EEG-Based Epileptic Seizure Detection Using Optimized Spatio-Temporal Graph CNN

Palepu Vijaya Santhi
Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation
India
pvijayasanthi3@gmail.com

Sarat K Kotamraju
Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation
India
saratkkotamraju@gmail.com

ChSri Kavya
Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation
India
chinnarisrikavya@gmail.com

Abstract: *Epilepsy is a widespread neurological disorder, and accurate seizure detection remains a critical challenge for improving patient safety and treatment. This study proposes an EEG-based Epileptic Seizure Detection using optimized Spatio-temporal Graph CNN (ESD-EEG-CSGCNN). The approach integrates artifact removal through Sub-Aperture Keystone Transform Matched Filtering (SAKTMF), dynamic frequency feature extraction using a Holistic Dynamic Frequency Transformer (HDFT), and classification with a Complex-valued Spatio-temporal Graph Convolutional Neural Network (CSGCNN). To enhance performance, the network parameters are optimized using the Wader Hunt Optimization Algorithm (WHOA). Experimental evaluation on the Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) EEG dataset demonstrated that the proposed method achieved significant improvements, with up to 21.19%, 23.45% and 22.76% higher accuracy and 26.88%, 25.89%, 32.90% lower computation time compared to existing approaches. These results highlight the efficacy of the proposed approach in delivering efficient seizure detection, contributing a novel optimization-driven GCN solution for clinical decision support.*

Keywords: *Epileptic seizure detection, holistic dynamic frequency transformer, wader hunt optimization algorithm.*

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1. Introduction

Nearly one billion individuals worldwide are impacted by neurological disorders, which include a broad spectrum of ailments that affect the brain, spinal cord, and peripheral nerves [18]. Among these disorders, epilepsy is one of the prevalent, affecting approximate 50 million people worldwide and rank as the fourth most neurological condition [2, 5, 12]. Excessive and aberrant electrical discharges in the brain cause epileptic seizures, which momentarily disrupt regular brain activity [1]. These disturbances manifest as diverse symptoms range from brief lapses in attention and muscle spasms to severe convulsions, unconsciousness and in some cases, sudden unexpected death [16, 20, 26]. Reducing the risk of death and enhancing patients' quality of life depend on the quick and accurate identification of seizures. Continuous seizure monitoring facilitates personalized treatment plans and early intervention [6]. Electroncephalography (EEG) remains the gold-standard diagnostic tool for epilepsy, as it records spontaneous brain electrical activities in a non-invasive manner [3, 10, 19, 30]. Standardized electrode placement ensures reliable signal acquisition, enabling neurologists to evaluate abnormal neural patterns associated with seizures [8]. Nonetheless, manual EEG interpretation is labour-intensive, time-consume, and prone to subjectivity, often requiring long term monitoring by expert neurologists [14, 27].

Seizures can occur unpredictably in daily life situations such as driving or swimming, posing serious safety risks to both the patient and others [7, 15]. Therefore, the development of automated as well as accurate seizure finding systems is essential to anticipate episodes and minimize potential accidents. Recently, advanced computational intelligence and machine learning strategies have been increasingly employed to improve EEG-based seizure prediction, offering more reliable and efficient clinical support [21, 25].

Millions of people suffer from epilepsy worldwide, often leading to sudden and uncontrollable seizures that pose serious risks to patient's safety. For management and intervention to be effective, seizure detection must be done accurately and promptly. Traditional methods rely on manual annotation of EEG signals by neurologists, which has time-consume, expensive and no scalability. Existing method fail to adequately address the non-stationary nature of EEG signals, leads to suboptimal detection presentation.

The motivation is that there is a need of significant advancements in data-driven models for epileptic seizures detection. Existing methodologies are limited in their ability to provide fully accurate and timely seizure detection. A complete solution with integration of modern technology and intricate methodology is needed to overcome such challenges and provide accurate detection of epileptic seizures.

The novelty of this work lies in employing the Holistic Dynamic Frequency Transformer (HDFT) module extracts discriminative features by dynamically capturing both local and global frequency variations, enabling more informative signal representation. The Complex-valued Spatio-temporal Graph Convolutional Neural Network (CSGCNN) serves as the core classifier, where its spatio-temporal graph convolution layers preserve both amplitude and phase information to model complex EEG dependencies. Furthermore, the Wader Hunt Optimization (WHOA) algorithm optimally tunes the weight parameters of CSGCNN, improving learning efficiency and reducing computational time. This unified design provides a robust solution that not only surpasses the limitations of existing standalone methods but also achieves superior accuracy and computational time.

Remaining section of this paper is structured as follows: section 2 exposes literature review; section 3 discusses the proposed methodology; section 4 shows results and discussion; and section 5 presents conclusion.

2. Literature Survey

Various research suggested in the literature depends on deep learning according to epileptic seizure detection, here are some recent works that are mentioned, Zarei *et al*. [31] have presented EEG feature embeddings for improving epileptic seizures. Enhancing seizure detection by transforming raw EEG signals into informative embeddings, which fed into Support Vector Machine (SVM), logistic regression and gradient boosted trees. Their approach demonstrated that embedding EEG data could improve classifier performance while maintaining less computational cost suitable for real-time applications. Nevertheless, the method suffered from low accuracy, limiting its reliability for practical seizure detection. This highlighted the need for models that can better capture complex spatial and temporal relations in EEG signal to improve detection performance.

Jibon *et al*. [9] have presented linear graph convolutional network with DenseNet based hybrid approach basis epileptic seizure detection from EEG signals to exploit temporal correlations and implicit information in EEG signals. They applied the Stockwell transform for preprocessing and extracted time-frequency blocks for classification and feature selection. While the method achieved high precision, its low recall indicated that many true seizure events were missed, which is a critical limitation in clinical applications. This gap emphasized the importance of designing models capable of balancing precision and sensitivity in seizure detection.

Shoka *et al*. [24] have presented an effectual CNN basis epileptic seizures diagnosis utilizing encrypted EEG signals in safe telemedicine applications. It focused on secure telemedicine by employing a CNN-based framework that processed encrypted EEG signals using chaotic baker map and arnold transform algorithms. The encrypted EEG data were converted into 2D spectrogram images and analyzed using transfer learning models such as GoogleNet and ResNet50. Although the framework achieved a high F1-score, its low Receiver Operating Characteristic (ROC) value suggested difficulties in effectively distinguishing seizure from non-seizure events. This indicated that security-focused approaches still need robust classification performance to be clinically viable.

Shoeibi *et al*. [23] have presented deep learning techniques for the identification of epileptic seizures depending on neuroimaging modalities. It highlights convolutional neural network-based Computer-Aided Diagnosis (CAD) systems capable of predicting epileptic seizures, achieving high Cohen's Kappa values that reflect strong agreement between predicted and actual outcomes. Nevertheless, low precision remained an issue, implying a higher occurrence of false positives and reduced reliability in real-world applications. This suggested that even sophisticated neuroimaging-based Deep Learning (DL) methods require enhancements in precision and consistency.

Pidvalnyi *et al*. [17] have presented categorization of epileptic explosions using basic machine learning methods: utilization in animal EEG data. It examined seizure detection in animal models using intracranial EEG, Principal Component Analysis (PCA) based feature selection and SVM classifiers. This approach was lightweight and achieved a high detection rate while reducing data complexity. However, low overall accuracy and limited applicability to human EEG constrained its clinical usefulness. This demonstrated that while lightweight Machine Learning (ML) methods are efficient, their reliability and generalizability remain limited, motivating the exploration of optimized deep learning architectures.

Kunekar *et al*. [13] have presented a technique for using deep learning including machine learning to find epileptic seizures in EEG data. Where, compared various machine learning and Long Short-Term Memory (LSTM) based deep learning in University of California, Irvine (UCI) epileptic seizure recognition dataset for automated seizure identification. The findings showed that LSTM models achieved high detection rates but required substantial computational resources, highlighting the trade-off between performance and hardware requirements. This emphasized the need for models that deliver high accuracy without excessive computational cost.

Kode *et al*. [11] have suggested a technique for applying machine learning along deep learning to identify epileptic seizure in EEG data. EEG-based seizure detection using 1D CNNs and optimized classifiers including TabNet, XGBoost, and Random Forest. Their method achieved a high detection rate and was suitable for early seizure identification, but low Cohen's Kappa values revealed weak agreement between predicted and actual seizure events. It suggested that even with optimization, classifier reliability remained a concern, reinforcing the need for integrated architectures that effectively capture both spatial and temporal EEG features. Table 1 shows comparative assessment of existing epileptic seizure detection methods.

Table 1. Comparative analysis of existing epileptic seizure detection methods.

Author	Objective	Method	Advantages	Limitations
Zarei *et al*. [31]	Improve seizure detection by transforming raw EEG into informative embeddings	SVM, logistic regression, gradient boosted trees	Low computational cost; embeddings enhance classifier performance	Low accuracy; limited ability to capture spatial-temporal EEG dependencies
Jibon *et al*. [9]	Exploit temporal correlations in EEG signals for seizure detection	DenseNet+Linear Graph convolutional network; stockwell transform preprocessing	High precision; hybrid framework leverages spatial-temporal information	Low recall; many seizures undetected; balance between precision and sensitivity needed
Shoka *et al*. [24]	Enable secure seizure detection for telemedicine using encrypted EEG	CNN with chaotic baker map and arnold transform; transfer learning (GoogleNet, ResNet50)	High F1-score; ensures data security	Low ROC; difficulty distinguishing seizure vs non-seizure; robustness issues remain
Shoeibi *et al*. [23]	Review deep learning methods using neuroimaging for seizure detection	CNN-based CAD systems	High Cohen's Kappa; strong agreement between predictions and labels	Low precision; false positives reduce clinical reliability
Pidvalnyi *et al*. [17]	Lightweight ML approach for seizure detection in animal EEG	PCA feature selection+SVM	High detection rate; low data complexity	Low overall accuracy; limited applicability to human EEG
Kunekar *et al*. [13]	Compare ML/DL methods to identify optimal seizure detection approach	ML and LSTM models	LSTM achieves high detection rate; identifies effective model	Computationally expensive; hardware intensive
Kode *et al*. [11]	Optimize seizure detection using tuned ML and DL classifiers	1D CNN, TabNet, XGBoost, random forest	High detection rate; suitable for early detection	Low Cohen's Kappa; weak agreement between predictions and actual events

The reviewed literature demonstrates that while traditional machine learning approaches offer computational efficiency, they often lack sufficient accuracy and fail to capture the complex spatial-temporal patterns of EEG signals. DL and hybrid graph-based models improve detection performance and exploit temporal correlations, but many suffer from high computational costs, low recall, or weak agreement between predictions and actual seizure events. Security-focused approaches ensure data privacy but sometimes compromise classification robustness. Lightweight ML methods are efficient but often limited in reliability and generalizability to human EEG. Overall, existing studies reveal a trade-off between accuracy, reliability, and computational efficiency, highlighting the need for an optimized framework that balances these factors. This motivates the proposed ESD-EEG-CSGCNN, which integrates spatio-temporal feature extraction with optimized weight parameters to deliver accurate, reliable, and efficient seizure detection suitable for clinical application.

2.1. Contribution

The main contributions and originality of this work are outlined below:

- EEG signals are often corrupted by motion artifacts and baseline drifts, which reduce the reliability of seizure detection. By employing Sub-Aperture Keystone Transform Matched Filtering (SAKTMF), the framework ensures accurate artifact removal and baseline correction, producing clean and stable input signals for further analysis.
- HDFT focus on limited aspects of the frequency spectrum, by capturing its both local and global frequency variations dynamically. This enables the model to extract richer and more discriminative patterns from EEG signals, which are critical for identifying seizure activity.
- The CSGCNN serves as the core classifier, where its complex-valued graph convolution layers preserve amplitude and phase information while modeling spatio-temporal dependencies across EEG channels. This allows the framework to better capture intricate brain connectivity patterns associated with seizures.
- To improve training stability and reduce computational time, the WHOA algorithm is used for parameter tuning in CSGCNN. Its bio-inspired strategy balances exploration and exploitation, enabling faster convergence, improved generalization, and reduced risk of overfitting compared to standard optimizers.

Comparative Advantage

The integration of these modules forms a unified framework that strategically addresses limitations in existing approaches. While existing models DenseNet-LGCN [9], CNN-based secure frameworks [24] achieved improvements in precision and sensitivity individually. Also, the existing models suffered from high recall loss, weak agreement scores and excessive computational demand. In contrast, the proposed method achieved 99.4% of accuracy, 98.3% of precision, 98.4% of recall and 0.96 of ROC with a 99 sec of computation time, representing clear superiority over state-of-the-art models.

3. Proposed Methodology

This section describes about the proposed ESD-EEG-CSGCNN technique. The block diagram of the ESD-EEG-CSGCNN approach is shown in Figure 1.

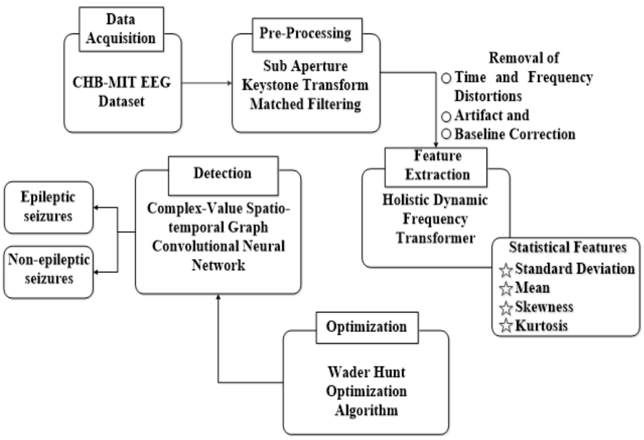

Figure 1. Block diagram of the proposed ESD-EEG-CSGCNN seizure detection framework.

The proposed methodology focuses on improving the epileptic seizures detection under EEG signal. The process begins with data collected from Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) EEG dataset, which is preprocessed to remove artifact and base line correction. This is followed by feature extraction using transform method to find important indicators. Then neural network is used for detection in epileptic seizures. After that, an optimization technique improves neural networks for better epileptic seizure detection.

3.1. Dataset Acquisition

The input data is taken from CHB-MIT EEG dataset [4]. The dataset has 664 files in this collection as well as a list of the 129 files contain one or more seizures. The file contains the age and gender of each subject. These records contain 198 seizures (182 in the original set of 23 cases); the seizure annotation files that accompany each of the files mentioned document the beginning and ending of each seizure. The files also provide information about the montage utilized for each recording and the duration in seconds between the beginning and end of each recorded seizure. Training uses 70% of the dataset, while testing uses the remaining 30%.

3.2. Preprocessing under Sub Aperture Keystone Transform Matched Filtering

The pre-processing is performed using SAKTMF [32]. It offers significant advantages in improving signal detection by compensating for time and frequency distortions, remove artifact and baseline correction. SAKTMF was incorporated because EEG signals are highly non-stationary and prone to artifacts and baseline drifts, which reduce the reliability of downstream analysis. SAKTMF compensates for time–frequency distortions and removes artifacts, ensuring that the data fed into the feature extractor is both clean and clinically meaningful. This preprocessing step is essential to enhance the robustness of the entire framework. The SAKTMF corrects motion-induced changes and Doppler shifts, ensuring better alignment in both time and frequency domains. This process efficiently handles complex, non-stationary signals providing better resolution and signal quality which is crucial for applications such as radar and sonar systems EEG signal analysis in medical fields, communication systems and seismic data processing. By improving signal accuracy, it enhances the detection of relevant events and features making it invaluable in environments where precise and noise-free signals are necessary for accurate interpretation and further analysis.

The coherent integration gain between various sub apertures enhances the SAKTMF method in virtue. A special SAKTM.0F method is created based on the derivation of the phase connection between sub apertures. Thus, the aperture is given in Equation (1).

$$CQ(i_t, i_n) = \sum_{l=1}^{M} RS_l(i_t, i_{n,l}) \tag{1}$$

here, CQ denotes the whole data, (i_t, i_n) indicates the demodulation operation, l denotes the sub aperture index, M represents the sub blocks, and RS_l indicate transition matrix. Equation (2) then displays the information data's Doppler direction.

$$nS_l(g_t, i_n) = DB_{kn}\left[mr_l(f_t, f_n, l)\right] \tag{2}$$

here, $DB_{kn}(.)$ represents the performing operation through f_n, i_n signifies Doppler frequency and n indicate multi scale value. The process of integrating sub apertures incoherently carried out and expressed in Equation (3).

$$L\{\alpha\} = \sum_{l=1}^{L} \left| qR_l\left(\frac{2}{a}u(\alpha, lG_a), i(\alpha, lG_a\right) \right| \tag{3}$$

here, $L\alpha$ represents baseline correction, $u(\alpha, lG_a)$ and $i(\alpha, lG_a)$ represents range along Doppler location equivalent to sub aperture index l. After alignment, matched filtering is performed to further enhance the important information in the EEG signals. In this step, the system compares the processed signals with reference patterns that represent expected brain activity. Signals that match these patterns are emphasized, while unrelated disturbances are suppressed. This improves the clarity of seizure-related features in the frequency using Equation (4).

$$\left(\frac{e_a}{e_t + e_a}\right)^l \approx 1 - l\frac{e_t}{e_a} \tag{4}$$

where, e_t represents the seizure-related frequencies, e_a denotes the reference patterns and t indicates the noise frequencies in brain activity. Finally, the outputs from all the sub-apertures are combined to reconstruct a clean and corrected version of the EEG signal. At this stage, the signals are free from most artifacts, properly aligned and emphasize the relevant brain activity. Thus, the SAKTMF of the data is given by the Equation (5).

$$\hat{z}_1 = -\frac{2}{\chi}[Arg\max\{SAKTMF(l_t, i_n; \hat{z})\}] \quad (5)$$

here, $\hat{z}$ symbolizes the sub-apertures, l_t indicates the relevant brain activity, i_n represents the aligned frequencies and X denotes corrected version of the EEG signal. Finally, SAKTMF filter for removed artifact and baseline correction, these preprocessed data are given into feature selection.

3.3. Feature Extraction using Holistic Dynamic Frequency Transformer

This sector discusses feature extraction with HDFT [22]. Features such as object, pose and optical flow features are extracted using HDFT. HDFT was chosen extracting features, since it uniquely captures both local and global frequency variations. HDFT adapts dynamically to signal fluctuations, thereby preserving subtle discriminative patterns in the EEG that are often linked to seizure activity. This ensures that the subsequent classifier operates on a rich and informative representation of the signal. The HDFT enhances feature extraction by dynamically adjusting to frequency variations, leading to more accurate and comprehensive analysis. Its precision in identifying critical attributes improves epileptic seizure detection capabilities utilizing the HDFT technique; this procedure entails analyzing and transforming the frequency components of the preprocessed data. Then, output attention of data feature is calculated in Equation (6).

$$C = img\max(QI^S / \sqrt{e_h})K \quad (6)$$

here, C indicates the output attention of video, imgmax is denoted as the maximum data value, Q indicates the total number of features, I^S indicates the constant variable, e_h is the constant size, K represents the time variant function. The instantaneous modulation function is calculated as given in Equation (7).

$$Q_e * I_e = e_h(Q) \times k_h(I) \quad (7)$$

where, Q_e denotes the query of matrices dimensionality, I_e is the instantaneous data length, k_h is the frequency domain of dimensionality. An integral part of signal data analysis is featuring extraction, particularly in scenarios where the raw signal is complex or contains a multitude of variables. Then, the element-wise multiplication is calculated as given in Equation (8).

$$X_e = Q_e \otimes I_e \quad (8)$$

where, X_e denotes the dimensionality of the video data value, $\otimes$ is the element-wise multiplication in operator. By using HDFT, the features like standard deviation, Mean, skewness, and kurtosis features were extracted.

- **Mean**: according to Equation (9), the mean of a dataset is the average value that emerges from adding up all of the values and dividing that sum by the entire count of values.

$$Mean = \sum_{i=1}^{r} \frac{q(i)}{r} \quad (9)$$

here, $q(i)$ signifies individual value in database, r denotes random values in database.

- **Standard Deviation**: the standard deviation, which is determined by Equation (10) and quantifies the degree of variant of a set of data from the mean.

$$\sigma = \sqrt{\sum_{a=1}^{t} \sum_{b=1}^{t} \frac{(z(a,b)-k)^2}{ng}} \quad (10)$$

where, σ implies standard deviation measures, $\sum_{a=1}^{n}\sum_{b=1}^{n}$ is the quantity of data in the database $z(a, b)$ is the mean of the database k is the every data point, ng is the variant of data intensities.

- **Skewness**: a measure of asymmetry in data processing can be analyzed to help understand the frequency and distribution of intensities by Equation (11).

$$T_b = \sqrt{\frac{1}{w}\sum_{w}^{a=1}(q_{ba} - w_b)^3} \quad (11)$$

where, T_b denotes the skewness calculation, $\frac{1}{W}\sum_{W}^{a=1}$ is computation of weight value, q_{ba} is observation point.

- **Kurtosis**: it determines the distribution's steadiness related to normal distribution using Equation (12).

$$Kurtosis = \sum_{j=1}^{N}\sum_{i=1}^{M} \frac{(p(j,i)-t)^4}{(NM)\partial^4} \quad (12)$$

where, M denotes features distribution, N refers stability. Once the feature extraction process is finished, the features are used to identify epileptic seizures.

3.4. Epileptic Seizure Detection Based on Complex Value Spatio Temporal Graph Convolutional Neural Network

The epileptic seizure detection utilizing CSGCNN [29] is discussed here. The novelty of adopting CSGCNN lies in its capacity to capture complex spatio-temporal dependences in EEG signals. The complex-valued graph convolution layers preserve both amplitude and phase information, which are critical for accurate seizure characterization. This enables the model to represent dynamic brain connectivity more effectively. This makes CSGCNN more robust and accurate in distinguishing epileptic from non-epileptic signals. By leveraging complex-valued representations, it preserves both phase and amplitude information, leading to improved detection accuracy and robustness. Complex-valued graph convolutions extract frequency-phase dependencies, while temporal modeling layers' capture dynamic patterns before the detection. To obtain cross-scale information acquire robust features is accomplished, then the popular CSGCNN is given in Equation (13).

$$L(V)=\sum_{h=0}^{h-1} L_h V^h \tag{13}$$

where, L denotes information of epileptic seizure, h represents vector of the function, V is biases, and is activation function. The fusion feature map is expressed using numerous scale-specific structures using the concatenation technique. The operation of global average pooling, as expressed in Equation (14), is used to obtain the global feature map.

$$v_t=\sum_{\tau=0}^{t} L_{t-\tau}(V) z_\tau \tag{14}$$

where, v_t denotes data property, τ denotes input data z and the processing time of input data is denoted as t. The proposed CSGCNN approach use convolutional layers that are specifically built to operate on graph data. These layers combine information from surrounding nodes in the graph, taking into account both node attributes are shown in the Equation (15).

$$M(x)=\sum_{t=0}^{h_{t-1}} z_t y^{-t} \tag{15}$$

here, M indicate the data from the end-node, y represents the layer specific trainable matrix. Deeper layers focus on learning spatio-temporal patterns. These layers examine the brain activity evolves over time while still considering the relationships between electrodes. This ensures that the CSGCNN detects both localized seizures at specific nodes and global patterns spreading across the network by Equation (16).

$$L(V\otimes y)=\sum_{t=0}^{h_{t-1}} J_h(y) V^h \tag{16}$$

where, $\otimes$ denotes the prediction analysis and J indicates the frequency for affective computing via gathered data. CSGCNN integrates the across different scales to provide a unified representation. This integration process allows the network to balance fine-grained details, such as short spikes, with broader patterns like rhythmic seizure activity. By fusing features across scales, the CSGCNN l becomes more robust in recognizing seizures of varying intensities and durations in Equation (17).

$$\bar{v}=\sigma[v]=\sigma\left[\sum_{h=0}^{h-1} l_h V^h z\right] \tag{17}$$

here, $\overline{v}$ and v are the loss vectors and σ signifies activation function. The combined features are then passed through pooling layers, which condense the information by keeping only the most relevant signals. This step removes redundancies and reduces the complexity of the feature space, making the network more efficient while ensuring that critical seizure-related information is preserved. Then the features are fed into the output layer, which classifies the signal as epileptic or non-epileptic. By this point, the model has effectively combined graph-based spatial analysis, temporal dynamics and phase-preserving features in Equation (18).

$$E(x)=L(V\otimes x)\ M(y) \tag{18}$$

here E represent epileptic seizure detection. The CSGCNN for detecting epileptic seizures is now complete. In this work, the WHOA is utilized to optimize the parameters of CSGCNN V^h and z_τ by effectively tuning its weights and biases.

3.5. Optimization utilizing Wader Hunt Optimization Algorithm

The weight parameter V^h and z_τ of CSGCNN is optimized using the WHOA [28] is discussed. Weight parameters V^h and z_τ are optimized to improve accuracy and reduce computation time, respectively. The WHOA has the advantages of rapid convergence, robustness in complex model optimization, and efficient worldwide search capabilities. Because it adapts to changing conditions and improves precision and accuracy in parameter adjustment, it is particularly helpful for fine-tuning CSGCNN for epileptic seizure detection. The WHOA algorithm is employed to fine-tune the weight parameters of CSGCNN, ensuring efficient learning and faster convergence. Its bio-inspired strategy combines global exploration and local exploitation, which helps to avoid premature convergence and overfitting. This makes the optimization more adaptive to the highly dynamic nature of EEG signals. Consequently, WHOA enhances both accuracy and computational time of the proposed framework. The searching and following, chasing, encircling, immobile and attacking behavior of scavengers are categorized as their hunting behavior. In this scenario, the advantages of both hunting and migrating behaviors are combined. The WHOA optimizer applies these concepts to its optimization strategy.

- *Step* 1: Initialization.

WHOA population includes wader hunt that modifies its populations in the search space to find better solutions. Each wader hunt belongs to the WHOA population. This is expressed in Equation (19).

$$X=\begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1e} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2e} \\ & \ldots\ldots & & & \\ x_{n1} & x_{n2} & x_{n3} & \cdots & x_{ne} \end{bmatrix} \tag{19}$$

Assume that the wader hunt population is initialized and each position is x_n. Initial status of wader hunt at search position is arbitrarily unwavering in the start of WHOA execution.

- *Step* 2: Random generation.

Random creation is used to create the input parameters. Considering their particular hyperparameter circumstances, the weight V^h and z_τ factor is generated at arbitrary through WHOA technique.

- *Step* 3: Fitness function.

The random solution is created from initialization. This is used to select the features, and is articulated in Equation (20).

$$Fitness\ Function = optimized\ [V^h\ and\ z_\tau] \tag{20}$$

- *Step* 4: Attacking phase for optimizing.

When the group members are searching for prey and moving apart to attack it, the scavengers target them. Consequently, the behavior of global searches is improved by employing this search strategy, as shown in Equation (21).

$$N = \frac{1}{R}\sum_{j=1}^{R} V^h (B_j - \vec{B}_j)^2 \tag{21}$$

The locations of the prey are indicated by j, the other scavengers' positions are indicated by R, the feasibility solution is implied by N, the total sample is N, and the targeted output is $\vec{B}_j$'.

- *Step* 5: Searching prey phase for optimizing.

During the exploitation phase, the solutions selected are usually subjected to local search or improving processes. Local techniques to look for superior solutions nearby by examining a solution are surrounding area. The phrase attacking the prey is expressed in Equation (22).

$$\vec{D}(j+1) = \frac{\vec{F}_q}{z_\tau} \tag{22}$$

where, $\vec{B}(j+1)$ indicates the best solution, $\vec{F}_q$ signifies the updated position and. The updated position, which takes into account the wader's migratory behavior is labelled in Equation (23).

$$\vec{D}(j+1) = \vec{D}(j) + s_p \cdot \tau \left[\vec{\underset{c}{D}}(j) - \vec{\underset{no}{D}}(j) \right] \tag{23}$$

where, $\vec{D}(j+1)$ signifies the relates to the warder's position at $(j+1)^{th}$ iteration, $\vec{D}(j)$ indicates the relates to the wader's position at the j^{th} iteration, δP^d represents the computational time, $\vec{\underset{c}{D}}(j)$ refers to the wader's optimal position throughout the j^{th} iteration $\vec{\underset{no}{D}}(j)$ refers to the wader's n^{th} and o^{th} position at the j^{th} direction at the iteration's first and τ is the gaussian random number population. Figure 2 shows flowchart of WHOA to optimize CSGCNN parameter

- *Step* 6: Termination.

The weight parameter V^h and z_τ CSGCNN is optimized through WHOA; otherwise repeat step 3 until met its halting condition X=X+1. The ESD-EEG-CSGCNN effectively optimizes CSGCNN by increasing accuracy and decreasing computation time for epileptic seizure finding.

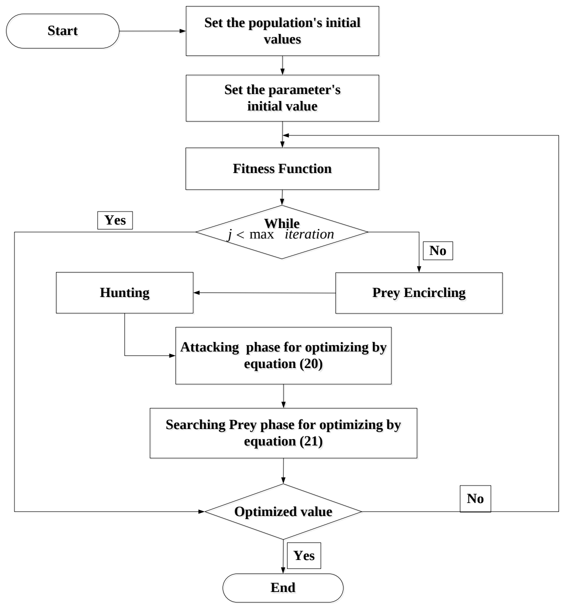

Figure 2. Flowchart of WHOA for optimizing CSGCNN parameter.

4. Result and Discussion

The simulation outcomes of the ESD-EEG-CSGCNN are discussed here. An Intel(R) Core(TM) i7 CPU working in 2.80 GHz was used for the Python implementation. The mentioned metrics are examined. The efficiency of the ESD-EEG-CSGCNN method is compared with existing methods like: Enhancing epileptic seizure diagnosis including EEG Feature Embeddings-SUV (EESD-EEG-SVM) [31], Epileptic seizure detection from EEG signals utilizing linear graph convolutional network with DenseNet dependent hybrid method (ESD-EEG-LGCN) [9], an effectual CNN dependent epileptic seizures detection under encrypted EEG signals for safe telemedicine applications (ESD-EEG-ReN) [24].

4.1. Performance Metrics

It is an important step in choosing the best epileptic seizure detection employing EEG Signals. The mentioned metrics are examined to scale the efficiency of the proposed method. The following confusion matrix is required for this.

- True Positive (TP): Epileptic seizure is accurately detected as epileptic seizures.
- True Negative (TN): Epileptic seizure is accurately detected as non-epileptic seizures.
- False Positive (FP): Epileptic seizure is wrongly detected as non-epileptic seizures.
- False Negative (FN): Epileptic seizure is wrongly detected as epileptic seizures.

4.1.1. Accuracy

It calculates the system provides accurate epileptic seizure finding. It is computed by dividing the rate of true positive samples by total samples through Equation (24).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

4.1.2. Precision

It computes the system's capacity to recognize positive cases accurately out of all detected positive cases, which is determined by Equation (25).

$$Precision = \frac{TP}{TP + FP} \tag{25}$$

4.1.3. Recall

It scales the method's capacity to find all pertinent samples within the dataset. It is calculated in Equation (26).

$$Recall = \frac{TP}{TP + FN} \tag{26}$$

4.1.4. F1-Score

It combines sensitivity and precision into a single metric. It is determined by Equation (27).

$$F1 - score = \frac{TP}{TP + FN} \tag{27}$$

4.1.5. ROC

It assesses the model differentiate normal or suffered with epileptic seizure using Equation (28).

$$\mathrm{ROC} = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + TP} \right) \tag{28}$$

4.1.6. Detection Rate

The rate of true positive cases that are detected out of all actual positive instances in a given dataset. It is computed by Equation (29).

$$detection\ rate = \frac{TP}{TP + FN} \times 100 \tag{29}$$

4.1.7. Matthew Correlation Coefficient

Matthew correlation coefficient is correlation coefficient among binary classifications that were detected. This is determined by Equation (30).

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}} \tag{30}$$

4.1.8. Cohen's Kappa

It evaluates the degree of agreement between two rates on a categorical variable using Equation (31).

$$Cohen's\ \ Kappa = \frac{P_0 - P_e}{1 - P_e} \tag{31}$$

where, P_0 indicates relative observed agreement and P_e indicate expected agreement.

4.2. Performance Analysis

Figures 3 to 14 illustrate the performance outcomes of the ESD-EEG-CSGCNN method. The results are compared with existing EESD-EEG-SVM, ESD-EEG-Linear Graph Convolutional Network (LGCN) and ESD-EEG-ReN models.

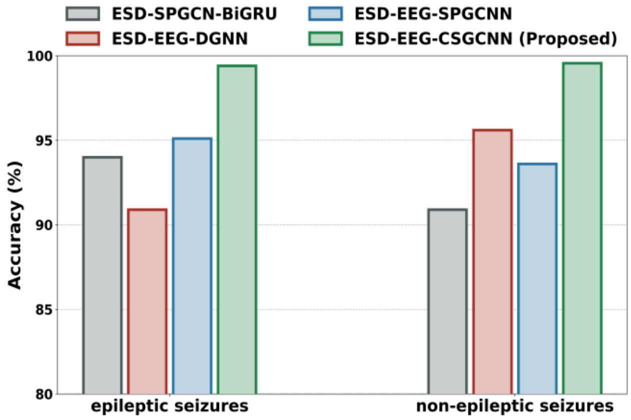

Figure 3. Accuracy comparison between proposed model and other seizure detection methods.

Figure 3 shows accuracy analysis. The proposed ESD-EEG-CSGCNN demonstrates high accuracy in epileptic seizure detection. This high accuracy is achieved through advanced CSGCNN, which enhance the method's capability to distinguish the epileptic seizure. The ESD-EEG-CSGCNN method attains 21.19%, 23.45% and 22.76% higher accuracy for epileptic seizures; 23.19%, 22.42% and 21.19% higher accuracy for non-epileptic seizures when compared with existing EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN models.

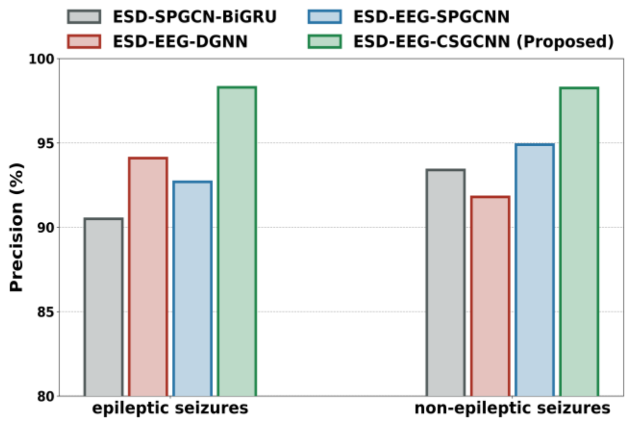

Figure 4. Precision analysis of proposed ESD-EEG-CSGCNN versus baseline techniques.

Figure 4 displays precision analysis. The high precision in the ESD-EEG-CSGCNN is attributed to its effective handling the epileptic seizure detection. The model refines it's detected across various regions and time periods. CSGCNN has the ability to minimize detection errors under different conditions, resulting in more accurate epileptic detection. The ESD-EEG-CSGCNN method attains 26.32%, 27.82% and24.50% higher precision for epileptic seizures;24.32%, 22.78% and 25.67%higher precision for non-epileptic seizures when compared with existing method like EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN correspondingly.

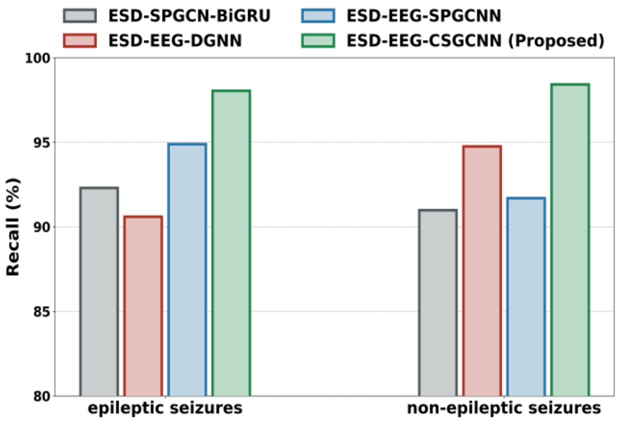

Figure 5. Recall performance comparison of proposed approach with existing frameworks.

Figure 5 shows recall analysis. Recall is high in the proposed ESD-EEG-CSGCNN method because it effectively detects the epileptic seizures, ensuring that most actual problems are detected. The HDFT extract the features ensuring the model focuses on the most significant indicators of seizure. Furthermore, the WHOA fine tunes the model parameters, enhancing to detect seizure in higher recall. The ESD-EEG-CSGCNN method attains 27.75%, 25.62%, 24.56% higher recall for epileptic seizures; 23.45%,22.76% and 30.56% high recall for non-epileptic seizures when compared with existing method such as EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN correspondingly.

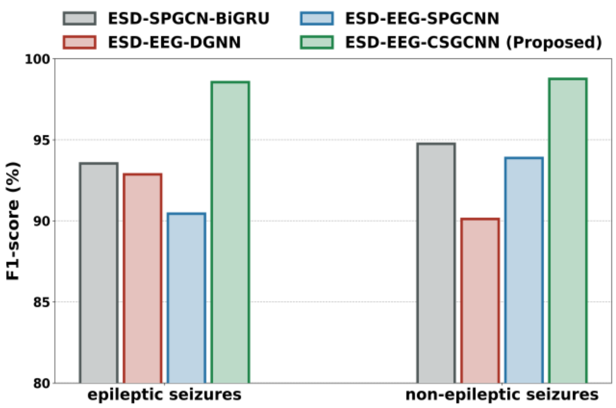

Figure 6. F1-score evaluation comparing proposed method against other baseline models.

Figure 6 shows F1-score analysis. The proposed ESD-EEG-CSGCNN achieves a high F1-score due to its balanced precision and recall. Comprehensive feature extraction and optimized learning algorithms further enhance accurate epileptic seizure detection, boosting overall performance. The ESD-EEG-CSGCNN achieves 24.34%, 25.46%, 26.32% better f1-score for epileptic seizure; 22.47%, 23.79%, 25.88% better f1-score for non-epileptic seizures over the existing EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN models respectively.

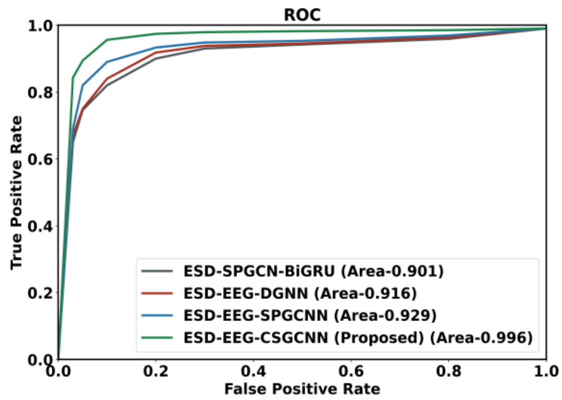

Figure 7. ROC analysis showing discriminative ability of proposed seizure detection.

Figure 7 shows ROC analysis. The ROC curve for the proposed ESD-EEG-CSGCNN is high due to advanced features of the model demonstrating its superior performance in distinguishing the epileptic seizure. The CSGCNN enhance accuracy by effectively prioritizing important information, precise detection outcomes. The ESD-EEG-CSGCNN method attains 0.90%, 0.92% and 0.94% higher ROC values when compared with existing method like EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN correspondingly.

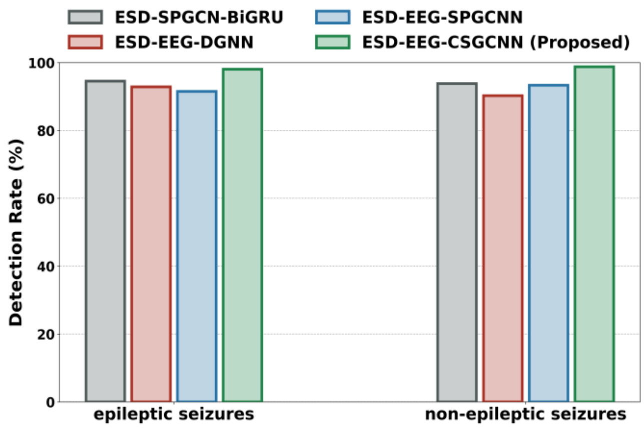

Figure 8. Detection rate comparison across proposed model and existing techniques.

Figure 8 shows detection rate analysis. The proposed ESD-EEG-CSGCNN demonstrates high detection rate in predict the epileptic seizure. This high detection rate is achieved through advanced CSGCNN, which enhance the model's capability to differentiate types of epileptic seizure. The ESD-EEG-CSGCNN method attains 24.36%, 25.39%, 26.46% higher detection rate for epileptic seizure; 25.11%, 23.96%, 24.23% higher detection rate for non-epileptic seizure when compared with existing method like EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN respectively.

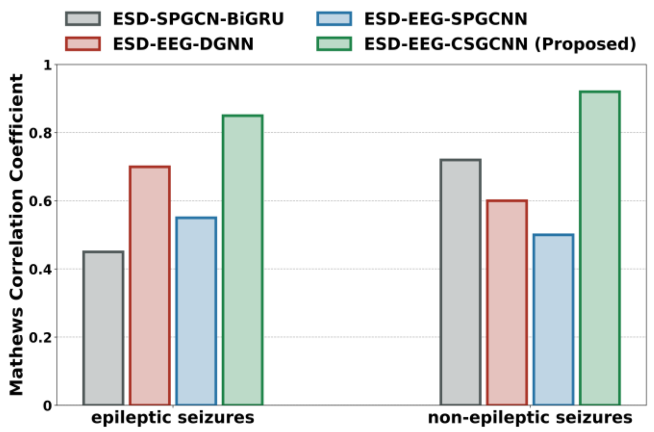

Figure 9. Matthew correlation coefficient analysis for proposed versus baseline methods.

Figure 9 shows the performance analysis of Matthew Correlation Coefficient. The high correlation coefficient is achieved through advanced CSGCNN, which enhance the model's ability to detect the epileptic seizure. WHOA method is most closely aligned with actual detection levels, highlighting its potential for more accurate detection in epileptic seizure. The Y-axis represents the correlation coefficient, with values closer to 1 indicating a stronger match between detected and actual epileptic seizure levels. The ESD-EEG-CSGCNN method attains 26.20%, 24.49%, 25.62% high Matthew correlation coefficient for epileptic seizures; 20.45%, 26.65% and 29.76% high Matthew correlation coefficient for non-epileptic seizures when compared with existing method like EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN respectively.

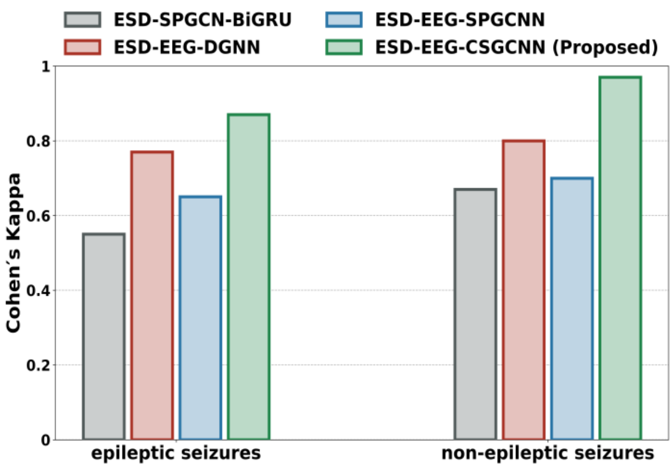

Figure 10. Cohen's kappa comparison showing agreement levels amongst models.

Figure 10 depicts Cohen's kappa analysis. The ESD-EEG-CSGCNN achieves higher Cohen's kappa in epileptic seizure detection. The WHOA further refine the network's parameters, enhancing the accuracy of feature extraction and detection. The ESD-EEG-CSGCNN method attains 23.31%, 24.68%, 25.39% higher Cohen's kappa for epileptic seizures; 22.68%, 23.34%, 26.76% higher Cohen's kappa for non-epileptic seizures when compared with existing method like EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN respectively.

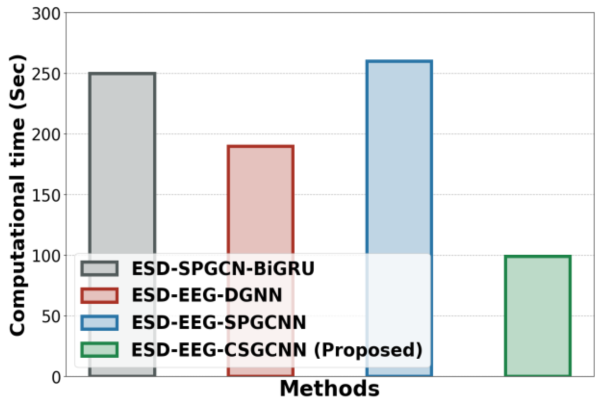

Figure 11. Computational time comparison of proposed approach with existing methods.

Figure 11 shows computational time analysis. The effective feature extraction procedure via HDFT and the enhanced detection capabilities of the CSGCNN are responsible for the indicated ESD-EEG-CSGCNN method's shorter computation time. The model guarantees quicker processing without sacrificing accuracy by emphasizing flow-based features and reducing pointless computation, which reduces computation time overall. The proposed ESD-EEG-CSGCNN method attains 26.88%, 25.89%, 32.90% lower computational time compared with existing method like EESD-EEG-SVM, ESD-EEG-LGCN and ESD-EEG-ReN respectively.

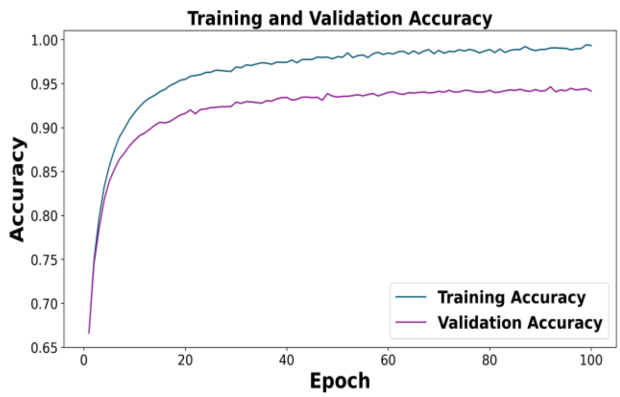

Figure 12. Training and validation accuracy of proposed method across epochs.

Figure 12 shows analysis of the ESD-EEG-CSGCNN method across different epochs reveals that the system consistently improves performance as the number of Epochs increases. The ESD-EEG-CSGCNN technique attains value of training accuracy, 0.91% with number of epochs 20; 0.97% with number of epochs 60; 0.99% with number of epochs 100 respectively. The ESD-EEG-CSGCNN technique attains value of validation accuracy, 0.87% with number of epochs 20; 0.91% with number of epochs 60; 0.99% with number of epochs 100 respectively.

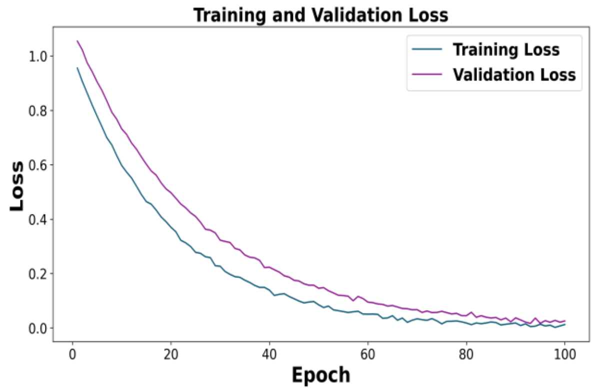

Figure 13. Training and validation loss performance analysis over multiple epochs.

Figure 13 shows Analysis of the ESD-EEG-CSGCNN method across different epoch's reveals that the system consistently improves performance as the number of Epochs decrease. The ESD-EEG-CSGCNN technique attains value of training loss, 0.3% with number of epochs 20; 0.1% with number of epochs 60; 0.0% with number of epochs 100 respectively. ESD-EEG-CSGCNN technique attains value of validation loss, 0.5% with number of epochs 20; 0.3% with number of epochs 60; 0.1% with number of epochs 100 respectively.

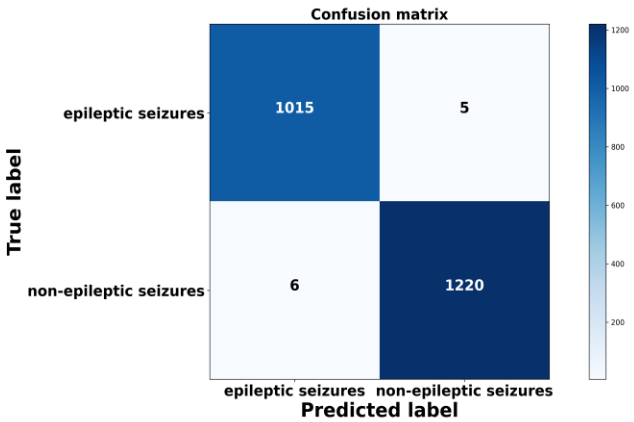

Figure 14. Confusion matrix illustrating classification results of proposed model.

Figure 14 shows confusion matrix. It categorizes epileptic seizure into four types: epileptic seizures and non-epileptic seizures. True negatives show accurate detection of negative labels in this matrix, whereas True positives show correctly detected samples. False negatives are samples that are mistakenly labelled as negative, whereas false positives are samples that are misclassified and mistakenly recognized as positive. Table 2 displays the benchmark table for literature review.

Table 2 displays the Benchmark analysis for literature review, which investigates the use of a CSGCNN based approach for big data analytics, specifically validating the data security and protection in cloud environment. The ESD-EEG-CSGCNN demonstrates superior performance in accurately detect the epileptic seizure as epileptic seizures and non-epileptic seizures compared to existing techniques. The ESD-EEG-CSGCNN achieves accuracy of 99.4% and precision reaching 98.34%, underscoring its efficacy in accurately detecting the seizure. The model has a low calculation time of 99s, indicating that it can process data efficiently without sacrificing speed.

Table 2. Benchmark comparison with state-of-the-art seizure detection models.

Methods	Accuracy (%)	Precision (%)	Recall (%)	ROC (%)	Computational time (s)
Zarei *et al.* [31]	85.13	85.77	92.31	0.901	250
Jibon *et al.* [9]	76.27	86.23	90.64	0.916	169
Shoka *et al.* [24]	79.19	75.41	94.89	0.929	200
Shoeibi *et al.* [23]	85.43	78.95	90.98	0.942	390
Pidvalnyi *et al.* [17]	80.76	79.54	94.75	0.938	187
Kunekar *et al.* [13]	82.22	80.87	91.48	0.912	179
Kode *et al.* [11]	86.78	70.09	93.89	0.921	157
ESD-EEG-CSGCNN (proposed)	99.42	98.34	98.42	0.996	99

4.3. Ablation Study

To ascertain the significance of each component, the ablation analysis of the proposed ESD-EEG-CSGCNN is performed both with and without each individual component.

Table 3. Ablation study of the proposed ESD-EEG-CSGCNN framework.

Ablation model	Metrics				
	Accuracy (%)	Precision (%)	Recall (%)	ROC (%)	Computational time (s)
Without SAKTMF	92.19	93.23	92.26	0.957	259.68
Without HDFT	95.43	95.41	94.93	0.975	192.7
Without WHOA	98.32	96.87	95.76	0.989	136.1
ESD-EEG-CSGCNN (proposed)	99.42	98.34	98.42	0.996	99

Table 3 displays the ablation study for the proposed ESD-EEG-CSGCNN model, demonstrating the impact of removing key components like SAKTMF, HDFT and WHOA on performance. The full ESD-EEG-CSGCNN model achieves the highest metrics, with an accuracy of 99.4%, precision of 98.34%, and recall of 98.42%, highlighting the effectiveness of each component. Without WHOA, accuracy and validation rate drop to 98.32 and 92.19%, respectively.

4.4. Discussion

The proposed ESD-EEG-CSGCNN method demonstrates significant improvements in epileptic seizure detection by leveraging optimized deep learning techniques. The integration of SAKTMF in the preprocessing stage effectively removes artifacts and ensures baseline correction, enhancing the quality of

EEG signals. The HDFT successfully extracts grayscale features, preserving essential spatio-temporal patterns crucial for seizure classification. The use of the CSGCNN enables the method to capture intricate dependencies in EEG signals, leading to improved classification of epileptic and non-epileptic seizures. The incorporation of the WHOA fine-tunes the weight parameters of CSGCNN, ensuring robust and precise seizure detection. Experimental results show that the ESD-EEG-CSGCNN achieves better performance in outperforming existing techniques. The significant improvements in classification metrics highlight the efficiency of the proposed framework in dealing the complex as well as dynamic nature of EEG signals, making it a promising approach for real-time epileptic seizure prediction. These findings suggest that the ESD-EEG-CSGCNN method can contribute to early seizure detection, potentially aiding in timely clinical interventions for epilepsy patients who do not respond to conventional treatments.

5. Conclusions

The proposed ESD-EEG-CSGCNN framework significantly advanced epileptic seizure detection by achieving 99.4% of accuracy, 98.3% of precision and 0.96 ROC, while reducing computation time to 99 seconds, outperforming existing methods such as EESD-EEG-SVM, ESD-EEG-LGCN, and ESD-EEG-ReN. These results highlight the value of integrating SAKTMF for robust preprocessing, HDFT for comprehensive frequency-based feature extraction, CSGCNN for modeling spatio-temporal dependencies and WHOA for efficient optimization. Unlike prior approaches that struggled with high false positives, low recall and excessive computational cost, the proposed model delivers both high reliability and efficiency. Nevertheless, reliance on the CHB-MIT dataset and the current lack of interpretability tools remain limitations. Future research will extend validation to diverse patient datasets and incorporate explainable AI to ensure transparency and practical deployment in clinical environments.

Author Contribution

Mrs. VijayaSanthi P-(Corresponding Author)-Conceptualization Methodology, Original draft preparation. Dr. Sarat K Kotamraju -Supervision
Mrs. K.Ch. Sri Kavya-Supervision.

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Palepu Vijaya Santhi is currently doing PhD in the Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India. Her research interests include Machine Learning and Deep Learning Applications in Seizure Detection and Prediction.

Sarat K Kotamraju is a Professor of Electronics and Communication Engineering, Director (Research and Development), ECE, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India. His areas of interest include RF and Microwave Engineering, Satellite Signal Propagations, Designing of Antennas, Artificial Intelligence and Agricultural Applications, Block Chain Technologies, Atmospheric Radars, and Applications, Development of Mobile APPs. Foreign VIsits-18, Sponsored Projects worth 4.59 Crores from DST, AICTE, UGC, SERB, ISRO etc.

ChSri Kavya is a Professor of Electronics and Communication Engineering, Director (Alumni), ECE, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India. Her areas of interest include RF and Microwave Engineering, Satellite Signal Propagations, Designing of Antennas, Artificial Intelligence and Agricultural Applications, Block Chain Technologies, Atmospheric Radars.