Artificial Intelligence based Epilepsy Seizure Prediction and Detection

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Abstract

The abrupt occurrence of repeated seizures caused by epilepsy, a chronic nerve illness that is on the rise in the world, has an impact on the lives of millions of patients every year. In a variety of mishaps, it might cause critical injuries or patient deaths. Therefore, automatic seizure prediction is crucial for warning patients well in advance of the actual commencement, boosting their chances of staying safe. Internet of Things-enabled technologies are currently investigating the offer deep learning-based treatments for such nerve illnesses In an integrated cloud-fog system situation, the previously presented article also suggests an autonomous seizure prediction model using convolutional neural networks. This model makes use of EEG segments with shorter time scales that exhibit discrete spectral characteristics including. experiments has been run to assess how well the lightweight solution performs. experimental results show that the approach has use in brain e-health applications and surpasses most of the 15-minute warning ahead of time) for all individuals.

Keywords: *Wearable technology, multisensor recordings, deep learning, and epilepsy.*

1. INTRODUCTION

Recurrent seizures, which are a common feature of the chronic condition epilepsy and are caused by erroneous neuron firing, cause an uncontrollable electrical disturbance in the brain. A patient's body may exhibit serious abnormalities after a seizure. behaviour, movements, emotions, consciousness level, which might cause harm or even death. And 30% of those who have it experience drug resistance issues while receiving medical treatment . When individuals have medication failure, epilepsy surgery is routinely performed. Surgery for epilepsy aims to eliminate the lesion that causes the malfunctioning neuron. Finding the lesion is occasionally challenging, though, due to factors like incorrect location of the lesion or limitations in particular medical equipment.

After temporal lobe epilepsy surgeries, statistics show that chance while chances of being seizure-free After operations for frontal lobe epilepsy are roughly 60% lesional patients and only 35% for nonlesional patients. If seizure onsets take place under unanticipated circumstances without access to medical personnel for individuals who cannot be fully healed through medication or surgery and sensed and processed in order to detect and forecast seizures (LFP). Recent advances in artificial intelligence, particularly the impressive performance made possible by cutting-edge networks through , have led to the employment of the deep learning strategy for find solutions in a variety of uses in medicine through . For nine people who took part in the clinical trial, the system exhibited prediction accuracy that was above the level of chance. Notably, three patients' seizures were correctly predicted at 86%, 100%, and 100%. The system's clinical trial featured nine participants. Take note that for three patients, seizure probabilities were 86%, 100%, and 100%. The remaining six people's sensitivities between 54% and 71%. This programme incorporates all essential elements and offers a useful a system's design for predicting seizures, but it still needs to be improved. For instance, a dedicated CPU can be used in place of the handheld device to make the system more compact. Direct wireless data transfer to an off-body device is possible The use of machine learning algorithms improved . Additionally, a system that is simple to use and uses less power should be implemented. a wearable in general or implantable method for seizure detection or prediction is shown in Fig. 1(a). It has a particular kind a set of electrodes special IC processing. For EEG, The electrodes may be gel-based or dry; example ECoG, they can be invasive non-penetrating electrodes; or, for recording LFP or action potential (AP), they can be invasive piercing microelectrodes. used to improve prediction performance. They include analogue circuits like filtration and equipment amplifiers to reduce noise and boost the signals that matter, analogue to digital converters (ADCs), which connect the analogue and digital worlds to make it additional digital processing circuits and algorithmic processing, which use pre-defined algorithms to analyse and categorise the stream of digital signals. Additionally, feedback circuits were set up for other procedures including providing electrical stimulation and medication release. In implanted devices, wireless power and data transfer blocks are frequently employed to facilitate long-functioning and reduce discomfort brought on by skin penetration. The signals that were captured include common brain states that can be categorised. In various brainwave states are depicted. Classifying preictal and ictal signals can be thought of as seizure detection and foreseeability. True positives and false positives, which provide additional metrics like the curve and area under the curve, can be utilised to evaluate success of the classification system (AUC). Section IV provides information on the vari ous epileptic brainwave states as well as the figures of merit.

2. RELATED WORK

The term "electrocorticography" describes recordings made using eletrodes put directly on the exposed cortex from above the brain but beneath the skull. When compared to EEG, ECoG electrodes (like the one in the middle right of have higher spatial resolution (5-10mm vs. cm [20]), a wider bandwidth (0-600Hz), a higher amplitude (maximum 500V vs. 50V), and are far less susceptible to artefacts like electromyography (EMG) . Beyond clinical epileptology, ECoG's enhanced spatial and temporal resolution makes it an invaluable tool for functional brain mapping (principally in the sensorimotor cortex and auditory cortex real-time brain activity imaging and translational opportunities like brain-machine interfaces (BMIs), which enable decoding brain signals linked to the user's intentions. employed as control elements to help the person engage with their environment more successfully .

Ahmed M. Fouad [1] he has published Another notable application is the conversion of signals using the transform to move from the time domain to the frequency or Fast Fourier transform (FFT). both transformational capabilities help with via means of precise and quick dynamic fluctuations are predicted using the spectral domain and separating EEG data into sub-bands, as it also describes changes in functional and behavioural characteristics

Smithk.khara and varun balaji [2] one of the paper The EEG signals' nature is complicated, non-stationary, and non-linear. As a result, visual screening of EEG data takes time, is laborious, and is subject to human mistake. The STFT requires a set size and window operation and presumes that the signal is stationary. While WVD experiences cross-term and low-frequency resolution in the frequency-domain, CWT and DWT do not require wavelet selection . Jingyi zheng and mingli liang[3] have applied We will use the EEG recording from one person who completed job 1 in research1 as an illustration. Assign the head EEG signal captured during the kth trial from the jth electrode channel the notation xkj (t). The signal for task 1 30 seconds or less long, plus the label for xkj(t) is binary, meaning it can either be moving or static). The next parts xkj(t), j=1,..., 64, k=1,..., K as our process unit. The tasks and individuals that make up Table I's summary all have different K values. On each xkj(t), we shall use the subsequent procedure for all j and k. For the sake of simplicity, We shall just use x(t) (t)to signify xkj(t) in order to prevent any misunderstanding brought on by additional subscripts.

Yang Li & Xu-Dong Wang [4] he applied To find EEG readings displaying regular and rhythmic discharges during seizure activity, Utilizing a time-domain method was Liu et al. Additionally, a well-liked Fourier-based spectral analysis method is frequently used in the frequency domain to analyse EEG signals. the signals are nonlinear and nonstationary, Traditional spectral analysis implies that the signals are local, whereas the Fourier transform does not. techniques like Since EEG signals are stationary, the Fourier transform often cannot effectively capture their characteristics.

Daniela De Venuto & Giovanni Mezzina[5] The development of the and rhythms, two movement-related potentials (MRPs), is thoroughly examined in this work, taking into account their timing and frequency reactions throughout various stimulation regimens. The employed method performs a time-frequency domain analysis of the EEGs obtained from five smart electrodes while taking into account the targeted frequency bands. The data that will be reviewed during the machine learning (ML) phase are subjected to a first dimensionality reduction using a special technique called MLE-RIDE.

Eliana M. Santos [6] The surface EEG was captured. of the scalp The foundation of (sensing space) is a head model, which in turn enables solving the inverse problem, or the localisation of the EEG signal source . A specific head model and electrode location can be attributed to the voxels in the brain model. Thus, utilising Brodmann areas that map the two hemispheres of the brain, Each region of interest in the brain model has potential solutions that include integrated. Finding how each individual dipole operates (cortical source) affects is the next stage in solving the inverse problem . To resolve the inverse EEG problem,

Mahmoud Malass & Wassim El Falou[7] he was applied The re-referenced EEG signals underwent spectral filtering in the 8–30 Hz region. Butterworth filters of the sixth order were employed. The frequency spectrum was selected because it includes the alpha and beta frequency bands, which research has shown to be crucial for classifying movements. Additionally, demonstrated that a broad frequency spectrum (e.g., 8–30 Hz) produces superior categorization outcomes to small bands. Kheira Djelloul [8] have applied the six steps listed above must be followed in order to create a real-time BCI system. Prior to feature extraction (such as alpha/beta bands), preprocessing, and decoding algorithms, it is necessary to capture the brain activity during a specific experimental paradigm. To save processing and analysis time and effort, BCI researchers have created a number of open source software programmes, including EEGLab Fie and Brainstorm.

Pilar Gomez- Gil [9] have also used Wavelet analysis was used in the experiment described in this study to separate EEG data into the spectral bands alpha , beta , delta , and theta , which carry information about the activity of the brain . Delta waves , which occur most frequently during profound meditation and deep sleep, range in frequency from 0 to 4 Hz. Theta waves are present in light sleep, meditation, learning, and remembering and range in frequency from 4 to 8 Hz. In the 8–12 Hz frequency range, alpha waves are produced by the brain both when it is at rest and while thoughts are fluid.

Catur Atmaji[10] have applied Before further processing, the EEG signals are subjected to a bandpass filter to remove extraneous data and noise. The 8th order digital butterworth filter is used to build an 8–30 Hz bandpass filter.

Wei Gao & Tianyou Yu [11] The right mastoid was used as a reference for EEG readings. during the experiment, and data were gathered using a EEG signals from the expanded 10-20 system were captured in a 30-channel EEG cap (LT 37) at a sampling rate of 250 Hz. each participant were gathered using a 40-channel NuAmps and a 64-channel SynAmps2 (Compumedics, Neuroscan, Inc., Australia) (Compumedics, Neuroscan, Inc., Australia).

Kai Li & Jiang Wang[12] he have applied Every EEG recording is first filtered using a band passed finite impulse digital filter based on wavelet package from 0.5Hz to 30Hz. to remove the power line interference (Morlet wavelet). The reference potential is then determined using the average of all channel signals. In order to eliminate potential systematic effects brought on by referencing to a specific channel, EEG data from each channel is re-referenced.

Seif Soliman[13] one of the paper Another notable application is the conversion of signals by employing the Fast Fourier transform or the Short-time Fourier transform, from the time domain to the frequency domain.Both transformational capabilities help with via means of precise It explains changes in functional and behavioral aspects, and makes rapid predictions by separating EEG data into sub-bands and employing the spectral domain.

Tarak Das;[14] have applied The artefacts include heartbeat, eye blinks, and eye movements (EOG) (ECG). In addition to these, brain impulses are also jumbled with muscle movements and interference from power lines.

In order to remove high frequency disturbances, we employ a Butterworth 40 Hz for the cut-off frequency of the low pass filter (LPF). 0.05 Hz is the cutoff frequency, and the third order Butterworth High Pass Filter (HPF) filters out low frequency noises like breathing and movement artefacts.

Ahamed Sedik [15] he spoke about how to predict EEG seizures using a straightforward thresholding method in the previous section. We shall combine artificial intelligence approaches with statistical analysis in this section. K-means clustering is used to apply clustering to the EEG signal characteristics. Based on neural networks, another categorization method is now in use. This method relies on band restriction, statistical analysis, and MLP network-based automatic categorization.

3.WORK PROPOSAL

The illustrates the suggested IoT framework for smart epileptic seizure prediction. In the beginning, portable EEG devices are used to collect and Bluetooth-transmit the EEG data of epileptic patients. Second, using a secure mobile communication network, smartphones upload EEG data to a hospital server. Systems for communication based on chaos have advanced significantly. They can offer a high level of data transfer privacy . Before processing the EEG data, the server stores it and links it to the patients' medical histories. Then, the server will run the MLF-CNN system based on SWT to forecast epileptic seizures. Last but not least, a warning will be provided to the patients and the doctors if the onset is anticipated (or family members). They are able to act quickly. While a short preictal data may not provide enough medical information to intervene as needed, a long preictal EEG time raises worry and anxiety for patients. Therefore, it was decided that a preictal time of 15 minutes was ideal, as illustrated in Figure 2. Interictal data was also collected at least 4 hours before the start of the seizure and 4 hours after it ended. To lessen the effect of noise on the model's forecast accuracy, this data was gathered.

He machine learning research in epileptic seizure identification spans both the feature extraction and classification-algorithm domains. is intriguing to explore. According to research by Karlik et al., k-NN, Backpropagation, and SVM perform better than As an algorithm for epileptic seizures on EEG, Nave Bayes. Hybrid SVM was used by Subadi et al analyzing EEG for epileptic convulsions. The outcomes showed decent performance, however the technique is complex and requires a lot of memory. Wavelet transform and the ANN ensemble approach were applied by Ebrahimpour et al, but the performance was only average. In this research, chose the Generalized Relevance Learning algorithm as the classification technique because, despite its high robustness, it is rarely utilised to identify epileptic seizures in EEG.

$$\text{Dij}= \sqrt{\quad} \sum_{s=1\forall s(Yik-Zjk)}^{m} 2 \qquad (1)$$

Transform using Wavelet:

In EEG datasets, extraction of wavelet features has demonstrated excellent performance in the identification of epileptic seizures. In contrast to PCA, which operates in a specific domain, Extraction of Wavelet Transform (WT) features operates in the temporal domain. The definition of A signal's WT in f (x)is:

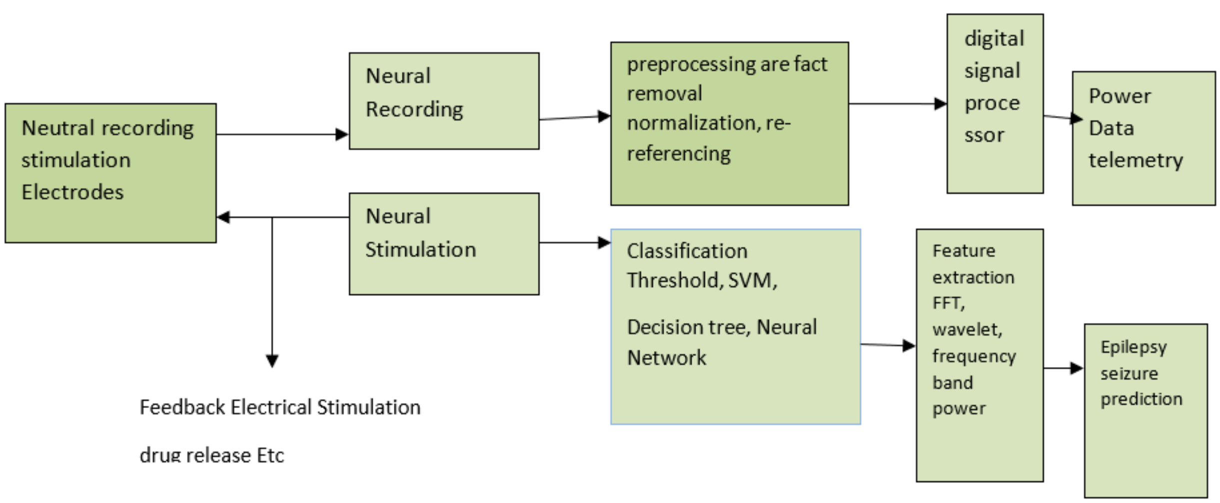
The categorization system known as random forest is largely according to random trees. In Rough Forest, the best match is determined by comparing each feature vector supplied to the one retained a dataset for trains. The accuracy of recognition is as high as the class that receives the most votes from the trees. Random trees are those that are selected from a list of probable trees at random. A decision tree known as a random tree takes into account k randomly selected attributes at every node. Using back fitting without pruning as a base, the class probabilities for each node are calculated . The procedures for raising a random tree include

The original dataset is used to substitute N cases in the training set, which is then used to grow the tree.

For each tree, m attributes are selected at random. Using common tree-building algorithms, the properties from the nodes and leaves. The nodes are divided using the best split on m, with m being held constant.Without pruning, each tree is developing to the utmost extent feasible.

The term "electrocorticography" describes recordings made using eletrodes put directly on the exposed cortex from above the brain but beneath the skull. When compared to EEG, ECoG electrodes (like the one in the middle right of have higher spatial resolution (5-10mm vs. 20cm)a wider bandwidth (0-600Hz), a higher amplitude (maximum 500V vs. 50V), and are far less susceptible to artefacts like electromyography (EMG) . Beyond clinical epileptology, ECoG's enhanced spatial and temporal resolution makes it an invaluable tool for functional brain mapping (principally in the sensorimotor cortex and auditory cortex real-time brain activity imaging and translational opportunities like brain-machine interfaces (BMIs), which enable decoding brain signals linked to the user's intentions.

FIG 2 CLOSED LOOP IMPLANTED EPILEPSY THERAPY SYSTEM



The closed loop implanted epilepsy therapy system described fig 2. This viewpoint is applicable to other domains as well, not just epilepsy. For instance, a spatial spectrum analysis of recordings from the motor cortex and superior temporal gyrus has shown that electrode spacing in humans should be 1.25 mm or less to capture the wealth of spatial information that is present. Using electrodes spaced 1mm apart or fewer, spoken words and motor control signals can be decoded with noticeably better performance. Micro-field evoked potentials in the occipital cortex have been shown to be able to identify ocular dominance columns in arrays with a 500 m spacing. As a result, many of the answers and methods considered in this project can also be used in other fields, like BMI.

The EEG monitor and wearable record data using separate clocks. We synchronised The device keeps time at thebeginning of the device recording to make up for the time difference involving the gadget and EEG clocks. We pressed that thing button and the EEG event marker button simultaneously after turning on the recording device. Both the gadget and the EEG recordings received a time stamp as a result patient's buttons were pressed simultaneously when we put two wearable gadgets on them. When we couldn't locate EEG event markers because of button push failures, we videotaped the synchronising procedure using video timestamps, confirm timings for placing devices. They were enrolled once more, the process was repeated, and they wore the recorder once more on a subsequent day or during a different admission.

Fig 3 EEG signal

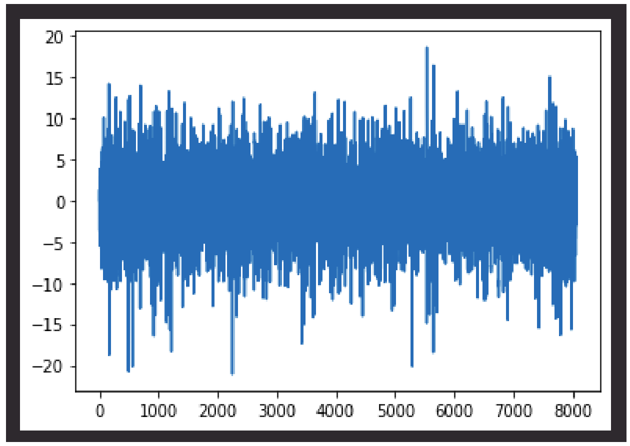
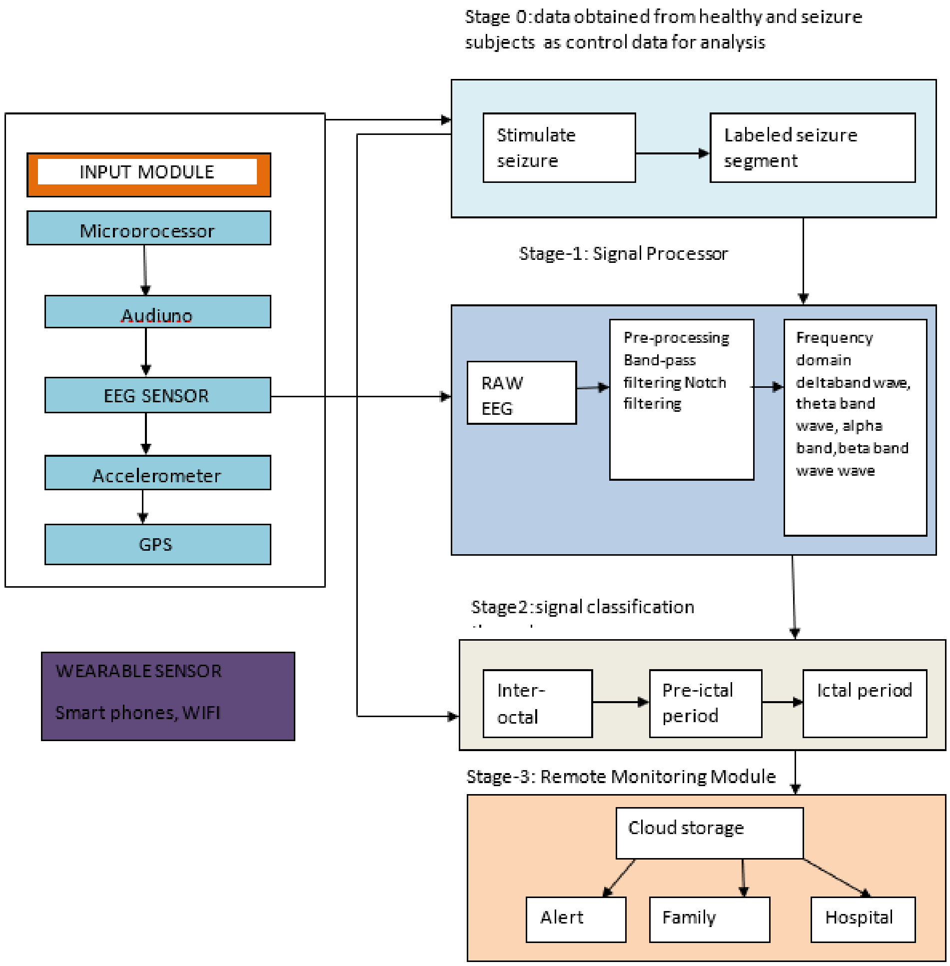


fig 3 described about EEG signal next thing that we are proceeding with, is the creation of the data set:- we have defined the channel=32, segment size, eeg sampling rate and data portion to further work with our given data.a common technique for obtaining brain activity related to various from the scalp's surface is electroencephalography. based on the signal frequency spectrum, which ranges from 0.1 hz to more than these signals are at 100 hz. categorised as alpha, beta, theta, gamma, and delta. for processing eeg the signals following frequencies are taken into account alpha (8-12 hz), beta (12-26 hz), theta (4-8 hz), and gamma (up to 4 hz) are all frequency bands (26–100 hz). the mind surface amplitude is roughly 1-2 mv, while the the scalp eeg signal is 100 mv. from peak to peak. the eeg signal's frequency range is between 1 and 50 hz.

FIG 5 PROPOSED OF WORKFLOW DIAGRAM



The above figure 5 shows all overall flow diagram for this work.in stage 0, we collected the labeled seizures from medical hospital.The information provided by the EEG signal for neurological conditions and other neuro diseases is significant. Five Delta (up to 4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–26 Hz), and Gamma are the different frequency ranges. are typically utilised for EEG signal analysis (26–100 Hz). The study's data set was derived from an EEG dataset For 23.6 secondsit contains records. the mind activity of 5 wholesome individuals and 5 epileptic subjects. 100 single-channel EEG segments make up the dataset, which is then divided into five categories. EEG signals come from healthy subjects who are awake and have their eyes open. EEG data from a healthy participant with closed eye

4. Performance Analysis

The proposed project consists of an improvised system which filters out signal artifacts, signal processing using wavelet transform and classification based on HBIS algorithm. EEG signals prove be an efficient tool in diagnosing brain related medical conditions. The EEG signal can be used as a marker for early detection and monitoring for epileptic seizures. Prior to the occurrence or during or after the occurrence of the seizure, a marked variation in EEG signal is observed In order to diagnose and treat epilepsy, seizure recording is crucial because it allows for time-shifted, off-line viewing of aberrant brain electromotive force. Medical staff are relieved from having to visually search through extensive records to treat seizures (which very uncommon within the ongoing timeline) thanks to signal processing techniques like audio transformation and automated detection methods. seizure detection software is also becoming more crucial for implantable therapeutic devices that give unsuccessful responses, start, storing data monitor people, etc.. Generic versus patient-specific approaches have been distinguished between methods, and at least three pattern recognition techniques have also been distinguished: (1) Syntactic anthropomimetic (imitating human grammar)and rule bases), (2) artificial intelligence (AI), statistics (classical discriminant analysis) (machine learning, neural networks, etc.)

Quantitative features must be extracted by all approaches.

The date discrepancy between the EEG clock and wristband at the start within the experiment Data visualization

Overview of the data

Fig 6: features in EEG

	Fp1	AF3	F3	F7	FC5	FC1	C3	T7	CP5	CP1	...	Cz	C4	T8	CP6	CP2	P4	P8	PO4	O2	Unnamed: 32
0	0.057813	-1.335266	4.640480	0.219573	7.473817	2.314842	1.918097	-9.257533	9.089943	-7.104519	...	-2.241480	1.415335	2.406646	12.864059	4.021099	-2.828598	-2.588735	2.637905	-5.226618	NaN
1	1.367408	10.259654	3.345409	7.897852	-2.446051	-1.655035	-6.301423	-7.290317	-3.546453	-5.705187	...	-2.568397	-5.651418	-0.096730	-4.930759	-1.722504	-6.111309	0.094893	-3.521353	1.887093	NaN
2	-1.783132	4.133553	-0.951680	-1.624803	-1.827309	-2.280364	-2.279225	9.151344	-0.239575	-0.057604	...	-2.132823	-0.521117	8.605298	-4.499946	-3.232839	-4.249645	-3.687167	-7.383004	-4.489537	NaN
3	-3.690217	-0.814000	2.295469	0.901445	8.323679	1.127906	6.356886	11.642082	9.354154	-1.662478	...	-0.506117	-1.154866	-3.940251	7.390881	2.129897	-0.794675	-1.959021	2.774530	-6.323060	NaN
4	2.137114	6.420466	6.122230	10.015321	3.106394	3.183129	3.658535	4.571793	4.917712	-2.325940	...	1.813907	-6.444635	-27.680880	0.641364	1.996658	-0.445779	2.614021	6.161845	3.308816	NaN

5 rows × 33 columns

is how We established the start time. inaccuracy between the EEG clock and the bracelet (Figure S1b). The distribution of start timing mistakes found in our investigation is shown in Figure Figure1A1A; absolute errors largely have a Gaussian shape and are less than 20 s in length.

The proposed algorithm is characterized as follows:

1. For i=1 to n
2. Design a bootstrap table from X^* of size S from the data of training.
3. Grow a random forest tree X_b towards the boost strapped data and apply the recursive steps for each node of the tree. This procedure is repeated for reaching the minimum node size.
4. Output is calculated based on ensemble of tree ${X_b}_1^m$
5. $P_b(x)$ be the class prediction of the random forest tree.
6. ${P_b}_1^m = Majority of {X_b}_1^m$
7. Hyper parameters are assigned as penalty parameters, max features from epilepsy data, estimators.
8. Reduce step size to find the global optimal hyper- specifications, repeat the preceding steps with a 0.1 step setting.

Figure 6 describe about the overview of the data Next After seeing the results of the above model we are load in another dataset which has the following parameters Data that is unbalanced indicates that there is a significant disparity in the number of each class. Predicting epileptic seizures is difficult since the ratio of the interictal to preictal stage is typically more than 10:1. We applied two techniques in two datasets to this issue. We introduced a class-weight to the loss function at training time in the iEEG datasets. Inverse to the ratio of the interictal and preictal states, the class-weight value was calculated. We retrieved the preictal samples from the EEG dataset to create the training dataset with overlaps of 5 s, however we did not extract the interictal records. Additionally, this technique simulates the use of real-time epileptic seizure prediction technology in actual settings to

Random Forest :

1.The relevancy and feature ranks algorithms have been updated online as follows:

2.Initialize the relevance vector, k=1n, k=1,..., n, and

3.Set the codebook vector to zero. Using Eq., update the book of codes vector

4. Update the relevance vector utilizing Eq. normalise the vector of importance.

Training the HBOS model

5.Calculate each feature's weight by taking the average of its input vector's before ordering position index.

6.For each training pattern, repeat steps 3-6.

Wavelet transform equation

$$Ws\ F(x) = F(x)\emptyset s - 1|x \int_{-\infty}^{\infty} F(t)\emptyset\ S - t|x)dt \ldots\ldots\ldots..(2)$$

Table I –ACCURACY OF CLASSIFIERS FOR EEG SIGNALS

SL. No	Accuracy Score
Naïve Bayes	56.66
Decision Tree	92
Logistic Regression	89.33
Random Forest	92.66

A well-liked and typical ensemble learning technique is Random Forest.At the training stage, it creates a large number of decision trees to do data classification. In Random Forest each tree is seen of as a classifier, and the final classification is made using a majority voting mechanism and the weighted classification output. A decision tree is built for each dataset, using the feature-based splitting method for the tree nodes.

Figure 8: From the above graph its looking like our model is performing good

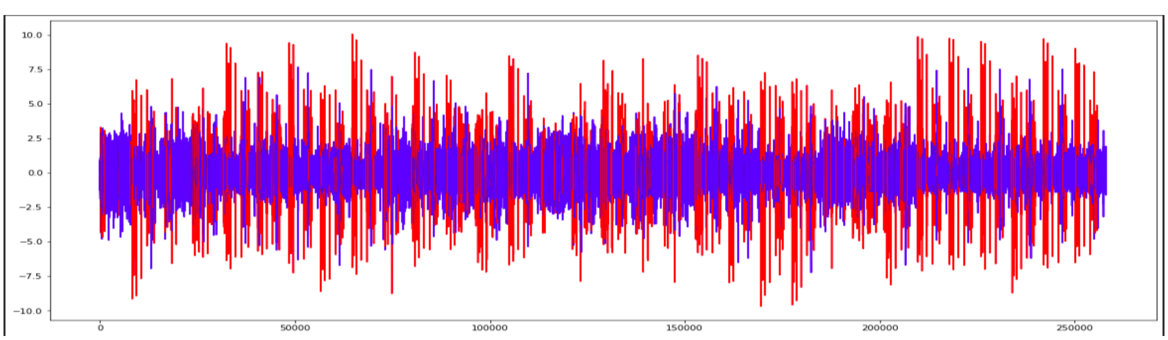


Fig 8 describe about the Training the HBOS model From the above graph its looking like our model is performing good enough. Process of detecting seizures illustrated. Sample EEG readings from 23 channels depicting a seizure that took place in the 1870s. The left panel displays the whole recorded session along with some early artefacts. The right panel displays a 10-second period of pre- and post-seizure activity. The EEG channels power spectrum demonstrating substantial power surges in several channels caused by artefacts before time = 1000s, some of which are stronger than the surge of power caused by a seizure.

CONCLUSION:

We described a transformer model for monitoring non-invasive epilepsy, which uses temporal electrode data to perform seizure identification on raw EEG signals. We looked at the training approach, highlighting the benefits of a two-step process that includes pre-training on a global scale and subject-specific amplification. The EEGformer has a novel SOA 15.2s average onset detection delay and a 65.5% sensitivity.achieving performance on par with the SOA. 0 FP can be attained by eliminating 5/40 outliers, the majority of which are brought on by EEG artefacts. The Apollo4 MCU's inference run on the EEGformer consumes 405 ms and 1.79 mJ at 96 MHz operational period, making it acceptable for deployment on discrete devices. This study illustrates the viability substantially less latency seizure detection by applying transformers on raw EEG data.

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