% Test	95.00
Acharya et al [54]	Entropies + HOS +Higuchi FD+ Hurst exponent+ FC	60% Train-40% Test	91.70
Musa Peker et al. [55]	DTCWT + CVANN-3	60% Train-40% Test	97
Ahmad Karim et al. [56]	Deep Auto-encoder based Taguchi Method	50% Train-50% Test	98
Proposed Framework	Average signal power + Deep auto-encoders + SoftMax	50% Train-50% Test	98.80

5. CONCLUSION

This study introduces a novel framework for epilepsy seizure detection, primarily rooted in the integration of IoT technologies, signal average power analysis, and deep sparse auto-encoders. The primary objective of this approach is to leverage the signal average power function as a feature extractor in conjunction with deep sparse auto-encoders. This combination allows the method to efficiently select more relevant features within a shorter execution time compared to traditional and previously mentioned methods. The proposed technique is subject to comparison with various computer-based applications within the same domain, as well as with existing studies in the field.

In future research endeavors, this framework can find applications in diverse domains, such as computer network security, voice and video classification. Additionally, there is potential for further refinement of the structure through algorithmic enhancements to optimize the performance of auto-encoders and employ methods for extracting the most effective features beyond average signal power. Furthermore, signal strength averages can be integrated with various deep learning techniques, including CNN, LSTM, and RNN.

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