Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Enhancing Early Seizure Detection Through Ensemble Machine Learning and Deep Learning Techniques

Puja Dhar[1], Dr. Vijay Kumar Garg[2]

[1]*Research Scholar, Lovely Professional University, Punjab, India*
[2]*Associate Professor, Department of Computer Science Engineering, Lovely Professional University, Punjab, India*
Email: phdresearchit@gmail.com

The term improve human seizure detection refers to the creation and application of cutting-edge, reliable, and effective techniques, technologies, or systems that improve the capacity to recognize and diagnose seizures in people with epilepsy or other neurological disorders. Traditional detection algorithms may produce false positives or false negatives as a result of this variability. To overcome these limitations, we propose an integration of ResNet50 and SVM that recognize and diagnoses seizures in people. Initially, we gather EEG dataset from the authentic sources like University and Hospital EEG and applied Min-Max normalization to process data and extract the relevant features from pre-processed data using temporal and spectral. Hybrid Particle swarm optimization (PSO)-Whale optimization is used for feature selection. To assess the given approach performs at the level of accuracy (98.38%), error (27.44%), sensitivity (93.9%), specificity (93.1%), precision (95.9%), false rate (6.86%) and F1 score (96.8%). As a result, addressing problems in human seizure detection through sophisticated machine learning algorithms, reliable data collection techniques and cooperative efforts between medical professionals and technologists holds the promise of developing precise and usable seizure detection systems.

Keywords: Hybrid ResNet50, Support Vector Machine (HResNet50 + SVM), seizure detection, PSO-Whale optimization.

1. Introduction

Monitoring and recognizing aberrant electrical activity in the brain or seizures is necessary for seizure detection in humans [1]. Early recognition is essential for prompt medical management because these episodes can have a variety of modest to severe causes and presentations [2]. To evaluate patterns of brain activity and identify seizures, seizure detection systems use EEG (electroencephalogram) data, wearable technology, or computer algorithms. The standard of living for persons with the condition and other seizure disorders is improved, thanks to this technology [3].

A crucial field for investigation and medical application is seizure detection using electroencephalogram (EEG) technology, which is interested in spotting abnormal electrical brain activity connected with seizures [4]. A powerful tool for documenting the small variations in neuronal activity that take place during seizures is the non-invasive technique known as EEG.

The construction of a hybrid model that combines the strength of RESNET50, “a deep convolutional neural network (CNN), with the sturdiness of Support Vector Machines (SVM)” is a potential strategy for improving the accuracy of human seizure detection [5]. With its superior ability to extract features from EEG data and recognize patterns, RESNET50 can discern minute details in a brainwave impulses hybrid model that makes use of deep learning capabilities but maximizes seizure detection precision by using SVM, a well-known algorithm for classification applications [6]. The goal of this study is to create a reliable, timely and accessible platform that can recognize seizures in individuals with epilepsy or other neurological disorders. This unpredictability may lead to false positives or false negatives in detection systems.

Contributions

- The data sets are gathered from the available open source EEG observations.
- To improve the data's quality and make it more appropriate for the specific data mining activity, Min-Max normalization is utilized.
- Hybrid PSO-Whale optimization is used to eliminate the unnecessary, pointless, or noisy features from the original feature set and choose the subset of the most relevant features.
- The information from the original data set remains unmodified after the raw data has been transformed into accessible numerical characteristics by temporal and spectral processing.
- Hybrid ResNet50 and SVM (HResNet50+SVM) are proposed to recognize and diagnose seizures in people.

The additional study components can be divided into the following groups: The associated works are discussed in Section 2. The procedures are discussed in Section 3. The experiment and outcomes are displayed in Section 4. Discussions are found in Section 5. The final paragraph is found in section 6.

2. Related works

The study [7] created a hybrid model for forecasting epileptic seizures using a “long-short-term memory (LSTM) with a Deep Convolution System (ResNet50)”. The suggested hybrid approach for obtaining and categorizing features was trained using spectrogram images. Research [8] presented an efficient technique for electroencephalogram (EEG) signal classification that was accurate and useful for the early recognition of epileptic episodes. They utilized artificial neural networks (ANNs), gradient-based techniques, genetic algorithmic methods (GAs), extracted features with discrete wavelet transforms (DWT), and fuzzy interactions.

The study [9] examined the effectiveness of 5 ML algorithms, including “Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB), K-Nearest Neighbour (KNN) and Neural Network (NN),” in terms of accuracy in diagnosing a syndrome and the computing cost to integrate it in a wearable device. The study [10] presented a Convolutional neural network (CNN) with extracting features and categorizes various epileptic seizures from EEG recordings. Using EEG signals, many characteristics were evaluated to categorize seizures.

Research [11] presented a hybrid dual neural deep learning network in clinical epilepsy categorization diagnosis processes where usual practice involves the use of surface EEG and audiovisual monitoring. The two main categories of feature extractors were convolution neural network models (CNNs) and neural networks with recurrent connections (RNNs) used in hybrid bilinear models and they were trained using the short-time Fourier transform (STFT) of one-second EEG. The study [12] developed a deep learning technique that combines CNN and LSTM networks to identify the binary and ternary classification for a benchmark database of epileptic EEGs that was accessible. Assessing the model's performance to deep learning models and regular machine learning models, it delivered a state-of-the-art result on the ternary classification challenge.

The study [13] proposed a DL approach to identify the Epileptic Seizure (ES) using EEG signals. LSTM model focused on assessing the effectiveness of various ML algorithms by using seizure-recorded EEG data. Research [14] developed a hybrid network that incorporates a "Long-Term Short-Term Memory (LSTM)" with a "Convolutional Neural Network (CNN)". The study [15] provided that "recurrent neural networks (RNNs) and bi-directional long short-term memories (BiLSTMs)” were employed to execute mechanized EEG signal interpretation for the detection of seizures associated with epilepsy, overcoming the previously mentioned informational challenges. The proposed approach was contrasted with cutting-edge methods and showed to be a more precise classification of such techniques. Study [16] proposed a method based on the fusion of machine learning classifiers with convolution neural networks (CNN). It provided the Butterworth filter to the EEG signal before performing feature extraction with CNN.

The study [17] implemented a hybrid approach based on a Fast Fourier transform (FFT) and a decision tree classifier to detect epileptic seizures in EEG recordings. An essential component of epilepsy diagnosis was the identification of epileptic form discharges in the electroencephalogram (EEG). Information was gathered from the EEG signals of seizure patients and healthy individuals. Research [18] determined the best support vector machine (SVM) parameters for classifying Electroencephalogram (EEG) signals, researchers created a combination of the two (SVM-LOA) to recognize epilepsy convulsions. The suggested approach seeks the best possible intersection of relevant data that identifies epilepsy and increases classification accuracy.

The study [19] was developed with CHB-MIT data for patient-specific seizure detection and exceeded the DL model currently in operation. The first model concentrated on “a one-dimensional CNN”, whereas “the second model concentrated on hybrid CNN-LSTM” architecture. The most common clinical method for detecting seizures was electroencephalography (EEG), in which the electrical activity of the brain was obtained as signals. Study [20] proposed method uses machine learning algorithms to identify the seizure.

The electroencephalogram (EEG) provides neurological information that may be utilized to spot seizures. While evaluating the classifier's accuracy, the goal was to assess the machine learning classifiers K-nearest neighbours (KNN), artificial neural network (ANN), support vector machine (SVM) and principal component analysis (PCA) performed.

3. Methodology

3.1 Dataset

We gather datasets from the EEG dataset consists of EEG recordings that were obtained from the Epileptology Department at the University of Bonn in Germany. For 23.6 seconds, the 100 signal channels of the EEG signals were recorded. Epilepsy duration, seizure type, and epilepsy start are among the data gathered. There are five categories for the data. Healthy patients' eyes were open when Set A was taken, and their eyes were closed when Set B was taken. Five patients suffering from epilepsy comprise sets C, D, and E. Seizures-free interictal signals are present in sets C and D, but only seizure signals are seen in set E. The EEG waves are captured for 23.6 seconds at 173.6 Hz. There are 4096 samples each segment. There are 500 datasets accessible in total.

Name of Dataset	Patient Type	Electrode Placement	Channel	Epoch rate	Total dataset
Bonn Database					
Set A	Healthy Patients	International 10-20 system	Single Channel	23.6s	500
Set B	Epileptic Patients	International 10-20 system	Single Channel		
Set C		Within epileptic zone	Single Channel		
Set D	Healthy Patients	Opposite epileptic zone	Single Channel		
Set E	Epileptic Patients	Within epileptic zone	Single Channel		
UCI Database	Epileptic Patients	International 10-20 systems	Multichannel (16)	10s	200
CHB	Epileptic Patients	International 10-20 systems	Multichannel (23)	10s	22

3.2 Data pre-processing

Effective data preparation is essential for raising the level of quality and dependability of input data, which in turn improves human seizure detection. Noise reduction and data augmentation techniques are used in the pre-processing process to develop the performance of ML models.

3.2.1 Min-Max scaling

As an alternative to the Z-score Method, the method is utilized. This technique converts any range of features or outputs into another range. The features are scaled between 0 and 1 or (-1) and 1. As shown below, the principle of equality used in the approach x_{mn} indicates minimum value, x_m indicates maximum value, x_i input value and x' normalized data,

$$x' = \frac{x_i - x_{mn}}{x_m - x_{mn}} \tag{1}$$

When the min-max strategy is applied, each feature occurs in the altered range while remaining constant. This method keeps relationship attributes in the data.

3.3 Feature selection

The process of choosing the most useful features from a collection of potential input variables is known as feature selection and it is crucial to improving human seizure detection systems. In this instance, feature selection seeks to increase model effectiveness, decrease computational complexity and improve interpretability.

3.3.1 Hybrid PSO-Whale optimization

Hybrid PSO-whale optimization produces the best results compared to other optimization since it has several advantages such as the fastest possible convergence, simple calculation and the most efficiency possible. The most sophisticated calculation for feature selection is this one. By continually trying to improve arrangements against the acquired quality metrics, this iterative technique resolves the problem. Hybrid optimization approaches are applied to optimization tasks. The method uses a minimal amount of additional populations and improves the strategy to generate new speed and depth feature searches to address the issues caused by conventional PSO. It is challenging to retrieve crucial characteristics that show the extent and location of the seizure detection impacted area.

The PSO estimate is based on the group members' social and intellectual habits. Due to the accessibility of sharing simple data and calculations, this technique is popular with consumers. The algorithm utilized in this PSO is scattered around a multi-dimensional space of applicants, where each person converses with one of them. Every arrangement's cost is determined by the issue's ability to be exhibited. There are two important elements that use inter-particle information and iterate to iterative information and affect particle motion.

3.3.2 G Best and P Best

Each particle that makes up a group in the G best model is knowledgeable about its current position and velocity in the resulting distances, at present P as best and so far the entire multitude as G best. Each particle uses the present speed, the P best and G best to point out an overall perfect structure. The G best model's expression is given as,

$$U_{ij}^{k+1} = wv_{ij}^{k} + c_1 r_1 \left(P_{ij}^{k} - y_{ij}^{k}\right) + c_2 r_2 \left(g_{j}^{k} - y_{ij}^{k}\right) \tag{2}$$

$$y_{ij}^{k+1} = y_{ij}^{k} + V_{ij}^{K+1} \tag{3}$$

Where u and y stand for velocity and location, i and j for particle number and direction, r_1 and r_2 for random values in the range[0 1] w and c_1 and c_2 for weight for every value. The P best arrangement, which emphasizes iteration to iteration data among different particles, is stored in the particle memory. The $i-$ th molecule's position and speed in multi-dimensional research space are represented by m-dimensional vectors,

$$z - i = z_{i1}, z_{i2}, \dots, z_{im} \text{ and } W_i = (w, w_{i2}, \dots, w_{im})^T$$
(4)

The ith particle's velocity is given as, c_1 andc_2, r_1 and r_2

$$v_{id} = v_{id} + c_1 r_1 (p_{id} - y_{id}) + c_2 r_2 (p_{gd} - y_{id}) \quad (5)$$

Where dimensions are indicated by d, particle indices and size are marked by I and s, respectively and the mental and relational scaling parameters are specified as c_1 and c_2, r_1 and r_2, respectively. Until the perfect answer to the issue is discovered, the process never ends. The WOA's goal is to take into account the circumstances in the research area that focuses on the advancement problem's objective capability. It is indicated as follows if there are N whales identified as agent i in iteration t:

$$X_i^l = \{X_{i,1}^t, X_{i,2}^t, X_{i,j}^t, \dots, X_{i,d}^t\} \; j = 1,2,3, \dots, N \quad (6)$$

Where d is dimension, $X_{i,j}^t$ is the position of i, j, and t for iteration. It uses hybrid PSO-whale optimizations to do a thorough search and determine the most effective function. The discovered answers are combined to create an alternative leader, if it is more adaptable than the previous one, it is employed to assume its place.

3.4 Feature extraction

Extracting essential details from raw data and making it more receptive to machine learning algorithms, feature extraction plays a critical role in enhancing human seizure detection. In this situation, it entails spotting specific patterns and traits in an EEG (Electroencephalogram) or other pertinent biological data during seizures.

3.4.1 Temporal and spectral

A crucial component in the seizure detection process is feature extraction, which converts electroencephalogram (EEG) initial information into useful information for accurate seizure identification and categorization. In such circumstances, the two main types of features, temporal and spectral features, are used.

Analysing EEG signals in the time domain and concentrating on their morphology over time are known as temporal characteristics. Multiple metrics occur under this classification, including time-domain waveform descriptions, statistical indicators, and intensity features. Amplitude characteristics, such as median intensity, root mean square, and the average deviation of amplitudes, characterize the signal's magnitude at various time points. The distribution and complexity of EEG signals across time can be understood by using statistical properties including distortion, kurtosis and entropy. Seizure-related patterns in the EEG data are clearly captured by time-domain waveform characteristics such as slope, area under the curve and zero-crossing rate.

Spectral characteristics, on the other hand, investigate the frequency elements in EEG data by going into the domain of frequency. They are essential in pinpointing specific spectral traits connected to seizures. Spectral entropy, relative band power, dominating frequency and Power Spectral Density (PSD), are common spectral properties. PSD allows for the detection of anomalous spectral patterns during seizures by displaying how signal power is divided across various frequency bands, including delta, theta, alpha, beta and gamma. In order to differentiate between regular brain activity and seizure occurrences, spectral entropy measures the complexity of the spectral distribution. In contrast, dominant frequency identifies the wavelength with the most power during a certain time period. Compared group power evaluates the amount of energy in particular frequency bands compared to the entire power.

To recognize the intricate structures, classifications utilizing ML and algorithms can be created indicating seizures in EEG data by the combined use of both temporal and spectral information. This multi-dimensional feature representation supports the creation of seizure detection systems that are more reliable and accurate, assisting in the diagnosis and treatment of epilepsy and other seizure disorders.

3.5 Support Vector Machine (SVM)

The main objective of the SVM is to find an instance with the best hyper-plane for separating the data should be identified. The hyperplane is denoted mathematically as:

$$\mathrm{Go}\ (\mathrm{w}) = \mathrm{x}^{\mathrm{s}}\mathrm{w} + \mathrm{au} = 0 \tag{7}$$

Where x is the weight vector, w is the input and au is the bias value.

Hard Boundary optimal results can be applied if perfect separation of training information classes can be accomplished. The hyperplane decision boundary in this instance is selected to optimize the distance between the hyperplane and the closest training data point.

The boundary is still the hyperplane in the case of complex classification, but there is one difference: the hyperplane is in the domain of features rather than the initial input.

$$\mathrm{x}^{\mathrm{s}}\ \phi(\mathrm{w}) + \mathrm{au} = 0 \tag{8}$$

Where the input vector w has undergone a nonlinear transformation $\phi(\mathrm{w})$.

The Lagrange multiplier's ideal weight vector can be computed using the formulas in Eq.

$$\mathrm{X} = \sum_{j=1}^{M} \alpha_j z_j \phi(\mathrm{w}) \tag{9}$$

With α_j being the Lagrange multiplier's coefficient

$$\sum_{j=1}^{M} \alpha_j z_j \phi(\chi_j)\ \mathrm{au} = 0 \tag{10}$$

By providing $u_{i=}\ \alpha_j z_j$ and $l\left(w, w_j\right) = \phi\left(\chi_j\right)$ as a result, the z function of choice is given as follows.

$$z = \sum_{j=1}^{M} V_j l\left(w, w_j\right) + \mathrm{au} \tag{11}$$

The output value z sign is the final word. If the input's sign (z) = -1 label indicates class -1, otherwise class 1. Figure 1 shows the SVM architecture.

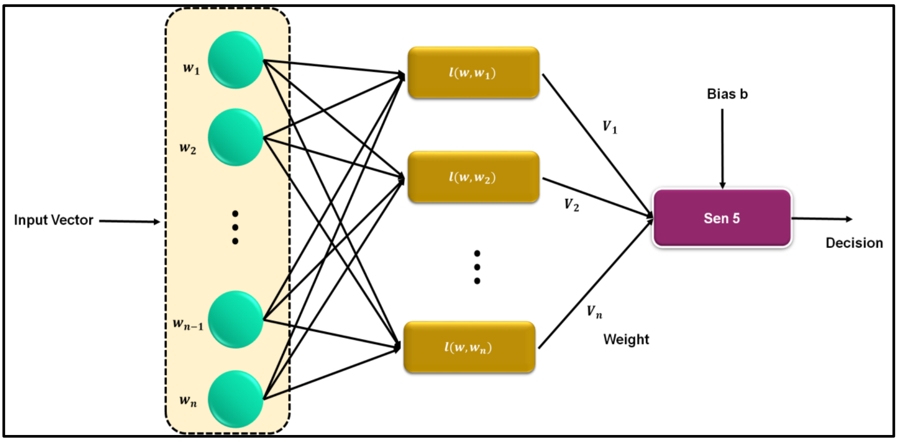

Figure 1: SVM architecture

3.5.1 ResNet50

The Residual Learning technique is used by the ResNets network design for particular in its parts. The specific level of linear participant associated with the computing system from involvement that is produced by operation E (w) is included in this method after it exceeds at least one of the provided layers to prevent the parameters' values from becoming saturated. The concept of remaining learning is founded on the claim that concepts with numerous levels have a basic meaning and that a complex function can communicate the outcome of many regressive layers. $E(w) = G(w) - w$, which can be transformed to $E(w) = G(w) + w$. From there, we are able to speed up learning and avoid vanishing gradients by adding an amount of x to the solution $E(w)$.

To address the issue of vanishing gradients, ResNets employed a shortcut connection that eliminates one or more levels. The structure used in this method is known as a residual block. Two different types of residual blocks, referred to as Identity Block and Convolutional Block, must be created in order to establish a ResNet. A typical Residual Block of ResNets is the Identity Block, which demands that the input size match the output size. Identity Block represented Eq. (12) and used the residual learning approach.

$$z = E\left(w, \{X_j\}\right) + w \tag{12}$$

The Identity Block's initial structure is depicted in Figure 2. ReLU acts as a factor that helps to bring about the model's transition into the exponential state indicated by the overall equation. $z = \max(0, w)$. Following completion, the weighted layer, which is a layer of convolution coupled with batch normalization technique, is applied to normalize the features that have a zero-mean state with an error from the average of 1.

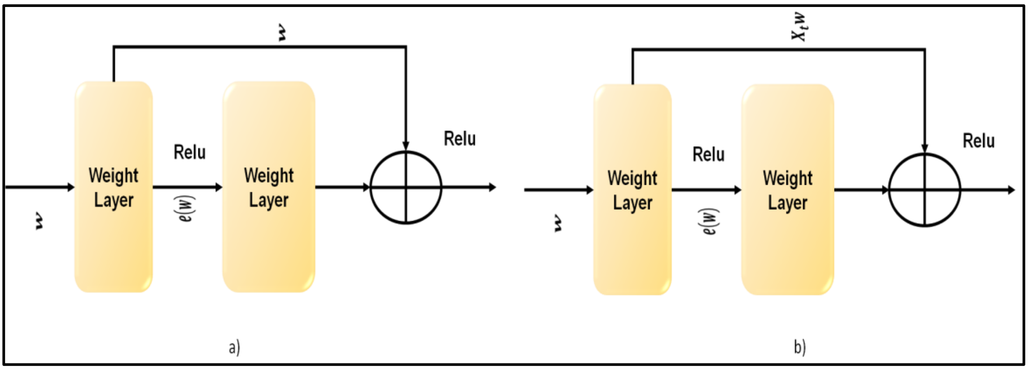

Figure 2: Identification block and convolutional block's basic structures

Comparable to Identity Block, Convolutional Block, another type of Residual Block, employs the method of residual training. However, a Weighted Layer used in the alternative was built and given the name X_t in order to adjust the amount of the input passed. Figure 2 depicts the structure and (3) is a representation of the Convolutional Block's general formula.

$$z = E(w, \{X_j\}) + X_t w \qquad (13)$$

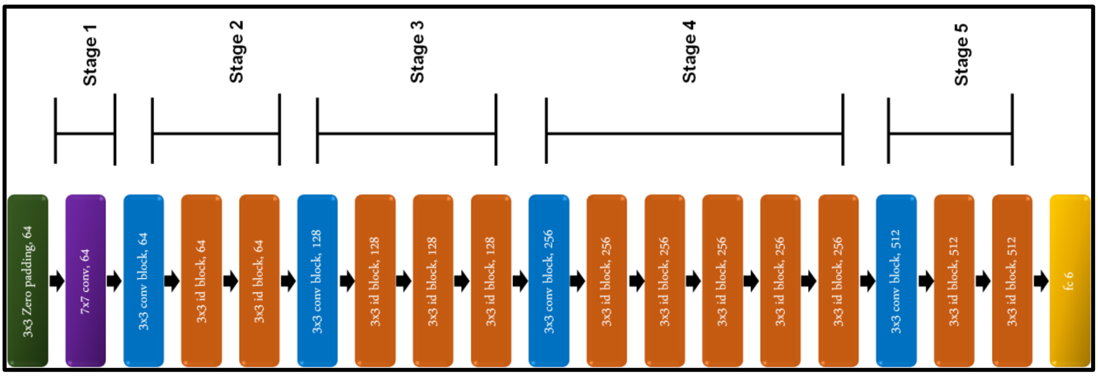

Figure 3: ResNet50 architecture

Figure 3 depicts the ResNet-50 model's structure, which includes a convolutional input layer with a 7x7 grid. Convolutional and modified identical blocks are among the 16 leftover bits and were allocated in stages 2 through 4 at stage 1, with each block having three convolution layers. Stage 2 comprises 2 identity blocks and 1 convolutional block, each with a block size of 64. Stage 3 consists of three identity blocks with a predefined block size of 128 and one convolutional block. Similar to stage 4, this stage has 5 identity blocks and 1 convolutional block, both with 256-bit blocks. Stage 5 has two identity blocks and one convolutional block, both with 512-block requirements. To adjust the dimension of the feature to match the size required in each stage, an additional convolution block is added at the start of each step.

3.5.2 Hybrid ResNet50 and SVM

In a variety of computer vision problems, “a hybrid model that combines a ResNet-50 convolutional neural network (CNN) and a Support Vector Machine (SVM)” classifier can be an effective strategy. ResNet-50, an already trained CNN, performs well at extracting structural features from images, making it appropriate for tasks like segmentation, object recognition, and image classification. Our requests may take use of its capacity to recognize complex representations and patterns in the data by using it as the feature extractor.

The hybrid model can improve performance, durability, and generalization in applications like image classification by fusing ResNet-50's feature extraction skills with SVM's discriminative strength. This method is frequently used to combine the benefits of DL and conventional ML techniques for better outcomes in a variety of applications, such as object detection, image recognition, and medical imaging.

4. Experimental analysis

In this study, the Python 3.11 platform has been used to implement the suggested hybrid ResNet50+SVM. a Windows 10 laptop with an Intel i7 processor and 32 GB of RAM. This part examines the metrics of "accuracy, error, sensitivity, specificity, precision, false rate, and F1-score". The current methods, including RNN[21], CNN[22], and ERT[21].

The possibility of a machine learning or signal processing model to correctly identify seizures and non-seizure events in a dataset is referred to as accuracy in the context of seizure detection. The definition of accuracy in mathematical equation (14) is:

$$\text{Accuracy} = \frac{\text{Number of correctly classified instances}}{\text{Total number of instances}} \times 100$$
(14)

The accuracy comparison between the conventional and recommended approaches is shown in Figure 4. When compared with the existing methods RNN, CNN, and ERT, which have scores of 86.77%, 88.9%, and 90.7% and the suggested approach HResNet50+SVM, which has a score of 93.8%. It proves that the suggested methodology is more precise than the existing methods.

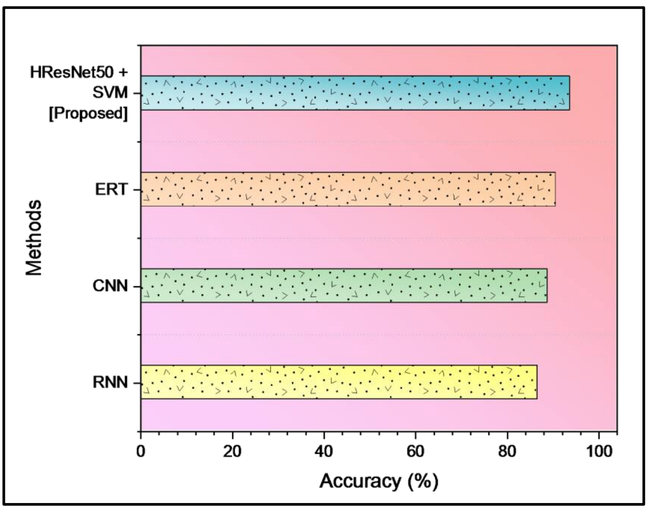

Figure 4: Accuracy

The frequency or percentage of inaccurate predictions produced by a seizure detection system when compared to the actual incidence of seizures is referred to as the error in the context of seizure detection. It is frequently stated as a percentage and can be discovered by solving the equation (15) shown below:

$$\text{Error}=\frac{\text{Number of incorrect predictions}}{\text{Total predictions}} * 100$$

(15)

The error comparison between the conventional and recommended approaches is shown in Figure 5. When compared with the existing methods RNN, CNN, and ERT, which have scores of 30.6%, 28.2%, and 29.4% and the suggested approach HResNet50+SVM, which has a score of 27.44%. This result directly contributes to our suggested method performing much better than the existing methods.

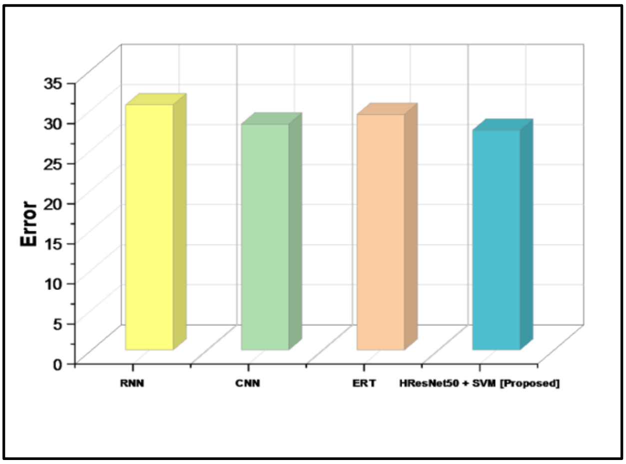

Figure 5: Error

Sensitivity, in the framework of seizure detection, refers to the ability of a diagnostic system or algorithm to accurately identify true positive cases of seizures. Sensitivity is typically expressed as a ratio, calculated using the following equation (16):

$$\text{Sensitivity}=\frac{\text{True positives}}{\text{True positives+false negatives}}$$

(16)

The sensitivity comparison between the conventional and recommended approaches is shown in Figure 6. When compared with the existing methods RNN, CNN, and ERT, which have scores of 82.9%, 84.9%, and 86.8% and the suggested approach HResNet50+SVM, which has a score of 93.9%. It proves that the suggested methodology is more precise than the existing methods.

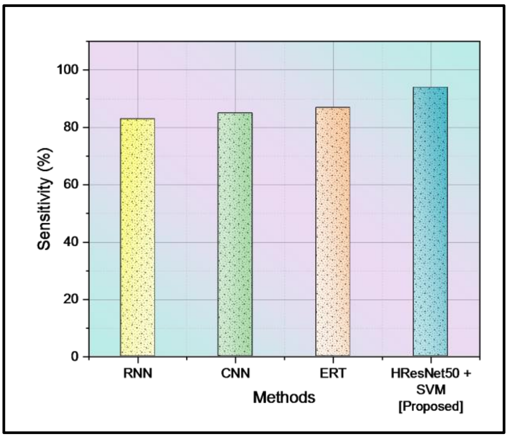

Figure 6: Sensitivity

In the process of seizure detection, specificity refers to a diagnostic test's or algorithm's ability to correctly classify those without seizures as "seizure-free" or "normal. "The following equation (17) is used to calculate specificity.

$$\text{Specificity}=\frac{\text{True negatives}}{\text{True negatives+false positives}}$$
(17)

The specificity comparison between the conventional and recommended approaches is shown in Figure 7. When compared with the existing methods RNN, CNN, and ERT, which have scores of 86.4%, 88.5%, and 91.8% and the suggested approach HResNet50+SVM, which has a score of 93.1%. It proves that the suggested methodology is more superior to the existing methods.

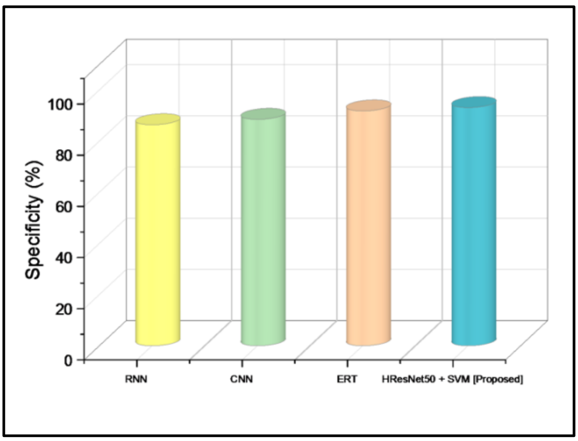

Figure 7: Specificity

The accuracy of the positive predictions provided by a seizure detection system is measured by precision, a critical performance metric in the seizure detection context. It calculates the percentage of positive predictions—both true positives and false positives that are true positives (properly detected seizures). The following equation (18) is used to calculate precision.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$
(18)

The comparison of precision between conventional and recommended procedures is shown in Figure 8. When compared with the existing methods RNN, CNN, and ERT, which have scores of 88.9%, 89.9%, and 92.9% and the suggested approach HResNet50+SVM, which has a score of 95.9%. It proves that the suggested methodology is more precise than the existing methods.

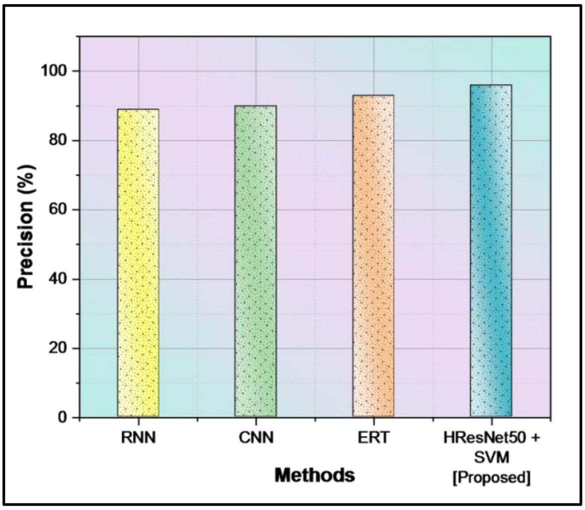

Figure 8: Precision

The frequency or percentage of inaccurate seizure predictions generated by a detection system, identifying non-seizure events for seizures, is known as the false rate in seizure detection. The following equation (19) can be used to calculate it, which is an essential indicator for assessing the system's specificity:

$$\text{False rate} = \frac{\text{Number of false alarms}}{\text{Total Non−Seizure Events}} * 100$$
(19)

In this equation, "Total Non-Seizure Events" is the total number of events that are not seizures, and "Number of False Alarms" indicates occasions where the system incorrectly classifies a non-seizure event as a seizure. The false rate comparison between the conventional and recommended approaches is shown in Figure 9. When compared with the existing methods RNN, CNN, and ERT, which have scores of 7.2%, 7.8%, and 6.97% and the suggested approach HResNet50+SVM, which has a score of 6.86%.This result directly contributes to our suggested method performing much better than the existing methods.

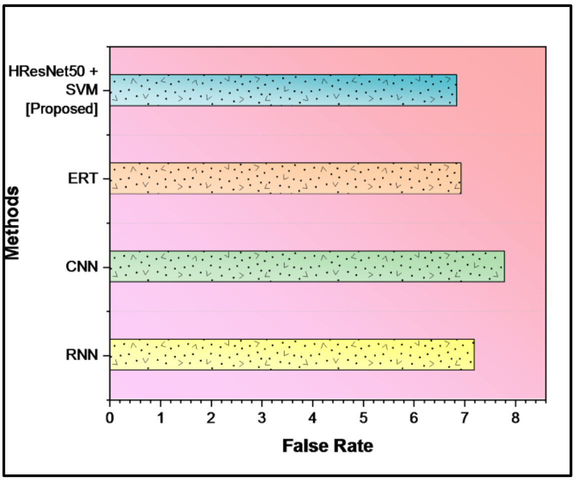

Figure 9: False rate

An important statistic for evaluating the effectiveness of a model is the F1 score. It creates an individual score that provides an accurate evaluation of a model's performance by combining precision and recall, two critical requirements. Equation (20) evaluates how accurately a method calculates its position based on the information available.

$$\text{F1-score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{20}$$

The comparison of the F1-score between conventional and recommended procedures is shown in Figure 10. When compared with the existing methods RNN, CNN, and ERT, which have scores of 85.6%, 88.4%, and 91.7% and the suggested approach HResNet50+SVM, which has a score of 96.8%. It proves that the suggested methodology is more accurate than the existing methods. Table 1 and 2 indicates the performance value of the proposed method.

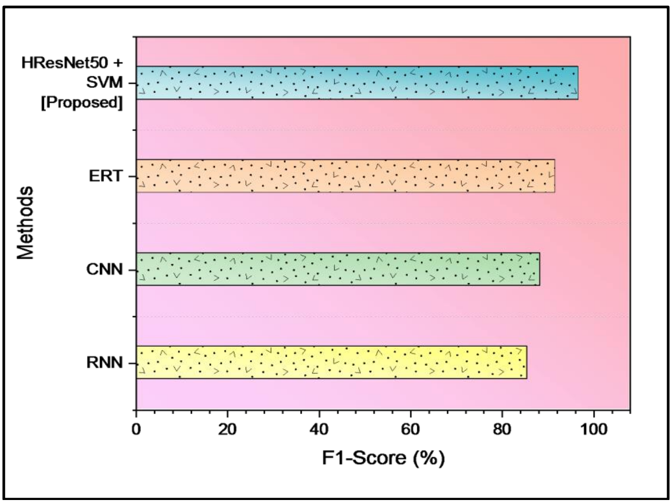

Figure 10: F1-score

Table 1: Performance value of the proposed method

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)	Error	False Rate
RNN [21]	86.7	82.9	86.4	88.9	85.6	30.6	7.2
CNN [22]	88.9	84.9	88.5	89.9	88.4	28.2	7.8
ERT [21]	90.7	86.8	91.8	92.9	91.7	29.4	6.94
HYDRL	98.38	93.9	93.1	95.9	96.8	27.44	6.86

5. Discussion

The existing methods are RNN [21], CNN [22], and ERT [21]. Due to the gradient disappearing problem, RNNs can discover it challenging to identify dependencies that persist in time series data, such as EEG signals. They may have explosive gradients, which may cause numerical instability after training. CNNs are not naturally good at capturing temporal dependencies because they are primarily intended for spatial data. The temporal variation of EEG signals must frequently be analysed in order to detect seizures. Various noise and artifact causes, including electrode motion, changes in tissue characteristics, and ambient influence, might affect how sensitive ERT data is performed. The effectiveness of seizure detection may be impacted by several elements. Multiple amounts of complication and computational power can be handled by hybrid models. For faster convergence, utilize pre-trained weights or modify ResNet50's size and depth.

6. Conclusion

The goal of this study is to create a reliable, timely, and accessible platform that can recognize seizures in individuals with epilepsy. This variability may lead to false positives or false negatives in detection systems. We suggested HResNet50+SVM, which can recognize and diagnose seizures in people, to get over these restrictions. We first acquired a dataset from the EEG observation, processed it using Min-Max normalization, and then performed temporal and spectral analysis to extract the pertinent characteristics from the pre-processed data. For feature selection, hybrid PSO-Whale optimization is employed. When compared to the existing method, the proposed method has an accuracy (93.8%), error (27.44%), sensitivity (93.9%), specificity (93.1%), false rate (6.86%), and F1 score (96.8%).To secure patient permission and data protection, ethical and privacy issues pertaining to constant surveillance and storage of information for seizure detection systems must be addressed. Real-time, non-invasive, and individualized seizure prediction and treatment may be made possible by the combination of wearable EEG equipment with cutting-edge machine-learning methods.

References

1. Khiani, S., Iqbal, M.M., Dhakne, A., Thrinath, B.S., Gayathri, P.G. and Thiagarajan, R., 2022. An effectual IOT coupled EEG analysing model for continuous patient monitoring. measurement: sensors, 24, p.100597.
2. Malik, N.I., Fatima, R., Ullah, I., Atta, M., Awan, A., Nashwan, A.J. and Ahmed, S., 2022.

Perceived stigma, discrimination and psychological problems among patients with epilepsy. Frontiers in psychiatry, 13, p.1000870.
3. Algarni, M., Saeed, F., Al-Hadhrami, T., Ghabban, F. and Al-Sarem, M., 2022. Deep learning-based approach for emotion recognition using electroencephalography (EEG) signals using bi-directional long short-term memory (Bi-LSTM). Sensors, 22(8), p.2976.
4. Rashed-Al-Mahfuz, M., Moni, M.A., Uddin, S., Alyami, S.A., Summers, M.A. and Eapen, V., 2021. A deep convolutional neural network method to detect seizures and characteristic frequencies using epileptic electroencephalogram (EEG) data. IEEE Journal of Translational Engineering in Health and Medicine, 9, pp.1-12.
5. Fawzy, M. and Mostafa, H., 2021, December. High Accuracy Epileptic Seizure Detection System Based on Wearable Devices Using Support Vector Machine Classifier. In 2021 International Conference on Microelectronics (ICM) (pp. 124-127). IEEE.
6. Baghersalimi, S., Amirshahi, A., Forooghifar, F., Teijeiro, T., Aminifar, A. and Atienza, D., 2022. Many-to-one knowledge distillation of real-time epileptic seizure detection for low-power wearable Internet of things systems. arXiv preprint arXiv:2208.00885.
7. Singh, Y.P. and Lobiyal, D.K., 2023. Automatic prediction of epileptic seizure using hybrid deep ResNet-LSTM model. Ai Communications, (Preprint), pp.1-16.
8. Kocadagli, O. and Langari, R., 2017. Classification of EEG signals for epileptic seizures using hybrid artificial neural networks based wavelet transforms and fuzzy relations. Expert Systems with Applications, 88, pp.419-434.
9. Resque, P., Barros, A., Rosário, D. and Cerqueira, E., 2019, June. An investigation of different machine learning approaches for epileptic seizure detection. In 2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC) (pp. 301-306). IEEE.
10. Dhar, P., Garg, V.K. and Rahman, M.A., 2022. Enhanced feature extraction-based CNN approach for epileptic seizure detection from EEG signals. Journal of Healthcare Engineering, 2022.
11. Liu, T., Truong, N.D., Nikpour, A., Zhou, L. and Kavehei, O., 2020. Epileptic seizure classification with symmetric and hybrid bilinear models. IEEE Journal of Biomedical and Health Informatics, 24(10), pp.2844-2851.
12. Wang, X., Zhang, J., Huang, X. and Ma, Z., 2022. Automated detection of Epilepsy EEG based on Hybrid Model of CNN and LSTM. Available at SSRN 4065237.
13. Cherukuvada, S. and Kayalvizhi, R., 2023, August. A Hybrid LSTM-DBN Approach for Automatic Epileptic Seizure Detection Compared with Normal Human Activity using EEG Signals. In 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 970-976). IEEE.
14. Neloy, M.A.I., Biswas, A., Nahar, N., Hossain, M.S. and Andersson, K., 2022, July. Epilepsy Detection from EEG Data Using a Hybrid CNN-LSTM Model. In International Conference on Brain Informatics (pp. 253-263). Cham: Springer International Publishing.
15. Samee, N.A., Mahmoud, N.F., Aldhahri, E.A., Rafiq, A., Muthanna, M.S.A. and Ahmad, I., 2022. RNN and BiLSTM Fusion for Accurate Automatic Epileptic Seizure Diagnosis Using EEG Signals. Life, 12(12), p.1946.
16. Hassan, F., Hussain, S.F. and Qaisar, S.M., 2022. Epileptic Seizure Detection Using a Hybrid 1D CNN-Machine Learning Approach from EEG Data. Journal of Healthcare Engineering, 2022.
17. Polat, K. and Güneş, S., 2007. Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform. Applied Mathematics and Computation, 187(2), pp.1017-1026.
18. Ali, M.A.S. and Abd-Elfattah, M., 2018. A Hybrid Model (SVM-LOA) for Epileptic Seizure Detection in Long-Term EEG Records Using Machine Learning Techniques. International Journal of Intelligent Engineering & Systems, 11(5).

19. Poorani, S. and Balasubramanie, P., 2023. Deep learning-based epileptic seizure detection with EEG data. International Journal of System Assurance Engineering and Management, pp.1-10.
20. Rajendran, P. and Ganapathy, K., 2022. Neural network-based seizure detection system using statistical package analysis. Bulletin of Electrical Engineering and Informatics, 11(5), pp.2547-2554.
21. Shah, S.Y., Larijani, H., Gibson, R.M. and Liarokapis, D., 2022. Random neural network-based epileptic seizure episode detection exploiting electroencephalogram signals. Sensors, 22(7), p.2466.
22. Malekzadeh, A., Zare, A., Yaghoobi, M., Kobravi, H.R. and Alizadehsani, R., 2021. Epileptic seizures detection in EEG signals using fusion handcrafted and deep learning features. Sensors, 21(22), p.7710.