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Machine Learning-Driven Robust Optimization of Communication Signals in Sensor Wearable Devices for Early Stage Epilepsy Seizure Prediction using EPCA

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Abstract

Objectives: To introduce a novel EEG signal optimization and epilepsy seizure detection method at an early stage with the aid of sensor wearable devices in order to treat the epilepsy in advance. For effective optimization and to boost the detection accuracy, the ROCS-EDS (Robust Optimization of Communication Signals for Early Detection of Seizures) technique is employed with EPCA (Enhanced Principal Component Analysis). **Methods:** EEG signal optimization, feature selection, and extraction such as time-domain, frequency-domain, time-frequency, movements, and statistical features are done by EPCA. IQAM and CPSK techniques are utilized for data transfer and reliability. The BCI C-IV (Brain Computer Interface Dataset from California) dataset is used in this study with a record of 4922 patients, a 400 Hz sample rate, 4 target classes, and 2 subjects. LD parity check, fast Fourier, and wavelet transform methods are deployed to track signals and optimize them at frequent intervals. For filtering the signals and reliability rate monitoring, the MMSEF error filtering method is employed. MATLAB software is used to measure the performance of the suggested model with baseline models such as VPSOGA-SVM, 2L-LSTM, and IoMT-ESD. **Findings:** With an accuracy rate of 98%, 96% and 97% sensitivity and specificity, a 98% F-score, 98.65% and 96.80% precision and recall, and 97% and 91% TPR and TNR, 5.46% and 7.10% FPR and FNR, ROCS-EDS outperforms baseline models in terms of signal optimization and seizure detection at an early stage. The method is deployed and tested in MF2Epi-alert wearable device for seizure activity. **Novelty:** The novel hybrid model ROCS-EDS with EPCA shown evident results and has capability in optimizing EEG signals and detect ES accurately at an early stage which helps the clinical experts to treat the epilepsy in advance. ROCS-EDS outperform the currently prevailing methods VPSOGA-SVM [(1)], 2L-LSTM [(2)], and IoMT-ESD [(3)].

Keywords: Epilepsy Seizure Detection; Machine Learning; Deep Learning; PCA; EEG Signals; Signal Optimization; Data Mining

1 Introduction

Epilepsy is a neurological disorder in humans characterized by recurrent and unprovoked seizures. Signal processing and optimization methods have paved the way for the development of problem-solving methods to analyze epilepsy activities. Real-time devices are a must in today's world which helps individuals with epilepsy monitor the condition to receive timely alerts for better precaution. Signal tracking, monitoring, filtering, modulation, transferring, and error detection, etc. are some of the major things focused on in this study to boost the accuracy of ES prediction and reduce the false positive and negative rates with the help of sensor wearable device MF2Epi-alert (used for this research study). Researchers tried using several techniques to identify the ES with the help of EEG optimized signals, such as i-spectral analysis, WT, and other ML models, which resulted in the detection of anomalous patterns indicative of seizures. It is noted that many computational methods are employed to detect the ES with minimal drawbacks, like early prediction, robust communication, EEG signal optimization, recording abnormal activity, etc.

In order to conquer the limitations of the prevailing approach, the new ML model ROCS-EDS with EPCA is suggested to detect epilepsy events in humans at an early stage with the help of wearable sensor devices and optimize the EEG signals in a robust manner to record normal and abnormal activity.

To optimize EEG signals for robust signal transfer to sensor devices and seizure detection various machine learning techniques were used. The ESP-ML [(4)] approach was proposed, and two diverse problems are addressed by the authors: automatic detection of epilepsy with the help of movement recording and muscle movement sensing, which focus on complete visual inspection of digital EEG signal filtering and analysis. The ML models are used here to point out the expressive states and record the overlying activities of humans. This performance and accuracy are achieved, but the system fails to transfer optimized signals while using wearable devices. A PSM method based on DRSN and GRU was proposed, and the pre-ictal period was calculated with the help of optimized signals. The CHMBLT scalp dataset was used to train and test the data. PSM acts as a multiple seizure prediction method where joint seizures are also detected with the help of the temporal dependence of optimized EEG signals. This PSM model has drawbacks during deployment in sensor devices where it fails to sense the R&L track movements [(5)]. The authors introduced new ESF-based frameworks for seizure prediction where the system tracks and filters the EEG signals and processes them in sensor devices. The HSOT ensembled classifier works on embedded systems to sense normal and abnormal activity in the human brain and pass the signal to the devices through WT. This method works successfully on all frequency bands and all sets of features. The CSFM-B9 dataset is utilized to test and train the HSOT ensemble classifier for efficient prediction [(6–8)]. Bi-LSTMES models were proposed to optimize the MD sample entropy, which helps effectively during clinical diagnosis for both prediction and classification. Detection speed is increased when the system uses advanced ML methods with a 2-LC classifier to identify the nature of epilepsy. The shortcomings of the system are that it doesn't transfer the EEG signals to wearable devices for real-time sensing [(9)]. The sliding window weight method (SWWM) was employed by the author for noise element removal in EEG signals, where an SVM classifier was used to train and extract the features. The system will predict the inter-ictal epilepsy state and classify the signals effectively with the help of an autoencoder framework. However, accuracy, FPR, and FNR were not consistently achieved [(10)]. Clinical records from the BFNT dataset were used by the researchers to identify epilepsy with the help of biomedical concepts, where the system automatically optimizes the signals and encodes them at frequent intervals. During the scanning process, the signals are transferred to the sensor devices to filter and give alarm notifications of epilepsy activity. This system effectively works with a minimum false rate. But the system takes too long to predict the seizure activity in a real-time scenario where the patients have to wait a long time [11,12]. ADM-ELM-based neural network method was proposed by the researchers to classify the EEG brain signal for seizure prediction. The Moth-Flame optimization technique was employed for signal optimization to remove noise and increase the QOS of the extreme ML model. The error rate is minimized in this model, and the accuracy level of prediction is boosted. The University of Bonn epilepsy dataset was used for this study. At the time, the ELM model was so promising in detection, and the only drawback found in this model is speed and time consumption [13]. Supervised ML models were used for effective FS and FE of EEG brain signal optimization, and I-RVSRP genetic bio-inspired techniques were used to optimize the sensors in wireless devices in the search space for efficient data transfer during link failures. The system uses the RWS and CMM methods to split and track the signals in a robust manner. It acts as a personalized seizure detection model during the real-time scenario. A few drawbacks are noted in this model: noisy filtering and tracking of the EEG signals are not monitored at frequent intervals, resulting in slow transformation of signals [14,15]. Theresearchers developed a pre-ictal state recognition model to help drug-resistant epilepsy patients. To increase prediction accuracy, the LR classifier records 710 hours and 49 seizure activities. With the aid of frequency modulation and time-bound motions in the human body, an alternative construction search algorithm was implemented in sensor devices to detect activity in real-time. Data partitioning is done to effectively divide training and test data, which enhances TPR and TNR [16]. A new seizure prediction model was attempted by the researcher based on neuro-imaging modalities for effective rehabilitation tools to improve the patient's lifetime. Significant findings show that the NIM model outperforms all existing rehabilitation techniques and acts as a computer-based ES finding system in a forceful way. Continuous EEG monitoring, recording and tracking, sensing, optimizing, and other commonly used procedures all contribute to the system's efficiency. The implementation of NIM in epilepsy wearable devices for quick sensing is proven to be slow [17]. EEG-based ES detection models and genetic VSPO models were proposed by the authors to effectively optimize the signals. The Andrzejak R. G. dataset is utilized for training and testing purposes, and DWT was used for effective fraction extraction and partition of EEG signals. This method overcomes the existing MPSO and KMODE models. The filtering technique was not applied as the model was not trained for wearable epilepsy devices [1,18]. Communication classification and the RAB-CRP model were used by the authors, while ML and bio-inspired models were employed for signal transformation and data routing in the embedded devices. The purpose of data transfer at a single point is to help the system access all the centroid levels in an effective manner. The sensors sense the signals or movements in a dynamic way, which will make the system work vigorously. Effective FS and FE were done using RAB-CRP [19,20]. The2LSTM approach was attempted to overcome the Bi-LSTM model in sensing the human movements of epilepsy activity via wearable devices. Wrist movements (left and right) are calculated and recorded for training and testing the model. The model works in a dynamic way to detect abnormal activity and reports it as an alarm notification to the user for early prediction of epilepsy activity [2]. The Internet of Medical Things technology is used by the IoMT-based EEG epilepsy prediction model to evaluate EEG data and apply cutting-edge machine learning algorithms for precise seizure prediction. With the use of this approach, epilepsy treatment may be improved while patient outcomes are improved by remote monitoring, early identification, and individualized care [3,21]. TheEMRM based EEG epilepsy prediction model uses cutting edge deep learning techniques to accurately predict seizures by integrating patient's electronic medical records with EEG data. To improve epilepsy management and patient care, this approach makes use of the detailed patient data for tailored monitoring, early identification, and proactive intervention [22]. ED detection and wearable devices optimization is done by authors to boost accuracy but the drawbacks are signal filtering and tracking. AI and ML optimization models found for ESD where the accuracy is up to 91% [23–25]. All the existing approaches have not shown the impressive performance, the new ROCS-EDS model is proposed along with EPCA to boost the prediction and accuracy in an effective way. Few unique methods are followed here is,

- **Signal Transition:** Enhanced data sampling with robust transition of EEG signals to wearable devices is done effectively in ROCS-EDS to capture critical movements of epilepsy activity and mitigate the locations to track the signals.
- **EEG optimization:** EEG optimization is done by the IQAM and CSPK techniques for proactive sensing of signals in wearable devices. The MF2Epi-alert wearable device is tested.
- **Monitoring and Tracking:** Efficient monitoring and tracking of MF2Epi-alert transferrable signals with the help of the ROCS-EDS model
- **Segmentation of EEG signals:** SS is done through filtration and deployment of ROCS-EDS, as shown in further sections, where the system helps the clinical experts with early prediction of epilepsy. The complete process is tested in alert-device for testing purpose.

2 Methodology

The proposed technique mainly pays attention to EEG signal optimization, signal tracking and filtering, frequency rate, and reliability monitoring in wearable devices to predict epilepsy at the initial stage. ROCS-EDS in combination with enhanced PCA works with a unique model for feature selection and extraction in the given dataset. It extracts the linear and non-linear dynamics and temporal structure of EEG signals, which provide accurate information about normal and abnormal brain activity. By optimizing these signals and deploying them in wearable devices, we can make clear predictions about the early occurrence of epilepsy. Immediate Quadrature Amplitude Modulation Computed phase shift keying approaches are used to encode the amplitude and phase information of EEG signals. The signal or communication transfer will happen when abnormal activity is recorded by the device. ILDPC, FFT, WT, and MMSEF methods are employed for tracking, monitoring, filtering, and optimizing the EEG signals at frequent intervals. This approach aims to improve accuracy in ES detection and EEG signal optimization in wearable devices compared to prevailing methods.

2.1 Proposed Methodology

The newly introduced method of ROCS-EDS with EPCA is specifically tailored for EEG signal optimization and robust detection of epilepsy at an early stage. Here, the communication signal that is sensed from human activity is trained and tested using the BCI C-IV dataset. The right and left body movements are calculated and monitored at different levels. After the initial processes like data acquisition, FS, and FE, dimensionality reduction is done to capture the variance of EEG signal data. The reduced signal is used for tracking and monitoring. Then the signal is filtered and transferred to the alarm notification system on the wearable devices. As soon as the signal is triggered, the device will sense it and give an alarm notification in the form of wireless messages, visual alerts, or audio signals. Assume that $n\_components$ is the number of data points you want to load or specify for the parameter object initialization. The eeg_pca defines the reduced-dimensional representation of the original loaded EEG signals from the BCI C-IV dataset. Include a placeholder $classify\_eeg\_sample()$ for real-time signal detection while using wearable devices during human movements. Allocate the value S for signal recording based on movements and transfer the signal to mark as eeg_pca and $O-Value$. Derive the optimal value for signal recording with the following equation,

$$O-Value = \left(\frac{S_{1-n}}{n_{components}}\right]^{*}\left(classify_{egg_{sample}}\right) \mid egg\_pca \tag{1}$$

where, S_{1-n} is the signal recorded at n-intervals and transferred to the wearable devices. The $classify_{egg_{sample}}$ denotes the signal optimization at all levels and keep in ready state when there is an abnormal activity. The abnormal and normal activity in human movements are calculated by using the below equation,

$$Activity\ NR = \left(\frac{Movements\ H}{Trained\ MH}\right]^{\hat{}}\ Total\ movements \frac{recorded}{Frequent} intervals \rightarrow WDS \tag{2}$$

where, $Activity\ NR$ is to identify the normal and abnormal monitoring value passed to wearable devices. The $Movements\ H$ defines human activity movements recorded by the device and transferred to WDS signal for optimization and detection.

2.2 Data collection and pre-processing

This proposed model uses the BCI (Brain-Computer Interface) C-IV dataset from California, using 4922 patients' data as a sample for movement recording to identify the abnormal and normal activity of the brain. Some of the main features are signals, movement record rate, frequency rate, HR rate, etc. The patent number is specified to differentiate between abnormal and normal as 1 and 0. Four target classes are set for recording the signals, such as left, right, foot, and tongue, and two subjects (normal and epilepsy) are monitored. Enhanced PCA with machine learning models is used to preprocess the EEG signals with relevant sets of features. Table 1 shows the detailed BCI C-IV dataset features of 1 to N patients available with sample data.

For more effectiveness, the absolute data distribution is done. ROCS-EDS with EPCA focused on feature selection and extraction to achieve a better accuracy level in EEG signal optimization and epilepsy seizure prediction during the initial stage. The preprocessing steps include,

- Data acquisition from the BCI C-IV dataset at a specific frequency for wearable devices
- Remove nosy signals, artifacts, and baseline drifts.
- Extract the robust features like MRR, HR, and FR. etc
- Reduce the dimensionality of feature space

Table 1. BCI C-IV California Dataset (Samples are given)

S.No	Time	MRR	FR	HR	Left	Right	Opt. Value
1.	-0.1	2.245496	-0.15835	1.163765	3.299057	3.928189	0
2.	-0.096	0.587559	1.65051	0.970672	3.838386	2.514392	0
3.	-0.092	1.499758	0.121302	2.859433	2.162693	1.522294	0
4.	-0.088	-1.80724	1.843603	2.286812	2.078354	-1.98001	1
5.	-0.084	-2.4531	0.221178	0.127278	0.309444	-3.3583	1
6.	-0.08	-2.05138	-0.40249	0.529	0.711166	-1.73587	0
7.	-0.076	-2.15125	-2.94377	-0.49861	-3.63676	-1.83575	1
8.	-0.072	-4.76578	-4.82587	-3.30845	-1.80792	-2.30184	0
9.	-0.068	-2.96358	-6.09984	-3.31289	-0.88463	0.379272	0
10.	-0.064	-1.96482	-5.05226	-5.3903	0.358272	1.670997	0
11.	-0.06	-3.5362	-4.32872	-6.57105	3.425566	1.710948	1
12.	-0.056	-3.07233	-3.91368	-5.27711	4.475371	1.78419	0
13.	-0.052	-2.51747	-1.55217	-4.62459	6.543908	1.801946	1
14.	-0.048	-0.44671	-1.82516	-0.79602	3.536539	1.431296	0
15.	-0.044	0.185837	0.565194	-0.65175	2.411273	0.403686	0
16.	-0.04	0.0904	-0.50681	-0.69836	1.143961	1.040671	1
17.	-0.036	-0.68863	-1.48115	-2.74692	-1.2464	-0.27547	0
18.	-0.032	1.974722	0.107985	-0.91365	-2.09867	0.337102	1

(Out of 4922 samples, 18 are displayed as test data to measure epilepsy)

- Track signals are transferred for filtering
- RT classification is done when signals are transferred to wearable devices
- Record movements at frequent intervals
- Alarm notification signals are triggered for epileptic events

2.3 ROCS-EDS with EPCA method for EEG signal optimization & ES detection

ROCS-EDS with the EPCA machine learning model works with a unique signal EEG optimization feature to boost the accuracy of epilepsy seizure detection at an early stage. The unique technique behind ROCS-ECS with EPCA is that it follows a data augmentation process to increase the diversity and size of the training dataset loaded from BCI C-IV. The EEG signals are fine-tuned using the target value to achieve accuracy. Once the algorithm is trained, optimize the feature matrix to meet the constraints of the MF2Epi-alert wearable device used for the study. Utilize the optimized feature matrix as the input to the classification. Once it is applied, the epilepsy type is identified with the help of tested data to assess its performance. The optimal accuracy value, if found, the steps for EEG optimization using ROCS-EDS with EPCA are as follows:

- ROCS-EDS Input: BCI C-IV Dataset with the sample of features and
- ROCS-EDS output: EEG signal optiization and alarm notification
  - Load the dataset, de-noise and select for training
  - Check the constraints of the MF2Epi-alert wearable device
  - If constraints are suited, begin the process with the help of mapping the extracted features from the loaded dataset for optimization
  - The optimized signals are tracked and filtered before testing in MF2Epi-alert
  - Test the process using MF2Epi-alert and check whether it captures all human movements based on extracted features and attributes
  - Execute the process with the help of trained data to check the sensors and alarm notification

Let us assume $pca.fit\ (eeg\_data)$ is the optimized EEG signals ready for transfer and test in epilepsy wearable device. The $Load\_D$ is signals of wearable devices transferred from $pca.fit\ (eeg\_data)$ and $pca.transform(eeg_{data})$ is the transferred data signals which is optimized already.

$$pca.eeg\ (optimize) = \ pca.fit\ (eeg_{data})\ \frac{pca.fit\ (eeg_{data})}{pca.transform\,(eeg_{data})} \tag{3}$$

where, eeg_{data} is optimized EEG signals and the frequency intervals can be marked as, $F_x = (T_1,\ T_2,\ T_3,\ T_n\ \}$. Here, T refers the time duration of the signals monitored.

1. **ROCS-EDS with EPCA algorithm**

   (a) **Input:** MATLAB settings with BCI C-IV Dataset / 400Hz SR for 4C & 2S
   (b) **Begin**:
   (c) Load the EEG dataset , including the EEG signals and corresponding labels
   (d) Perform pre processing and mark as
   (e) **Apply EPCA**
   (f) **Set** new value
   (g) Optimize the EEG signals using EPCA
   (h) Classify the data to ensure balanced representation of N (Normal) and E (Epileptic)
   (i) Compute the value e
   (j) Evaluate the process of notification
   (k) Apply in MF2Epi-alert
   (l) Update the EEG signals
   (m) ***End***
   (n) **Output:** Sensing of epilepsy
   (o) End

2.4 Data Transfer and Reliability using IQAM & CPSK

IQAM and CPSK are used for signal amplitude and phase shift keying modulation in EEG signal monitoring and optimization. It encodes signals from analogue to digital and shifts the phase to career signals used for epilepsy detection. Mapping the digital data from each frame to the appropriate IQAM and CPSK symbol constellation with the encoded data Transmit the modulation signal over robust communication channels. For more reliability and smooth transmission, deploy FEC (Forward Error Correction Code) in the encoded data. Let's assume that the modulation signals are $(QAM_{eegsignals}\ ,\ PSK_{eegsignals})$ and encoding signals is measured as$(Signal_{encode})$. $Optimize_{fecsignals}$ is the signals captured after FEC.

For effective data transfer and reliability the following are the IQAM and CPSK steps are followed.

- Modulation - It combines both signals phase and amplitude
- Encode the EEG signals using ADC
- IQAM/CPSK modulation to modulate the career signal with encode signals
- Transmit the signals and implement FEC
- Decode and Demodulation if necessary
- Optimize signals and apply in wearable device
- Detect 0 or 1 (Normal or Epilepsy)

The optimized signals $Optimize_{fecsignals}$can be evaluated with the help of below equation,

$$Optimize_{fecsignals} = \ (Signal_{encode})\ |\ (QAM_{eegsignals}\ ,\ PSK_{eegsignals}) \tag{4}$$

where, (It_{1-n}) n-times encoding can be done during the process of modulation.

2.5 LDPC, FF, WT, MMSEF technique for signal tracking, error filtering & monitoring

Improvised LDPC is employed to record the optimized EEG signal rate and length with the help of IPCM (check matrix). The modulated IQAM/CPSK signal is passed through the LDPC encoder to generate the wearable device signal parity bits with the help of encoded data derived in equation 4. In situations where the communication signals of EEG systems or storage channels are subject to errors, such as wireless communication or faulty storage systems, ILDPC codes are used to optimize the situation.

FFT and WT are deployed for EEG signal bifurcation into its time-frequency representation and to position the time-frequency components of signals such as alpha, beta, theta, etc. In equation 5, the improved LPPC performance is presented.

$$LDPC_{EGGSignals} = \ (Trained_{EEGdata}) \mid (Tested_{EEGdata}) * (It_{1-n}) \ * \sum_{i=0}^{n-1} \left(\frac{i}{j}\right) x^{i} \tag{5}$$

where, the term It_{1-n} denotes the number of iterations or parity checks done in the signal optimization scenario. The MMSEF is employed for error filtering and monitoring the EEG optimized signals, The following are the EEG error filtering steps,

- Estimation of EEG_Signals noise power & signal power spectrum
- Compute the EEG filter transfer function
- Apply MMSEF filter to filter signals which helps to transfer to epilepsy wearable device
- Post process to improve accuracy or signal quality
- Record the signals at frequent intervals using$Signal_{recorder}$.

2.6 Comparative Analysis using MATLAB-R2022a

The new identified method, ROCS-EDS for ESP and signal optimization designed for wearable epilepsy devices, is compared with the ML and DL baseline approaches to assess the performance of various metrics by utilizing the MathWorks tool. The software program well illustrates data analysis, image and signal processing, control systems, ML and DL, prototyping, simulation modelling, and other domains. With the aid of MATLAB, the performance is evaluated and validated using this approach. This makes it possible to use the newly developed seizure prediction model in real-time applications or for further in-depth study. For simple access, a complete range of toolboxes is provided. Different subsets of PEM can also be reviewed for greater precision and performance measurement. These tools allow implementing classification algorithms (RF, SVM, ANN, etc.), genetic and bio-inspired algorithms, and evaluating their performance.

2.7 ROCS-EDS - Performance Evaluation Metrics

The PEM for the newly identified technique ROCS-EDS is compared to the existing machine and deep learning methods VPSOGA-SVM[1], 2L-LSTM[2], and IoMT-ESD[3] chosen in the preceding section. The following equation is used to assess ROCS-EDS performance throughout the implementation phase.

$$PAccuracy = \frac{(TPR + TNR)}{(TPR + TNR + FPR + FNR)} \times 100 \tag{6}$$

$$PSensitivity = \frac{TPR}{(TPR + FNR)} \times 100 \tag{7}$$

$$PSpecificity = \frac{TNR}{(TNR + FPR)} \times 100 \tag{8}$$

$$PPrecision = \frac{TPR}{(TPR + FPR)} \times 100 \tag{9}$$

$$\mathrm{Cov.Comp} = \frac{T_1}{\sqrt{T_2 \times T_3 \times T_{4\times} T_5}} \times 100 \tag{10}$$

where, P denotes the performance and the PEM equation is derived using,
$T_1 = (TPR \times TNR - FPR \times FNR), T_2 = (TPR + FPR), T_3 = (TPR + FNR), T_4 = (TNR + FPR)$, and $T_5 = (TNR + FNR)$.

- **Sensitivity and Specificity** - It is used to measure the positive instances correctly identified by the ROCS-EDS. Mathematically, SS can be expressed as (TP + False Negative (FN)).
- **Accuracyand F score** - Accuracy measures the overall correctness of ROCS-EDS in terms of balanced datasets, and Fscore is used to balance the positive and negative instances.
- **True Positive Rate and True Negative Rate** - Used to evaluate the diagnostic test of the ROCS-EDS model. TPR shows the correctly spotted actual positive instances where TNR shows the actual negative instances spotted among all signals.
- **False Positive & False Negative** - Evaluate the misclassifications or errors occur during the communication signal optimization and transformation.
- **Precision and Recall** - P & R estimates the TPR among all positive predictions and estimates the amount of TPR among all true positive instances.

3 Results and Discussion

This chapter shows the evaluation results obtained by the newly proposed ML-based technique ROCS-EDS for robust optimization of communication signals and compares them against the current techniques VPSOGA-SVM [1], 2L-LSTM [2], and IoMT-ESD [3]. The new model performs well and shows remarkable output in early prediction of ES and signal optimization of epilepsy wearable devices. ROCS-EDS overcome the shortcomings of the prevailing methods. The IQAM (Immediate Quadrature Amplitude Modulation) and CPSK (Compute Phase Shift Keying) approaches are used to optimize the data transfer rate and reliability of wearable devices. The graphical representations of the findings are displayed below in Figures 1, 2, 3, 4, 5 and 6 for all PEM plotted graphs with the X axis and the Y axis measures.

3.1 Analysis of Sensitivity and Specificity

The sensitivity and specificity comparative analysis is shown in Figure 1. The novel ROCS-EDS method is compared with existing ML and GA approaches such as VPSOGA-SVM [1], 2L-LSTM [2], and IoMT-ESD [3]. It is noted that the new method shows the actual number of positive predictions through communication signals. Due to signal optimization and reliability checks, the proportion of positive predictions is high. As the new method addresses the class imbalance and handles outliers, signal optimization is done effectively. Data classification and extraction are done effectively. 96% and 97% S&S are achieved when employing ROCS-EDS, which is high compared to other models.

Table 2. Comparative Values of Sensitivity and Specificity

Metrics / Schemes	VPSOGA-SVM [1]	2L-LSTM [2]	IoMT-ESD [3]	ROCS-EDS
Sensitivity	70.01	79.88	82.36	96.09
Specificity	64.37	72.69	80.20	97.68

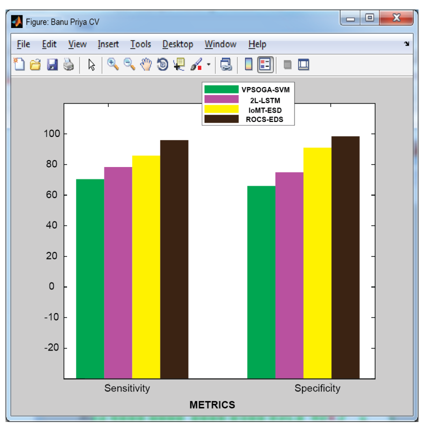

Fig 1. Analysis of Sensitivity and Specificity

3.2 Accuracy Analysis in ESD

Accuracy in the prediction of epilepsy seizures at an early stage is presented in Figure 2. The proposed ML technique ROCS-ESD is compared against the prevailing methods such as VPSOGA-SVM [1], 2L-LSTM [2], and IoMT-ESD [3]. As the labelling and annotations are done for the ES or NES period with the help of clinical experts, the model is trained for robust optimization. Iterative refinement results in a high accuracy rate of ES detection at early occurrence. The accuracy level was met up to 98%, even when different feature sets were explored.

Table 3. Comparative Values of Accuracy

Metrics / Schemes	VPSOGA-SVM [1]	2L-LSTM [2]	IoMT-ESD [3]	ROCS-EDS
Accuracy IT-1	79.87	81.07	83.33	97.19
Accuracy IT-N	80.06	83.25	85.69	98.64

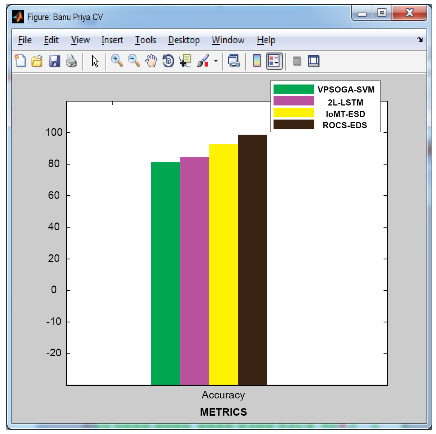

Fig 2. Analysis of Accuracy in ESD & classification

3.3 Analysis of True Positive and True Negative Rate

Figure 3 shows the TPR and TNR of the proposed ML-driven epilepsy seizure detection approach, ROCS-EDS. The suggested technique is compared with the baseline versions of VPSOGA-SVM [1], 2L-LSTM [2], and IoMT-ESD [3] selected for comparative analysis. On the selected BCI C-IV dataset with the target attributes L, R, F, and T, the ROCS-EDS outperforms the existing approaches in accurately sending signals and alarming during epilepsy attacks. Due to frequent monitoring of tasks, it acts as a brain-computer application interface for effective EEG signal monitoring. High TPR and TNR are achieved with percentages of 97.56 and 91.25, whereas other baseline algorithms have not shown standard performance in real-time scenarios.

Table 4. Comparative Values of TP and TN

Metrics / Schemes	VPSOGA-SVM [1]	2L-LSTM [2]	IoMT-ESD [3]	ROCS-EDS
True Positive	59.10	65.25	78.90	97.56
True Negative	50.23	60.10	76.19	91.25

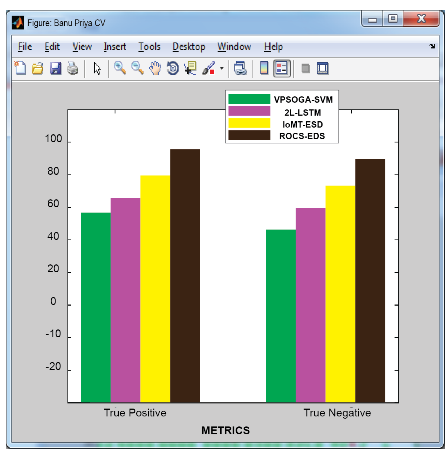

Fig 3. Analysis of TP and TN

3.4 Analysis of False Positive Rate & False Negative Rate

Figure 4 showcases the FPR and FNR of the proposed seizure detection model, ROCS-EDS. Comparative analysis is done to measure the false rate against the existing models, VPSOGA-SVM [1], 2L-LSTM [2], and IoMT-ESD [3]. The new method has proven results with high accuracy, less FPR and FNR, and speedy performance. As the ROCS-EDS monitors signals continuously with a 1.0 frequency rate, the process of identifying the accuracy in positive instances is high. In this case, the FPR and FNR are reduced. The BCI C-IV data is trained and tested with repeated iterations to maximize TPR and minimize FPR up to 5.46%.

Table 5. Comparative Values of FPR & FNR

Metrics / Schemes	VPSOGA-SVM [1]	2L-LSTM [2]	IoMT-ESD [3]	ROCS-EDS
False Positive	38.54	21.26	18.50	5.46
False Negative	38.90	22.59	19.25	7.10

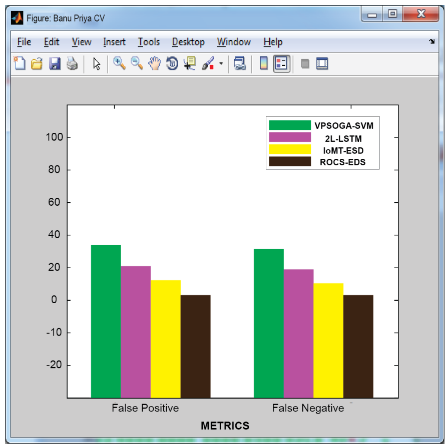

Fig 4. Analysis of FP & FN

3.5 Precision and Recall Analysis

Figure 5 presented the precision and recall analysis of the suggested ML optimization technique ROCS-EDS and evaluated it against the prevailing algorithms VPSOGA-SVM [1], 2L-LSTM [2], and IoMT-ESD [3]. In ROCS-EDS, the process of monitoring and optimizing EEG signals starts as soon as movement is monitored. Based on movement, the results are marked. The signals are captured at a high frequency, which helps to achieve remarkable output in terms of accuracy, calculating actual positive instances, and transferring data in real time.

Table 6. Comparative Values of Precision and Recall

Metrics / Schemes	VPSOGA-SVM [1]	2L-LSTM [2]	IoMT-ESD [3]	ROCS-EDS
Precision	62.89	80.05	85.16	98.65
Recall	60.32	78.56	81.65	96.80

3.6 F-Score Analysis

Figure 6 demonstrates the F-score analysis of the novel ROCS-EDS method to overcome the drawbacks of the current methods VPSOGA-SVM [1], 2L-LSTM [2], and IoMT-ESD [3]. On the selected BCI C-IV dataset and after continuous iterations the model outperforms the prevailing methods. The new model records the movement time and ICTAL-HR changes and transfers the data to the device. It is noteworthy that the suggested approach gives proven output up to 98.22%

Table 7. Comparative Values of F-Score analysis

Metrics / Schemes	VPSOGA-SVM [1]	2L-LSTM [2]	IoMT-ESD [3]	ROCS-EDS
F-Score (It 1)	62.21	79.26	81.05	95
F-Score (It N)	64.47	80.29	84.28	98.22

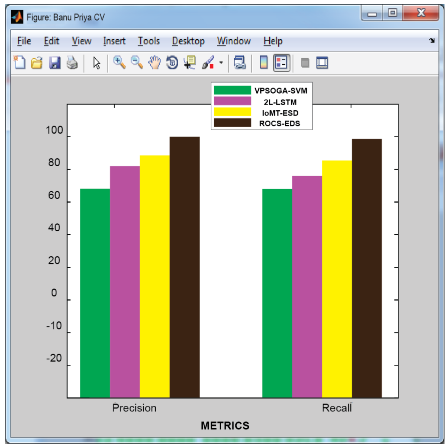

Fig 5. Analysis ofPrecision and Recall

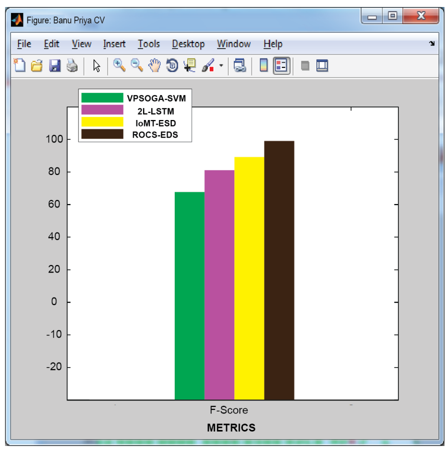

Fig 6. Analysis of F-Score

4 Conclusion

The newly introduced seizure prediction approach ROCS-EDS (Robust Optimization of Communication Signals for Early Detection of Seizures) is used to optimize EEG signal communication in wearable devices. The BCI C-IV (Brain Computer Interface Dataset) dataset is collected, and features such as signals, movement record rate, frequency rate, HR rate, etc. are extracted. 4922 patient's data were taken as samples for this study. The sample rate is 400 Hz for four classes and two subjects. In this model, IQAM and CPSK methods are employed for effective data transfer and high reliability. Improved Low Density Parity Check (ILDPC) is the new technique employed in ROCS-EDS along with FFT (Fast Fourier Transform) and Wavelet Transform (WT) to track the signals in every segment and optimize the signals. EPCA is used for the optimization of EEG signals and to measure the accuracy rate. 98% accuracy is achieved with the capability of early detection of epilepsy seizures with the help of wearable devices. Minimum Mean Squared Error Filtering (MMSEF) is applied to filter the signals and monitor the rate of reliability. ROCS-EDS produced remarkable results in early prediction of ES and signal optimization with 96% and 97% sensitivity and specificity, 98% F-score, 98.65% and 96.80% precision and recall, and 97% and 91% TPR and TNR. Some of the limitations are noted in RPCS-EDS during the course of study, where the EEG signals are optimized only for the availability of wearable devices without faulty sensor nodes. If the devices have faulty sensor nodes, the performance of this model goes down and affects accuracy. This method may be enhanced further to monitor EEG signals in all types of sensor devices, which will help the medical field with the early diagnosis of epilepsy seizures.

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