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Leveraging Wearable Sensors And Supervised Learning Progression As a Configurable Solution For Epileptic Patients

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Abstract: Epileptic seizures are among the most frequently occurring and unpredictable chronic neurological disorders that disrupt the lives of affected individuals. Thus, it paved the way for including Machine and Deep Learning models in the present frameworks for intelligent, self-driven epileptic seizure management. The few commonly deployed methods are Electroencephalogram (EEG), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Electrocardiography (ECG). However, low amplitude and fluctuations make it difficult for ML algorithms to achieve satisfactory results in ambient, harsh environmental conditions. Moreover, several proficient models, such as CNN and Random Forest, take excessive computational time in the training phase of the program. Furthermore, EEG hampers the flexibility of patients by its monitoring procedure confined to one room. Moreover, techniques like Auto encoding face issues of false negative rates (FNRs). The paper presents a novel and robust framework using wireless sensors, with increased data points for a competent KNN algorithm. The model demonstrated is compatible with the patient's daily routine activities and can predict the frequency of seizures with a 1.61% error rate. Instead of using 5–22 subjects as in prior studies, the algorithm is applied under 32 patients, which optimizes its performance rate. The practice fostered the durability of the model by preparing it for various unusual circumstances. This paper also presents a comparative overview of the novel paradigm with the current systems based on accuracy rate and dataset size. It also sheds light on the limitations of presently deployed architectural configurations and presents a sustainable solution for the need for a pliable and credible epileptic monitoring regime.

Keywords: WSNs, Epileptic seizures, Deep learning, Sensors, KNN

1. INTRODUCTION

Over the last decade, epilepsy has been the most compelling domain and is the domain area of interest of many research aspirants because its cure is not found yet. Therefore, many researchers are working on predicting the occurrence of seizures by including dynamic and self-computational technology, Artificial Intelligence. The effort is primarily to collect the data more precisely and accurately for the model's training to predict future occurrences based on past and present data. To make the model robust and efficient for anticipation, the model has to pass a certain number of trials in the training and testing phase. If passed tests match with the past and present actual results, then only the proposed model will be found adequate for prediction.

Numerous researchers have presented strategies for the identification of epileptic seizures that are diverse. The most frequently employed detection methods were computed tomography (CT) and magnetic resonance imaging (MRI). However, either electrocardiography (ECG)[1], [2] or electroencephalography (EEG) are the foundations of modern technology. Despite the highly reliable results produced for seizure [3], [4] identification with EEG [5], this method requires the patient to wear a complicated headpiece made of electrodes that capture the entire scalp of a human. Because of this, the patient experiences discomfort while going about their typical daily activities. Such a complicated architectural setup also makes it difficult to monitor patients continuously from a practical standpoint.

The proposed methodology introduces the concept of WSN's [6], [7] and IoT-based [8] operational system that is highly efficient in terms of reliability, scalability, power consumption, and deployment cost. Furthermore, the wireless-connected sensor units are lightweight, easy to wear [9], and miniature-sized. Therefore, as the patient can freely move from one place to another, unlike in EEG, it makes the system versatile and flexible in collecting real-time data without preventing the patient from performing normal

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daily activities. In addition, the collected data has a diverse range owing to the contemporary readings of activities like sleeping, brushing, eating, and walking that will be noted by dynamic sensors.

2. LITERATURE OVERVIEW

The contribution [10] uses the Computed tomography (CT) technique to detect various stages and types [14] of epilepsy. The process is phenomenal in detecting hemorrhage, infarctions, and malformations in infants, whereas, in adults, it can detect hydrocephalus with significant structural changes frequently. Nevertheless, its efficiency is much lower than expected for the uncategorized dataset. The proposed work by authors [5] avail Artificial Neural Networks (ANN) Classier for data prediction, requiring large datasets unnecessarily consuming the system's memory.

In addition, the ECG setup [15] used a trained algorithm based on data gathered from epilepsy patients. The sample comprised 100 patients, with seizures recorded as 43 out of 100. The Detection sensitivity registered was 93% (approx.). Although the system can detect convulsive seizures, i.e., focal and bilateral Tonic-Clonic [16], [12] outbreaks and non-convulsive strokes, it is not flexible for the users. Table I, labeled below, gives a comparative overview of the proposed prototype with past contributions. Compared to MRI, CT scanning is more affordable and effective at finding abnormalities. Their accuracy rates, however, need to be improved for a reliable system.

Ijaz Ahmad et al. have given a comprehensive overview [13] of the machine and Deep learning algorithms used for epileptic seizure detection in EEG and compared them based on their performance rates and dataset sizes. Even though the Random Forest and AE prediction algorithms are competent with a high accuracy rate, they have time complexity problems during the training phases. Auto encoding with Principal Component Analysis is another skillful technique, with a 97% accuracy rate but having high false negative rates (FNRs).

This research strives to create an independent epilepsy detection system with wireless technology serving as its foundation. The principal amount of the MCC unit's data receiving and processing is included. As a result, the system will require less storage and more computing power. The data is wireless transmitted from the wearable devices to the remote node, which serves as a router in the deployed WSN and then delivers the data to the Mobile [17], [18] Cloud Computing Unit for processing. Since an epileptic patient cannot be kept in a small space within the room or clinic itself, this research effort presents a methodology for continuously monitoring an epileptic patient by including the idea of mobility using wireless communication systems.

The BAN incorporates portable sensors that gather real-

TABLE I. Literature overview

Configuration	Limitations
Year: 2005 Technology: CT Scan Proposed Work [10]: CT Scan uses ionization radiation; producing great results with good resolution. Features: • low cost • easy to handle capability • Fast studying of brain [11] activity.	• Sensitive • Efficiency <30% • Poor response (temporal fossa) • Not suitable for Mesial temporal sclerosis
Year: 2017 Technology: EEG and ANN Classifier Proposed Work[5]: Utilizing EEG signals to identify epileptic seizures; it subjects to detect the presence of seizures based on received EEG signals.	• Not Flexible • Tough to wear • Requires large datasize
Year: 2019 Technology: ECG Proposed Work [12]: Seizure detection relies on wearable ECG device to collect variations in heart-stroke rate of epileptic patients.	• Less mobile • Requires ambulatory monitoring.
Year: 2022 Technology: EEG Proposed Work:[13] Seizure detection based on an EEG setup using AE[a] *algorithm*− it extracts feature using PCA[a] and is efficient with 97% accuracy rate.	• High FNRs[a] • Less sensitive
Proposed Artwork: WSNs[a] and IoT Classifier: KNN Proposed Work: The bulk of the data reception and analyzing component is included in MCC unit. As a result, demands less space and high processing capacity.	

a. FNRs-False Negative Rates, AE-Auto-Encoding, PCA-Principal Component Analysis, WSNs-Wireless Sensor Networks

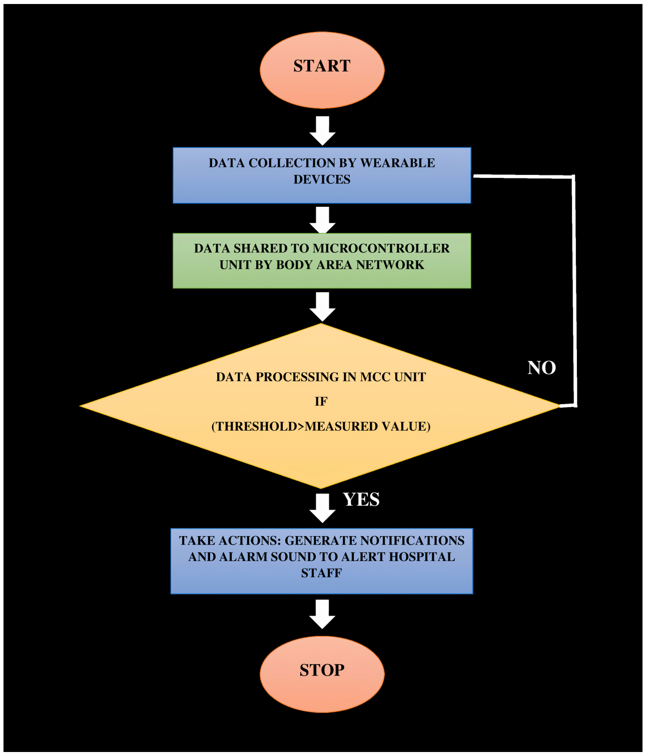

Figure 1. Performance Evaluation of System

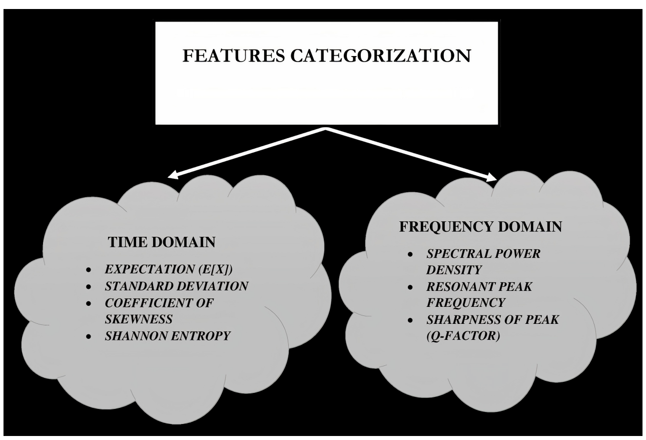

Figure 2. Working Mechanism of the Project

time data about the subject being surveyed. In reality, the sensors pile information from physical characteristics and wireless transmit it to the central hub.

Consequently, the constructed device is more adaptive to the patient's resting and loco-motor activities. Additionally, Wagyromag (wireless 2D tri-axial magnetometer, accelerometer, and sensor) [19], [11], Pulse and acoustic detector sensors are positioned all over a patient's body. The KNN classifier handles the data analytics and numerical computations part. However, Artificial Neural Networks (ANNs) is a rudimentary and inaccurate technique than KNN classification.

3. PROPOSED WORK

The primary objective of this project is to generate notifications based on the prediction of how frequently seizures[20] can occur while at the same time not compromising the accuracy of the system. Therefore, to make the system more accurate and efficient, there is a need for more data collected under wide variations of body gestures, daily activities, and environmental fluctuations. To conquer the latter objective, the artwork includes advanced, lightweight sensors[21], [22], [23] that provide mobility and flexibility to the user (in our case, it is the patient).

The proposed work provides the following features:

- *Efficiency:* The proposed system performs computations and generates predictions based on the calculations performed.
- *Flexibility:* The system comprises lightweight, wireless connected sensors, which allow the patient to follow their daily routines without any hindrance.
- *Less Power Consumption:* As the combined Local MCC unit and Cloud unit are replaced with the single MCC unit, power consumption is reduced for the entire system.
- *Reduced Hardware:* The proposed system is less bulky as the proposed approach is implemented using WSNs and IoT.

4. MATERIALS AND METHODOLOGY

The different sections of the setup perform distinct functions:

- Use of MCC unit for processing data
- The use of WSN is for the communication of sensors.
- Real-time data gathering while at the same time not compromising the mobility of the patient[24].
- Use the domain area of IoT to generate notifications and alarms based on the predicted values and send them to the MCC unit to make the concerned staff take necessary actions.

A. Stages of Study

1) Formation of Wireless Sensor Network(BAN):

On the epileptic patient's right arm and left leg, two bi-axial (2D) accelerometers are positioned. The chosen ACM sampling frequency is 3 Hz.

2) Data Collection and Sharing with MCC Unit:

The patient's kit establishes a BAN (body area network) that sends the sensor unit's instant data to a close-by ground station. The root server, BAN, and this network area all constitute the PAN (i.e., Personal Area Networks). The MCC unit, the user's smartphone, receives data from the BAN through the Base station, which acts as a transmitter and receiver node. The MCC unit processes the data, gets the patient's existing status, and then creates the appropriate emergency beacon messages. The MCC Unit's interface with the BAN forms the Central hub.

*3) **Data Processing in MCC Unit:***

After the MCC unit has successfully received the unprocessed data, processing of the data is required.
There are three main steps in data processing:

- *a)* ***Data Refining:*** Cleaning the data is essential to eliminate all extraneous disruptions from the original data to produce accurate projections and real-time computations. These disruptions include ambient noise signals, signs of inertial forces captured by the ACM, and sporadically patient body movement indicative of a fast stroke rate. One of the solutions proposed in the paper is the use of typical filters to remove these interruptions.
- *b)* ***Data Acquisition:*** Feature extraction is one of the most crucial steps in the data processing technique. Based on the cognitive methodology the user chooses and the training parameters, attributes may be extracted by the processing device itself.
- *c)* ***Classification:*** KNN is the algorithm utilized in this project. Compared to ANN, this method is more computationally efficient.

*4) **Implementing Architecture (Hardware Setup):***

Placing a system into use practically and deploying architecture involves several crucial factors, including battery backup, energy efficiency, network topology, Internet access, and sensor testing.

*5) **Synthesis of notifications based on information processing:***

Patients' inertial sensors connect to MCC through the base stations to exchange data. Nevertheless, fixed at specific locations, static nodes are the only ones that make data reception by base stations conceivable. Following data processing, which also involves KNN-based computations, acquired data samples are further compared to threshold values, and the resulting information is subsequently shared with the nearby rigid node. Each stationary node should be linked to the wearable of a single patient so that MCC can only communicate the processed data with that specific fixed node. Therefore, there are no concerns with patient identification. The medical personnel and doctors receive alert notifications for that patient whose brief seizure[25] attack was anticipated.

B. Features Description

The feature description of time-domain and frequency-domain systems is presented in Figure 1.

C. Flow Chart of Proposed Mechanism

There are four basic steps in the working of the proposed system which are neatly illustrated in Figure 2.

TABLE II. Publicly available databases

Database	Subjects
Kaggle	5 dogs and 2 patients
CHB-MIT	22
BONN	10
Zenodo	79 neonatal
Bern	5
Freiburg	21

TABLE III. Experimental findings

Patient No.	Age/Gender	Seizure Freq.	Predicted
1	18.5/M	7	7
2	23/F	3	2
3	16/M	4	4
4	21/M	6	6
5	35/M	3	3
6	29/F	3	2
7	25/M	5	5
8	32/F	4	4
9	12/F	3	3
10	16.5/M	4	4
11	24/M	40	40
12	22/F	11	11
13	25.5/F	8	8
14	28/M	10	10
15	31/M	18	18
16	39/M	6	6
17	45/F	3	2
18	35.5/M	8	8
19	33.5/F	16	16
20	20/F	4	4
21	29.5/M	3	3
22	41/M	9	9
23	43/M	5	5
24	51/M	11	11
25	26.5/F	8	8
26	20.5/M	6	6
27	21/F	15	15
28	19/F	9	9
29	32.5/F	3	3
30	24.5/M	7	6
31	27/M	4	4
32	22.5/M	2	2
Average	248		244

D. Hardware Description

Sensor node module for MICAz Motes wireless[26], [27] connection nodes. A wearable device called the MTS310 Sensor Board will make up a sensor network.

5. RESULTS

The classifier is trained to predict seizures with a 1.61% false error rate for 32 epileptic patients. It extracts the features in the time-frequency domain. Table II, labeled

TABLE IV. A Comparative Overview

Method	Technique	Features	Size	Performance Metrics			
				Time[b]	*Low-Price*	*Flexible*	*Accuracy(%)*
ECG[15]			100			X	43
CT[28]	Ultra and Slice Scanner		74			X	73
MRI[28]	1.5T using head coil		89		X		74
EEG[13]	CNN[a]		5	High			95.90
EEG[13]	CNN(2D)	Time-Domain	10	High			87.50
EEG[13]	CNN(2D)	Fast Fourier, WPD[a]	22	High			95.53
EEG[13]	RNN[a]	Independent	22	High			88.80
EEG[13]	RNN	Wavelet Transform	10	High			91.82
EEG[13]	RNN	Time-Frequency	21	High			93.75
EEG[13]	RNN	Independent	5	High			96
EEG[13]	AE	Time-Frequency				X	86.50
EEG[13]	AE	PCA[a]	79			X	97
EEG[13]	ANN, SVM, RF[a]	DWT[a]	22	High	X	X	100
EEG[13]	RF	9 statistical features		Less			96.67
Artwork	KNN	Time-Frequency	32	Less	Yes	Yes	98.39

a. CNN-Convolution Neural Networks, RNN-Recurrent Neural Networks, WPD-Wavelet Packet Decomposition, PCA-Principal Component Analysis, DWT-Discrete Wavelet Transform, RF-Random Forest
b. Time- It measures the time complexity of system in seconds to compute and run through the algorithm.

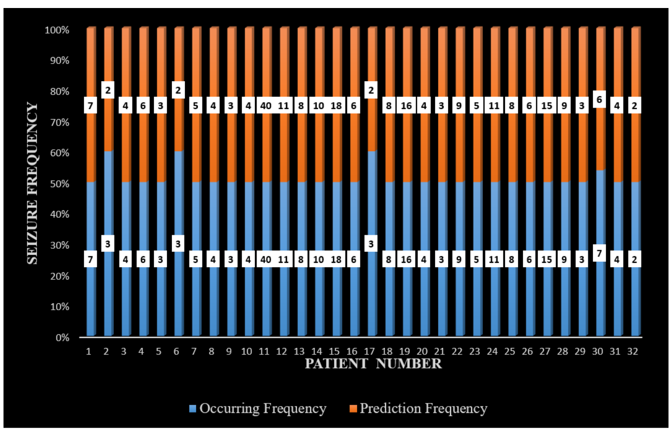

Figure 3. Study Findings

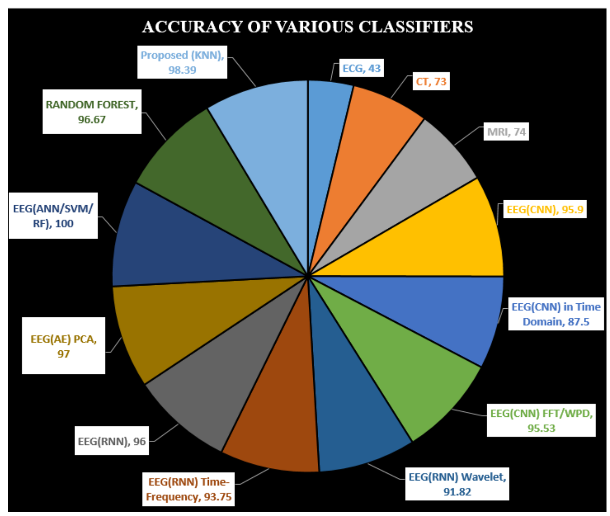

Figure 4. Distinction between Various Classifiers on the basis of their Accuracy Rates

below, highlights the open-access databases for epileptic patients of different age groups. The system's accuracy is calculated by dividing the number of correct predictions by the number of occurrences. The experimental results received from 32 patients with epilepsy are shown in Table III.

Table IV below examines and validates current techniques while taking into account; dataset size, time complexity, flexibility, and accuracy-like measures. Furthermore, it compares them to the suggested conceptual framework. Random Forest is far better than the decision tree mechanism, as it not generates the 'overfitting' problem. Additionally, Decision Forest has a flexible approach for constructing protocols based on a multi-faceted nodal approach. Moreover, DWT-based Artificial Neural Networks, SVM, and a hybrid of both techniques proved stupendous accuracy results by taking multiple feature selections such as power densities, skewness, sharpness of curve, and training under the CHB-MIT dataset. The dataset is an open-access database on PhysioNet. It consists of 5 males and 17 females of salient divergence in age groups for the training phase of machine [13].

Figure 3 illustrates a graphical overview of the study findings. It accounts the number of seizures predicted out of the number of occurred seizures of 32 patients, whereas Figure 4 compares the different models for seizure prediction based on their registered accuracy in Table IV. The Decision Forest marks 96.67% accuracy for the 9 statistical features including Deviation, Sharpness, Skewness coefficient, Energy, length of line, Mode, Hurst, Entropy, and Expectation. Thus, the feature selective method which considers the incorporation of 9 optimistic features reduces the model complexity and addresses high accuracy. In contrast, the RNN approach is comparatively faster than CNN but fails in providing accurate predictions. On the other hand, KNN has recorded slightly low accuracy because of its low precision and recall records. However, it has the capacity to maneuver tricky, tumultuous, multi-dimensional databases. It is an instance-based learning model that has low time complexity than ANN.

6. Conclusions and Future Work

The study methodology for developing a realistic and practically workable seizure detection system employing cutting-edge prediction algorithms like KNN is included in this paper. Successful WSN deployment allows for wireless monitoring of epileptic patients. IoT feature enables wireless access, data transfer, receiving, and manipulation. The hospital staff is then informed via notifications that are produced. Experimental findings demonstrate that the technique is highly efficient, with a 98.39% accuracy rate. Additionally, the KNN classification method is much more effective than other deployed methods using different ML algorithms. With the KNN Classifier, the model does not need to be trained repeatedly for each new epileptic patient. As a result, it is versatile for new information sets and always finds a way for the issue of previously collected records. As a result, the proposed model is scalable and faster as fewer computations are required, highly precise, and power-economical.

The research study effectively implements a system that can detect seizures. However, for the medical personnel to arrive at the specified place at the time of need, there is a need for a system that guards against severe damage and injuries to patients, such as deadly unconsciousness, undesired movements, and unstable mental conditions. A method is needed that, after seizure detection (i.e., using the suggested system in this research), may work to avoid imminent seizure attacks to prevent all these symptoms of epileptic patients from ever occurring. This can be achieved by making the patient feel happier and more hushed or cooling them off. Electrical disruptions and signal dissipation in the brain cause seizures. Nerve cells and maybe the scalp area experience additional heating because of this issue. By using the Focal Cooling framework [29], it may be possible to put the epileptic patient at ease and halt the seizure episode. More biological parameters, such as heart rate, oxygenation, and gaseous metabolism, among many others, can be considered to improve the system's accuracy and efficiency. Furthermore, for a comprehensive validation of deployed seizure-detection mechanisms, a large, publicly available dataset is required, which is yet to be available at present. This practice will train models for more accurate future projections.

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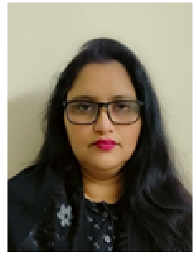

Dr. Shaheen Naz presently working as Assistant Professor in Electrical, Electronics and Communication Department, School of Engineering and Technology, Sharda University. She has an experience of 19 years. Her research areas are Material Science, Wireless Sensor Networks. She published 12+ papers in reputed journals with 3 patents.