

EEG-Based Seizure Detection with Blockchain Security and Transformer Graph Capsule Networks

C. Aravindan*

Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Tamil Nadu, India

E-mail: caravindece@gmail.com

ORCID iD: <https://orcid.org/0000-0001-9672-8677>

*Corresponding author

Rama Chaithanya Tanguturi

Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamil Nadu, India

E-mail: ramachait1@srmist.edu.in

ORCID iD: <https://orcid.org/0000-0002-9923-7360>

M. J. D. Ebinezer

Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India

E-mail: ebinezer.mjd@gmail.com

ORCID iD: <https://orcid.org/0009-0005-1147-2040>

N. Satheesh Kumar

Department of Electronics and Communication Engineering, PBR Visvodaya Institute of Technology and Science, Kavali, Andhra Pradesh, Pin 524201, India

E-mail: nandhikripa@gmail.com

ORCID iD: <https://orcid.org/0009-0003-8005-6871>

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Abstract: An electroencephalogram (EEG) is a critical diagnostic tool that monitors brain activity and detects epileptic seizures. The EEG signals, however, are complex and unwieldy, making it challenging to create an automated seizure-detection system. Additionally, sensitive healthcare data in clinical systems should be handled securely. This paper describes an EEG-based seizure detection using blockchain security and transformer graph capsule networks (PT-GG-CapsNet-AHA-Blockchain). This model integrates a superior signal processing system, machine learning, and blockchain to attain powerful seizure tracking and data protection. The structure takes EEG data of the CHB-MIT dataset, which consists of multichannel records of seizures in children. Preprocessing was performed using the Adjoint Bilateral Filter (ABF), which removes noise while preserving critical signal features. Using the Clifford Fourier Mellin Transform (CFMT), spatio-temporal features are extracted and thus capture the complex dynamics in EEG signals. Classification is performed by a Pure Transformer-Based Gated Graph Attention Capsule Network (PT-GG-CapsNet), leveraging transformers' temporal analysis capabilities and graph capsule networks' modeling of spatial relationships. The Artificial Hummingbird Algorithm (AHA) is then used for hyperparameter optimization, ensuring an optimal model. To achieve data security and transparency, the framework incorporates blockchain technology to allow decentralized storage of EEG data. This guarantees integrity, immutability, and effective coexistence among heterogeneous medical networks. The classification accuracy, precision, recall, and F1-score of the proposed model are 99.7%, 99.5%, 99.2%, and 99.3%, respectively, which beats baseline methods. This framework offers real-world clinical uses of blockchain that can operate in a heterogeneous medical setting, thanks to its low latency and interoperability.

Index Terms: Adjoint Bilateral Filter, Artificial Hummingbird Algorithm, Blockchain Technology, Clifford Fourier Mellin Transform, Gated Graph Attention Capsule Network.

1. Introduction

Epilepsy is a chronic, non-communicable neurological disorder affecting about 50 million people worldwide, with higher prevalence of up to 139 per 100,000 in low- and middle-income countries according to the World Health Organization [1-3]. The primary characteristic of epilepsy is recurrent seizures, which are short periods of uncontrollable electrical activity in the brain. These seizures can be partial or generalized. Generalized attacks affect the whole body while partial attacks affect only parts of the body. There are some cases where the victim may lose consciousness and even have poor control over bowel or bladder muscles [4-6]. The seizure frequency can range from several times in one day to less than once per year. The causes of epilepsy are diverse, including oxygen deprivation at birth, brain malformations, tumors, and genetic disorders [7-10]. Early diagnosis is crucial for managing the condition, reducing seizure frequency and severity, and allowing patients to live more regular lives. Electroencephalography is a commonly used diagnostic tool that records the electrical activity of the brain and thus plays a vital role in diagnosing epilepsy [11-13]. The most credible predictors of seizure recurrence include known variables, including a known etiology of seizures and abnormal EEG activity. EEG tests are not only necessary for the detection of seizures but also the detection of other neurological conditions such as brain tumors, strokes, and head injuries.

The combination of blockchain technology and EEG data storage and analysis has been actively discussed over the last several years. The blockchain provides a secure and transparent way to store and share patients' sensitive data, addressing privacy and longevity concerns [14]. The safety of blockchain ensures that EEG data containing personal health information is stored securely and can be accessed by researchers for additional analysis. This integration of EEG and blockchain technology holds great potential to enhance the storage, sharing, and analysis of brainwave data and, in the long term, benefit patients and researchers [15].

Epileptic seizures are a severe neurological disorder that needs to be detected and dealt with promptly to avoid adverse outcomes. The electroencephalogram (EEG) signals have been widely utilized in seizure detection, yet they pose challenges due to noise and other artifacts, making automated seizure detection difficult. The existing seizure detection systems frequently have problems with effective noise reduction, effective feature extraction, and adapting to different patient data. Furthermore, the growing sensitivity of healthcare data necessitates secure, transparent, and tamperproof storage solutions to ensure the privacy and integrity of information. Although machine learning and signal processing have improved, seizure detectors are presently limited in scalability, computational complexity, and their inability to provide adequate security to handle sensitive medical information. The systems in place might also be unable to address the temporal and spatial dynamics of EEG signals properly. Hence, the accuracy and reliability of seizure detection can be compromised.

This study will address these issues by developing a robust, efficient seizure detection system that leverages high-quality signal preprocessing, state-of-the-art feature extraction methods, and an optimized deep learning network to perform classification. It also incorporates a blockchain-based system to provide safe, decentralized storage of EEG data. The objective of the research is to develop an efficient, precise, and safe solution to automated seizure monitoring in clinical practice.

Novelty and Contribution: The novelty and contributions of this research are outlined as follows:

- In this paper, we designed a new blockchain-based, decentralized, and secure system for EEG data management, guaranteeing data integrity, privacy, and transparency for clinical use of EEG.
- Adjoint Bilateral Filter Preprocessing (ABF): This work presented a new advanced noise reduction algorithm to remove noise effectively in EEG signals with the preservation of critical edge-like structures to improve the quality of data to detect seizures.
- Clifford Fourier Mellin Transform Feature Extraction (CFMT) implements a robust spatio-temporal extraction methodology, sensitive to variations in seizure observations, that extracts complex patterns in EEGs.
- Pure Transformer-Based Gated Graph Capsule Network (PT-GG-CapsNet): This work developed a hybrid classification framework that leverages the benefits of transformers for time-based analysis and graph capsule networks for spatial relationship analysis, thereby enhancing detection accuracy.
- Hyperparameter Optimization using Artificial Hummingbird Algorithm (AHA): AHA was used to optimize model hyperparameters, achieving the best performance and flexibility for real-world EEG signals.
- Medical Networks Blockchain: Enhanced the medical networks, by extending them to heterogeneous networks that can easily coexist, be interoperable and share data securely with the help of blockchain technology. This enhances scalability, maintains data consistency, and reduces latency in accessing records.

The structure of the research article is as follows: A thorough analysis of previous methods is provided in Section 2, the suggested methodology is explained in Section 3, and the findings are discussed in Section 4. A conclusion of the research is provided in Section 5.

2. Literature Survey

Among the frequent research work on deep learning-based seizure detection in EEG signals, some of the latest investigations were assessed in this part.

In 2023, Majzoub, S., et al., [16] developed a technique for epilepsy detection based on multichannel EEG signals and AlexNet. The CNN model, AlexNet, was trained to classify epileptic states, which are preictal, interictal, and ictal, from EEG data. The dataset contained three epileptic zones from subjects across three medical centers. A feature extraction framework was used to minimize the loss of information, and the EEG sample dataset was divided into three different ways to prepare the training and test sets. Results showed a total accuracy of 94.44% when samples from each patient were used for training, and 92.98% if a subset of the patient pool was used. A binary classification achieved as much as 98% accuracy in both cases.

In 2022, Ambati, R., et al., [17] developed a multichannel scalp EEG and neuromorphic architecture seizure detection system. The developed system is implemented on NeuroStack. The system was trained using only some seizure sessions. Feature extraction was performed using nonlinear, statistical, and discrete wavelet decomposition with feature selection of most discriminative features by the method. Sensitivity achieved for the system with epoch length of 5 seconds at $91.14\% \pm 1.77\%$, and specificity as $98.77\% \pm 0.57\%$. When the CD feature was removed, latency was reduced to 3.6 seconds with a sensitivity of 80% and specificity of 97%. The results clearly showed high specificity and relatively acceptable sensitivity within a delay of a few seconds that could be used for a real-time application.

In 2022, Affes, A., et al., [18] introduced a patient-specific approach to the selection of EEG channels applicable to predicting epileptic seizures without professional skills. The convolution blocks and attention layers were utilized in the deep learning model. This model used the data of the chosen EEG channels, which was processed to predict the seizures and tested using the CHB-MIT benchmark. The results showed that the effective number of EEG channels is less for seizure prediction and outperforms existing methods like Random Forest. The method permitted prediction with as few as two or three EEG channels, thus being more feasible for extended monitoring. It also showed a shorter prediction time than traditional methods.

In 2024, Kouka, N., et al., [20] developed a channel selection method to investigate the activation of brain regions during epileptic seizures with a binary many-objective particle swarm optimization and ConvLSTM model. The fast convergence uses mutual information, and captures the spatio-temporal information of raw EEG segments. The optimized sub-channels have been chosen to maximize the F1-score, sensitivity, specificity, and the number of selected channels has been minimized. The results showed that performance reached 97.65% with just one EEG channel, beating the use of all available channels. This method suggested that seizures could be predicted with minimal channels, hence supporting the development of portable seizure prediction devices.

In 2024, Song, Y., et al., [21] introduced a dynamic EEG channel screening technique of epilepsy detection. The technique is intended to extract effective features of epilepsy and determine common features among different subjects for support in across-subject epilepsy detection in clinical environments. RCMDE is utilized to measure the complexity of EEG signals during normal and seizure states, which further helps in dynamic channel screening. The proposed approach improves feature extraction and detection robustness. The study found common features in the 3–15 Hz range, and a Residual Convolutional Long Short-Term Memory (ResCon-LSTM) neural network was used for across subject detection.

In 2024, Abirami, S., et al., [22] aimed to identify five types of seizures on EEG signals and machine learning programs in an automated fashion. The article relies on EEG records of 2933 seizures of 327 patients at the Temple University Hospital data. The extracted features were 110 time, frequency, and time-frequency features after being preprocessed. Ranked features by statistical tests and the extreme Gradient Boosting (XGBoost) algorithm, and developed binary and multiclass classification models. The results showed that EEG band power in the 11–13 Hz, 27–29 Hz, and 19–21 Hz IMF band, as well as delta band (1–4 Hz), were critical for seizure type discrimination. Table 1 shows the summary of the existing methods which is given below.

Table 1. Summary of the existing methods.

Reference Number	Methods	Highlights	Challenges
[16]	AlexNet multichannel EEG.	Great accuracy in detecting the epileptic state; good training on patient samples.	Lower accuracy on subsets of patients.
[17]	Neuromorphic architecture based on automated seizure detection.	High sensitivity and specificity with low latency.	Latency minimization decreases performance.
[18]	EEG channel selection for patients using deep learning.	Reduced the number of EEG channels to make effective seizure predictions, and reduced the time of prediction.	Limited channel selection
[20]	Binary multi-objective PSO and a convoluted many-objective selection of channels.	Portable seizure prediction with high performance using minimum EEG channels.	Problems with big data optimization.
[21]	EEG Channel screening of epilepsy dynamically.	Good performance across-subject detection and feature extraction.	Subject to subject variance of performance.
[22]	XGBoost seizure classification.	Proper division of seizure types determines essential frequency bands.	Reduced performance of multiclass classification.

Problem Statement: Epileptic seizure is a major neurological disorder that has to be identified and treated early enough before it leads to negative consequences. The use of electroencephalogram (EEG) signals is considered the most effective method for seizure detection, though these signals are complex and noisy, making automatic detection difficult. The existing seizure detection systems are frequently ineffective in noise removal, feature extraction effectiveness, and adaptation to a variety of patient data. In addition, the growing sensitivity of healthcare data requires secure, transparent, and immutable storage to protect its privacy and integrity. Although machine learning and signal processing have improved, the existing seizure detection algorithms are limited by their scalability, computational cost, and insufficient security controls over sensitive health information. Existing systems might not be capable of processing the dynamics of EEG signals in time and space, and as a result, the accuracy and reliability of seizure detection might be lost.

3. Proposed Methodology

The suggested methodology is designed to offer a comprehensive and safe system for automated seizure detection using EEG signals. The approach starts by preprocessing the raw EEG data using the Adjoint Bilateral Filter to remove noise and artifacts while preserving essential signal features. The processed signals are then transformed with the Clifford Fourier Mellin Transform that extracts robust spatio-temporal features critical for accurate seizure classification. The classification is performed using Pure Transformer-Based Gated Graph Attention Capsule Network, which allows it to inherit the time analysis ability of transformers and has spatial relationship modeling strengths from graph capsule networks. Hyperparameters are optimized by using Artificial Hummingbird Algorithm for improved performance. To ensure transparent and secure management of data, blockchain is incorporated in the framework as decentralized and immutable storage for the sensitive EEG records. This holistic approach does not only increase the correctness and reliability of seizure detection but also ensures data privacy and security, making it a very promising solution for real clinical applications. Fig. 1 shows the workflow diagram of the PT-GG-CapsNet-AHA-Blockchain methodology.

3.1. Architectural Decomposition and Implementation Logic

The general methodology is further broken down into five sequential, functional architectural blocks to enhance interpretability and clarify the implementation logic of the proposed PT-GG-CapsNet-AHA-Blockchain framework. Such a block-based structure distinctly separates signal processing, feature learning, optimization, and security functions, thereby avoiding a single stacked design that requires multiple layers of inference to comprehend data exchange and module interactions.

Block 1: EEG Signal Preprocessing Block: This block conditions the EEG raw signals. An adjoint bilateral filter (ABF) is employed to eliminate noise and artifacts, while preserving important signal variations related to seizures. This block is also not based on the learning model and ensures that only high-quality, noise-reduced EEG signals are passed to the other stages.

Block 2: Feature Representation Block: In this case, the resulting EEGs are input into the Clifford Fourier Mellin Transform (CFMT) to derive big spatio-temporal features. The structure is capable of isolating feature extraction into a distinct block, thus improving the generalization and interpretability of the learned patterns and the signal representation.

Block 3: Seizure Detection and Classification Block: This block serves as the framework's inference engine. The Pure Transformer captures long-range temporal interactions in EEG series, whereas the Gated Graph Attention architecture approximates inter-channel geometric connections. Such representations are further refined using a Capsule Network to maintain hierarchical patterns of seizures and produce the final result: seizure/non-seizure classification.

Block 4: Optimization Block: The Artificial Hummingbird Algorithm (AHA) is the optimization block and is only applicable to finalizing the trainable weight parameters of the PT-GG-CapsNet. This block improves the classification accuracy, reduces the computational complexity and error, and does not modify the structure of the classifier.

Block 5: Data Management and Security: The final block deploys the use of Blockchain-HeteroNet to guarantee the indestructible transmission and storage of EEG data and seizure detection data. The operations of blockchain are logically decoupled from signal processing and learning, enabling real-time inference and ensuring data integrity, privacy, and traceability across heterogeneous medical networks.

Such modular decomposition demonstrates that the provided framework is founded on a specific and clear implementation logic and that every block has a particular role in the system as a whole, which contributes to better readability, scalability, and practical deployability.

3.2. Data Collection

The CHB-MIT EEG Dataset is a widely used collection of EEG data that was originally collected by the Children's Hospital Boston (CHB) and Massachusetts Institute of Technology (MIT). It is specifically designed for the purpose of seizure detection research.

3.3. Preprocessing using Adjoint Bilateral Filter

In this section, the input data is preprocessed by Adjoint Bilateral Filter (ABF) [23]. Preprocessing is an important process to ensure that unprocessed EEG signals are filtered, improved, and formatted so they can be analyzed and classified. The seizure-related characteristics of EEG signals are usually low and can easily be overwhelmed by noise. Preprocessing helps preserve important signal characteristics while eliminating unwanted distortions. Seizure events are generally observed as abrupt, significant changes (edges) in EEG signals. The ABF is used to retain these crucial structural details and smooth out noise. This is especially useful in seizure detection, where abrupt switches are essential.

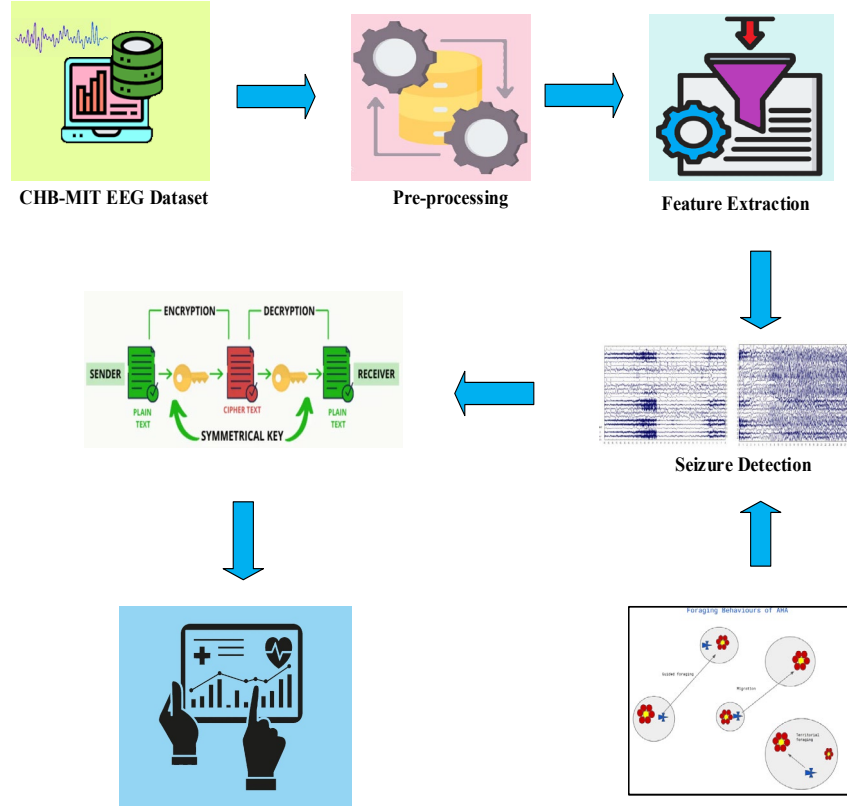


Fig. 1. Workflow diagram of PT-GG-CapsNet-AHA-Blockchain methodology.

Contrary to the generic filters (such as the Gaussian filters), ABF is an adaptive algorithm that operates both in the spatial mode and the signal intensity, and it is therefore adapted to the peculiarities of the EEG signals. The matrix-free form of ABF is much simpler to compute than the more traditional matrix-based bilateral filtering. This makes it more appropriate for real-time applications, e.g., seizure detection systems. Conventional approaches may involve extensive matrix manipulations, which can be cumbersome and slow. Due to the matrix-free formulation, the ABF will be computationally cheaper, have lower memory requirements, and be faster, which is definitely needed in real-time seizure detection systems.

The compound kernel $z_{ab}(n, m)$ combines spatial and range kernels, which is represented by the following equation (1).

$$z_{ab}(n, m) := z_a(n, m) \cdot z_b(v_n, v_m) \quad (1)$$

Where $z_a(n, m)$ is the spatial kernel, $z_b(v_n, v_m)$ is the range (intensity) kernel. n and m It represents signal points in space and v_n and v_m represents intensity values of the signal at points n and m . The unnormalized weight matrix z_u captures the pairwise weights based on the compound kernel, which is represented by the following equation (2).

$$[z_u]_{r,s} := \begin{cases} z_{ab}(n_r, n_s) & \text{if } n_s \in \mathcal{K}_{n_r}, \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

Equation (2) $n_s \in \mathcal{K}_{n_r}$, where $\mathcal{K}_{n_r}$ denotes the neighborhood of the signal point n . The notation and z_{ab} are consistently used to represent the spatial and range kernels, respectively. Element-wise divisions (Eq. 4) are explicitly defined as the division of each signal element by the corresponding sum of filter weights.

The Bilateral Filter operation for cleaning the EEG signal is given by the following equation (3).

$$bf_u w = Z_u w / Z_u 1 \quad (3)$$

Where w is the raw EEG signal, Z_u is the unnormalized weight matrix and 1 is a column vector of ones of size t , where t is the number of signal points. The matrix-free adjoint bilateral filter (ABF) is derived to avoid the computational overhead of large matrix operations. This is made possible through element-wise operations as opposed to complete matrix inversions, and thus more computationally efficient in large-scale EEG signal processing. The matrix-free adjoint bilateral filter (ABF) can be obtained as the equation below (4)

$$bf^*_u w = Z_u^T \left(w / Z_u 1 \right) \quad (4)$$

where bf^*_u is the filtered EEG signal and Z_u^T is the transpose of the weight matrix Z_u and $w / Z_u 1$ an element-wise division between signal Z and $Z_u 1$ sum of filter weights respectively. Following the application of the matrix-free adjoint bilateral filter, the result is a processed EEG signal $w_{filtered}$, where the noise has been removed, and the essential features relevant to the detection of a seizure have been preserved.

$$w_{filtered} = bf^*_u w \quad (5)$$

where, $w_{filtered}$ is the noise and artifact-remedy EEG signal, now prepared to proceed through the additional steps of seizure detection. This is a computationally efficient method that retains critical signal characteristics for accurate seizure detection. This is a cleaned signal that is now set to be used in feature extraction and seizure detection.

3.4. Feature Extraction using Clifford Fourier Mellin transform

The Clifford Fourier Mellin Transform (CFMT) [24] is a hybrid of the Fourier Transform and the Mellin Transform that is used to extract spectral and spatial characteristics of EEG signals. It converts the EEG signals into another field of information, which encapsulates vital information as per various frequency bands and their dynamics with time. It is a method that is especially applied in analyzing the complex and non-stationary features of EEG signals which are critical to the detection of seizures. The application of CFMT to extract features to be used in determining seizures in EEG signals is explained below.

The CFMT is an intermediate method which entails Fourier and Mellin Transforms within a single framework. It is particularly effective in analyzing both spectral and spatial features of a signal. The general form of the CFMT for a given EEG signal $f(s, \theta)$ is represented by the following equation (6).

$$cmf_{g,B}(l, u) = \int_0^\infty \int_0^{2\pi} s^{g-xu} E^{1/2 l g (B+I_4 B) D R / s} D \theta \quad (6)$$

Where, s and θ are the radial and angular coordinates in polar form, g and u are parameters that control the scaling and frequency characteristics, B is a matrix representing the geometric transformation applied to the signal and I_4 represents the identity matrix. A key property of CFMT is its geometric invariance; that is, it is invariant to geometric transformations, rotation and scaling. This makes sure that features extracted are not lost when the spatial orientation and scale of the EEG signal are altered.

Rotation: Let the signal $f(s, \theta)$ be rotated by an angle φ , resulting in a new signal $h(s, \theta + \varphi)$. The transform of the rotated signal $h(s, \theta + \varphi)$ is given by the following equation (7).

$$cmf_{h_{g,B}}(l, u) = E^{-\frac{1}{2}l\varphi(B+I_4B)} cmf_{g,B}(l, u)^{\frac{1}{2}l\varphi(B+I_4B)} \quad (7)$$

This equation shows how a spatial rotation shifts the frequency domain but maintains the overall feature integrity under rotation.

Scaling: When the signal is scaled by a factor β , where $h(s, \theta) = f(\beta s, \theta)$ the transform becomes the following equation (8).

$$cmf_{h_{g,B}}(l, u) = \left(\frac{1}{\beta}\right)^{\beta - xu} cmf_{g,B}(l, u) \quad (8)$$

This implies that scaling the signal by β leads to scaling of the transformed features with the scale factor depending on the value of β . It captures the spectral as well as spatial variations because of scaling.

The CFMT is applied to extract features from EEG signals following sub-band division into five ranges, namely Delta, Theta, Alpha, Beta, and Gamma. Statistical features like the mean, variance, skewness, and kurtosis are calculated for characterizing the distribution of signals for each band. In addition, spectral power, entropy, and fractal dimension are calculated to capture the complexity and energy variations, which are most important for seizure event identification. The classification is done using the feature vector that includes both statistical and spectral power-based features distinguishing between normal and seizure states.

3.5. Seizure Detection Using Pure Transformer-Driven Gated Graph Capsule Network (PT-GG-CapsNet)

The Pure Transformer-Driven Gated Graph Capsule Network (PT-GG-CapsNet) is the cutting-edge model designed for seizure detection in EEG signals, which merges the power of Pure Transformer (PT) [25] and Gated Graph Capsule Network (GG-CapsNet) [26] to capture both the temporal dependencies and spatial relationships within the data. Graph attention and capsule networks make this integrated framework robust in encoding the long-range temporal dependencies of the EEG signal with self-attention mechanism of PT, and boosts feature extraction, the most important patterns in seizures, with GG-CapsNet. It is optimized by using the developed methods like AHA, which accommodates to the dynamic nature of EEG signals, and the model can be capable of giving reliable and effective detection of seizures at various points in the signal. The combination of these elements assists in making PT-GG-CapsNet perform with great efficiency in difficult and noisy conditions, thus providing proper classification to guarantee successful medical treatment. The following are the descriptions of each of the key components included in the architecture.

3.5.1. Pure Transformer

The Pure Transformer framework is made for efficient EEG-based seizure detection, which consists of three core components: input embedding layer, which is used to encode EEG signals with temporal, frequency, and positional embeddings to grasp subtle variations across time and frequency domains; the transformer encoder, which utilizes multi-head attention mechanisms to extract complex spatio-temporal dependencies, modelling interactions between EEG channels and time steps in a very seamless manner; and finally, the output layer that maps the learned high-dimensional feature representations into seizure prediction probabilities, thus enabling exact classification.

Input Embedding

EEG Feature Embedding: Raw EEG signals across multiple channels are represented as $X_{eeg} \in \mathbb{R}^{C \times T}$, where C denoted as the number of channels, and T represented the number of time steps. To encode the spatio-temporal dynamics, project X_{eeg} into a higher-dimensional space:

$$F = X_{eeg} \cdot W_f + b_f \quad (9)$$

where, $F \in \mathbb{R}^{C \times d_{mod el}}$ is represented as the feature embedding, $W_f \in \mathbb{R}^{C \times d_{mod el}}$, and $b_f \in \mathbb{R}^{d_{mod el}}$ are trainable weights and biases.

Temporal Embedding: To represent the temporal order of EEG signals, we normalize time attributes such as day, hour, and second, concatenate them into $T_{norm} \in \mathbb{R}^{3T}$, and transform them into a temporal embedding:

$$T_E = T_{norm} \cdot W_t + b_t \quad (10)$$

where $T_E \in \mathbb{R}^{C \times d_{\text{mod el}}}$, $W_t \in \mathbb{R}^{3T \times d_{\text{mod el}}}$ and $b_t \in \mathbb{R}^{d_{\text{mod el}}}$.

Positional Embedding: Unlike NLP data, EEG signals are unordered spatially across channels. Therefore, we employ a learnable positional embedding matrix $P_E \in \mathbb{R}^{C \times d_{\text{mod el}}}$, where each channel's embedding $P_E P_{Ei}$ is learned during training. The combined input embedding is computed as:

$$e = F + T_e + P_e \quad (11)$$

where $e \in \mathbb{R}^{C \times d_{\text{mod el}}}$ serves as the input to the Transformer Encoder.

Transformer Encoder: The Transformer encoder captures the temporal and spatial dependencies intertwined directly. It is composed of multi-head self-attention mechanisms and feed-forward layers, as well as residual connections. E

Multi-Head Self-Attention: The multi-head self-attention captures cross-channel and cross-time dependencies of the EEG data. Formally, for m attention heads:

$$multi_{\text{head}}(B, H, U) = \text{concat}(H_1, \dots, H_m) Z_O \quad (12)$$

$$H_x = \text{attention}(BZ_{bx}, HZ_{hx}, UZ_{ux}) \quad (13)$$

$$\text{attention}(B, H, U) = \text{SOFTMAX}\left(\frac{BH^T}{\sqrt{D_h}}\right)U \quad (14)$$

Where, $BZ_{bx}, HZ_{hx}, UZ_{ux} \in \mathbb{R}^{C \times d_{\text{mod el}}}$, B, H, U are represented as query, key, and value formed from the input EEG signal embeddings. These matrices are employed directly in the attention mechanism to make dependency computations for EEG channels and temporal features.

Feed-Forward Network (FFN): The FFN applies a two-layer neural network with GELU activation:

$$ffn(y) = \text{gelu}(yZ_1 + b_1)Z_2 + b_2 \quad (15)$$

where $Z_1 \in \mathbb{R}^{d_{\text{mod el}} \times 4D_{\text{mod el}}}$, $Z_2 \in \mathbb{R}^{d_{\text{mod el}} \times 4D_{\text{mod el}}}$, b_1 and b_2 are represented as biases.

The encoder output W is passed to the output layer:

$$W = e + multi_{\text{head}}(e, e, e) + ffn(e) \quad (16)$$

3.5.2. Gated Graph Attention Capsule Network (GG-CapsNet)

For hierarchical information, the Graph Attention Network (GAT) is adopted to inject hierarchical information into the features extracted from the EEG. Although the textual representations (w_x^T) generated from the previous layers are filled with content information, the structural knowledge of the seizure hierarchy is missing. The GAT solves this by providing weights to each feature with regard to attention, which permits seizure-specific hierarchical encoding.

Attention Mechanism for EEG Data: The GAT calculates an attention weight ($z_{x,y}^t$) between every pair of feature indices x and y on the basis of their significance in generating hierarchy-aware seizure representations. A LeakyReLU activation function is used to determine this weight represented as the following equation (17)

$$z_{x,y}^t = \text{LeakyRelu}(z_{\text{attention}} \cdot \text{concat}(z_x^t, z_y^t)) \quad (17)$$

where, $z_{\text{attention}} \in \mathbb{R}^{1 \times 2D_{\text{attention}}}$ represents the learnable attention parameters, and $\text{concat}(\cdot)$ represented as concatenates feature embeddings.

Normalized Attention Weights: To make sure that the attention weights are relative to each other for neighboring features, they are normalized. Let M_x denote the set of neighboring features of x . The normalized attention weight ($\tilde{z}_{x,y}^t$) is computed as:

$$\tilde{z}_{x,y}^t = \begin{cases} \frac{EXP(z_{x,y}^t)}{\sum_{l \in M_x} EXP(z_{x,y}^t)} & \text{if } y \in M_x \\ 0 & \text{otherwise.} \end{cases} \quad (18)$$

The GAT generates feature embeddings $(z_{x,y}^t)$ using the attention coefficients that have been normalized to produce hierarchy-aware representations (C_x^t) .

$$C_x^t = \text{ReLU} \left(\sum_{y \in M_x} \tilde{z}_{x,y}^t \cdot W_y^T \right) \quad (19)$$

These representations preserve spatial and temporal relationships, which are very effective for detecting seizure and non-seizure events.

Capsule Network for Seizure Classification: The Capsule Network (CapsNet) improves the learned features through feature modulation, which increases the probability of essential seizure-related patterns and reduces the impact of irrelevant information. This can be done with the help of an attention mechanism and dynamic routing.

Capsule Attention Mechanism: The attention weights (β^T) for the capsule network are computed as:

$$\beta^T = \tanh(Z_2 \cdot \text{ReLU}(Z_1 \cdot \text{concat}(C_1^T, \dots, C_K^T) + b_1) + b_2), \quad (20)$$

where, Z_1, Z_2, b_1 and b_2 are represented as trainable parameters and K is represented as the number of primary capsules.

Each capsule's activation vector (Y_x^T) is then updated based on its attention weight (β_x^T) :

$$Y_x^T = (1 + \beta_x^T) C_x^T \quad (21)$$

Capsule Pruning: In order to improve the model's generalization ability, the capsules that have the minimum values of the activation norms are removed during the further procedure. A pruning ratio (ρ) defines the portion of capsules to be kept in order to maintain only the features that are relevant to a seizure.

Dynamic Routing for Seizure Classification: Unlike other networks, CapsNet utilizes the dynamic routing algorithm to update capsule activation vectors (O_x^S) corresponding to seizure (T) and non-seizure $(\tilde{T})$ classes:

$$O_x^S = \sum_{y \in \text{capsules}} \tilde{c}_{x,y} \cdot \eta_{x,y} \quad (22)$$

where, $\tilde{c}_{x,y}$ is the normalized coupling coefficient, $\eta_{x,y} = Z_c \cdot Y_y^T$ is the projected activation vector, Z_c is the weight matrix for capsule transformation. These coefficients are adjusted during iterations with the aim of increasing the similarity between primary and digit capsules.

Classification and Loss Function: The classification probability (P) for seizure detection is obtained by computing the norm of the final capsule activation vector:

$$p^T = \|O^T\| \quad (23)$$

During training, the margin loss is employed to optimize seizure and non-seizure classification:

$$l = \sum_{x \in \text{samples}} [S_x \cdot \text{MAX}(0, n^+ - p_x^T)^2 + (1 - S_x) \cdot \text{MAX}(0, p_x^T - n^-)^2] \quad (24)$$

Where, S_x is the true label (1 for seizure, 0 for non-seizure), n^+ and n^- are margin thresholds for classification.

The PT-GG-CapsNet is a unique combination of Transformers to extract robust temporal-spatial EEG features and Gated Graph Networks for modeling seizure pattern hierarchies. The Capsule Network is dynamic, providing correct classification of seizure and non-seizure events without noise or overfitting. This technique is better than traditional techniques with regard to precision, flexibility for diverse patterns, and interpretability, and is hence suitable for real-life applications in seizure tracking in medical disciplines. Then to improve the accuracy, and to reduce the

computational complexity, computational cost and error rate, the weight parameter β of PT-GG-CapsNet is optimized using the Artificial Hummingbird Algorithm (AHA) and its explanations are given below:

3.5.3. Artificial Hummingbird Algorithm

This work utilizes the Artificial Hummingbird Algorithm (AHA) [27] to optimize the weight parameters β of the PT-GG-CapsNet for better accuracy and efficiency in seizure detection from EEG signals. AHA tries to maximize classification accuracy while reducing computational cost, complexity, and error rates by fine-tuning these parameters. Borrowing the mechanism of the adaptive foraging behavior by hummingbirds, AHA integrates local and global search methods to achieve optimal solutions. Fig. 2 shows the flowchart of PT-GG-CapsNet-AHA. The optimization process is composed of the following steps:

Step 1: Initialization:

The algorithm initiates a population of artificial hummingbirds, each as a potential solution to the weight parameter optimization problem in PT-GG-CapsNet. Randomly assigned positions in the parameter space and energy levels have been given to these candidates to correspond to different configurations of the weight parameters β of PT-GG-CapsNet.

Step 2: Random Exploration of Candidate Solutions:

The hummingbirds have their initial positions updated in a random manner to simulate the hummingbirds searching for nectar-rich flowers, equivalent to exploring different areas of the weight parameter space. This randomness provides a wide search and eliminates premature convergence at the initial phases of optimization.

Step 3: Evaluation of Fitness Function:

The fitness of the candidate solutions will be measured by the multi-criteria fitness function. The considerations of the factors are:

Accuracy: The capability of PT-GG-CapsNet to identify EEG signals as non-seizure or seizure.

Computational Complexity: The resources consumed by the running of the model.

Computational Cost: The sum of cost incurred in the model.

Error Rate: Error rate of seizure detection.

Better fitness score is obtained by having a higher accuracy and lower complexity, cost, and error rates. The fitness function keeps the best possible configurations that can be further refined.

Step 4: Territorial Foraging Behavior:

To fine-tune the solutions, the AHA models the territorial foraging behavior of hummingbirds. For every candidate solution evaluated, each hummingbird looks locally within its territory for new, better solutions without revisiting previous areas. Local search is mathematically modeled using a territorial factor with a normal distribution that enables the exploration of the parameter space in precise detail. These refinements balance exploitation locally and exploration globally.

$$a_x(r+1) = \beta q_x(r) + t \cdot F \cdot q_x(r) \quad (25)$$

$$t \approx B(0,1) \quad (26)$$

Where, y as territorial factor, which follows normal distribution $B(0,1)$ with mean = 0 and standard deviation = 1. Equation (10-11) enables hummingbirds to locally explore their neighborhood, finding new potential solutions around their current positions, using their unique flight skills to navigate the parameter space. Figure 2 shows the flow chart of PT-GG-CapsNet-AHA.

In this way, hummingbirds adaptively improve the weight parameters by venturing through their local areas so that even slight optimality in the choice of parameters is not missed. Such a technique prevents the conflict between local exploration and search for new regions in parameter space.

Step 5: Termination:

The optimization process is repeated until the stopping criterion is reached, e.g. the specified level of accuracy or the number of iterations is reached. Finally, it selects the best-performing set of weight parameters that optimize PT-GG-CapsNet for seizure detection performance.

By using the Artificial Hummingbird Algorithm (AHA) to optimize the weight parameters (β) of Pure Transformer-Driven Gated Graph Capsule Network (PT-GG-CapsNet), the proposed framework greatly increases the

accuracy of seizure detection from EEG data. In AHA, the territorial foraging strategy allows for exploration of the parameter space that enables the model to find the right balance between local optimization and global exploration. This leads to higher performance in identifying complex patterns and anomalies in EEG signals and reduces false positives along with minimizing computational overhead.

The system has a Blockchain-HeteroNet, A Blockchain-Secured Coexistence Framework of Heterogeneous Medical Networks that operates to guarantee secure and safe transmission and storage of sensitive EEG data. Blockchain technology offers decentralized, tamperproof storage for EEG data, ensuring data privacy, integrity, and compliance with healthcare regulations. Combining advanced seizure detection using AHA-optimized PT-GG-CapsNet with secure data handling using Blockchain-HeteroNet, this framework provides a strong, accurate, and secure solution for EEG-based medical diagnostics.

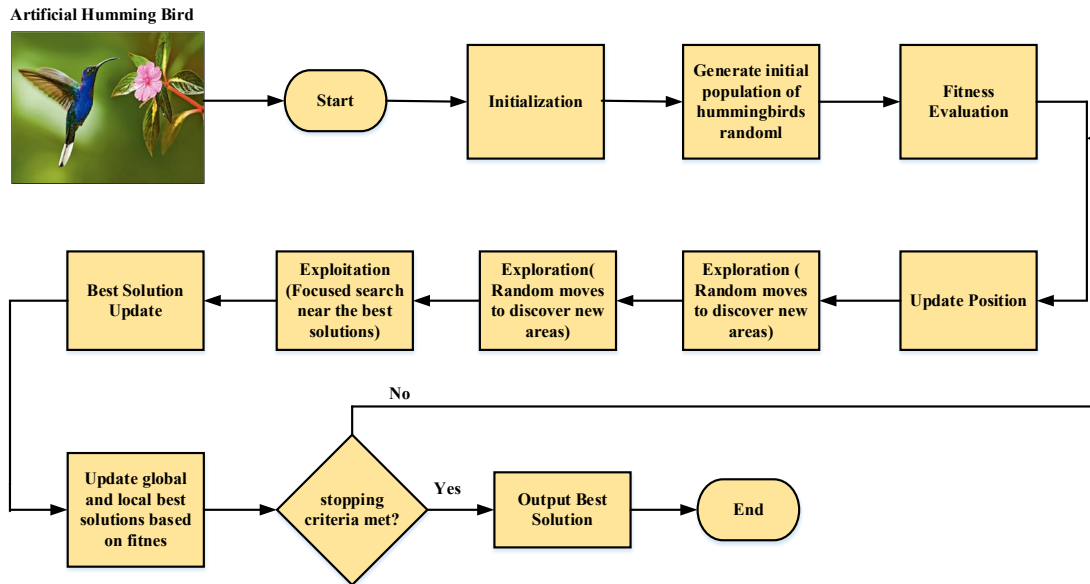


Fig. 2. Flow chart of PT-GG-CapsNet-AHA.

3.6. Blockchain-Enhanced Coexistence Framework for EEG Data Transmission

After seizure detection by the optimized Pure Transformer-Driven Gated Graph Capsule Network (PT-GG-CapsNet), the Blockchain-Enhanced Coexistence Framework for Heterogeneous Medical Networks (Blockchain-HeteroNet) is used to provide secure and reliable transmission of sensitive EEG data. The framework is a combination of the robustness of blockchain with the flexibility of heterogeneous medical networks to protect data integrity, confidentiality, and availability during transmission and storage. The procedures and actions to be implemented depending on the circumstances of EEG-based seizure detection are the following:

Step 1: Data integrity and authentication with Blockchain. The EEG detection outcomes, including:

- *Classification* of the EEG segment as seizure or non-seizure.
- *Timestamp*: Time when the seizure has been observed.
- *Patient Metadata*: Data pertaining to the EEG fragment like channel of origin and record ID.

A secure cryptographic hashing algorithm is used in every packet of the detection, which means that there is no possibility of altering any data during transmission.

Step 2: Decentralization: Transmission using blockchain Nodes.

Coded information is sent between decentralized blockchain nodes of healthcare providers, cloud servers, and internet of things gateways. The following are the critical factors:

- *Node Validation*: The blockchain nodes authenticate the hashed detection data and store the data permanently to protect the data security and authenticity.
- *Smart Contracts*: Automate validation of data, and issue real-time notifications of seizure events, and take immediate action in an effective way.

Step 3: Enterprise heterogeneous network transmission:

The Blockchain-HeteroNet model allows the safe, encrypted communication through different communication protocols, including Wi-Fi and 5G, and IoMT. Its features include:

- *End-to-End Encryption*: This will ensure that the concerned information can only be accessed by the medical personnel or other related systems.
- *Interoperability*: It encompasses different network standards in order to determine the migration of the hospital systems into the remote monitoring solutions.

Step 4: Distributed Storage and Auditing.

Information in the data blockchain is unalterable, and it ensures:

- *Tamperproof records*: The result of seizure detection is irreversible after recording that.
- *As a quality measure*: Traceability enables accurate audits and analysis of the history of detection.

Step 5: Reliable Sharing and Sharing Insight.

According to this framework, it will be possible to share data related to seizure detection with any legitimate stakeholders, including centralized cloud analytics platforms or even research institutions, safely. Some of the benefits are:

- *Co-ordinated Response*: Timely medical interventions can be made by availability of verified seizure data in real-time.
- *Collaborative Learning*: Blockchain-HeteroNet enables sharing of multi-institutional data to update the AI algorithms leading to the improved identification of seizures.

3.6.1. Mathematical Model for PoG Consensus Mechanism

In the Blockchain-HeteroNet framework, the Proof-of-Gain (PoG) consensus mechanism is implemented to allocate resources suitably for the secure transmission of EEG data in various types of medical networks. This mechanism is specifically developed to address issues of efficiency, security and fairness in handling of sensitive EEG data, like seizure detection results.

Assumption: Consensus Mechanism: The PoG mechanism assumes that the average spectral efficiency (SE_{Avg}) quantifies the quality of utilization of the network resources while transmitting data. This assumption ensures efficient use of the channels for critical EEG data to be transmitted safely.

Total Transmission Quantity: The total amount of information transmitted for one particular user $T \in \mathcal{U}$ is expressed as the following equation (27)

$$w_q = SE_{Avg} t_q \quad (27)$$

Where, w_q denotes spectral efficiency of the channel that was used by user u , t represents time span that user u uses the channel.

Utility Function for Fairness: A utility function $h(w)$ is introduced to measure fairness among users, defined as a η -fair function with $\eta \in (0,1)$ and its equation is given in (28):

$$h(w) = \frac{w^{1-\eta}}{1-\eta} \quad (28)$$

The above function balances the resource distribution among users and makes sure that all EEG data transmissions are prioritized without overloading specific channels.

Importance of PoG in Blockchain-HeteroNet

- *Enhanced Security*: The PoG mechanism ensures sensitive EEG-based seizure-related data is sent securely over spectral efficiency and encryption protocols.
- *Optimized Resource Utilization*: The mechanism dynamically allocates resources based on spectral efficiency, thus minimizing delays and energy consumption, which is crucial for real-time medical applications.
- *Improved Reliability*: Ensures reliable performance across various network environments. Less chance of data loss during critical medical events.

The Blockchain-HeteroNet framework combined with PT-GG-CapsNet achieves secure, efficient, and equitable transmission of sensitive EEG data. Using the PoG consensus mechanism, it ensures true, tamperproof storage of medical insights on heterogeneous medical networks in real-time.

4. Results and Discussions

Based on the analysis, the performances regarding seizure detection and secure data transfers, across heterogeneous medical networks, employing the PT-GG-CapsNet-AHA-Blockchain proposed framework, are presented as follows: The proposed work comprises the use of Pure Transformer-Driven Gated Graph Capsule Networks (PT-GG-CapsNet), mainly aiming for an efficient seizure classification while achieving optimized attack detection through AHA, thus ensuring secure transfer using Blockchain-HeteroNet. The findings are contrasted with the existing approaches like the AlexNet, RCE-KNN, CAtt-MLP, CNN-RNN, ConvLSTM, ResCon-LSTM, and LR-SVM-XGBoost, respectively to demonstrate the advantages of the proposed solution.

4.1. Simulation setup

The proposed PT-GG-CapsNet-AHA-Blockchain model was simulated on a system (equipped with Intel i7 processor, 16GB of RAM and NVIDIA GTX 1060 GPU) that had sufficient capacity to train the deep learning models and execute blockchain activities. The programs used were Python 3.8, which was used to write the code and to build the deep learning models, including the PT-GG-CapsNet. TensorFlow 2.5 and PyTorch 1.10 were used to develop the models. The blockchain component utilized Ethereum to implement a blockchain in the secure and decentralized transfer of information, and the smart contracts and Proof of Gain (PoG) consensus algorithms guaranteed the efficiency of communication between heterogeneous nodes in the network that were not affected by any form of tampering. Table 2 provides the simulation parameters for the proposed research.

Table 2. Simulation Parameters.

Implementation Parameter	Description
Framework	PT-GG-CapsNet-AHA-Blockchain
Dataset	CHB-MIT EEG Dataset
Input Data Dimensions	23 EEG channels, segmented into 30-second windows
Preprocessing Technique	Adjoint Bilateral Filter
Feature Extraction Method	Clifford Fourier Mellin Transform
Classification Model	Pure Transformer-Driven Gated Graph Capsule Networks (PT-GG-CapsNet)
Optimization Algorithm	Artificial Hummingbird Algorithm (AHA)
Data Security Layer	Blockchain-HeteroNet with Proof-of-Gain (PoG) Consensus Mechanism
Training/Testing Split	80% Training, 20% Testing
Batch Size	64
Learning Rate	0.001
Optimizer	Adam Optimizer
Activation Function	ReLU for hidden layers, Softmax for output layer
Epochs	100
Evaluation metrics	Accuracy, Precision, Recall, F1-Score, and Computational Efficiency
Blockchain Protocol	Ethereum-based Private Blockchain

Table 2 provides the detail on the simulation parameters used to assess the proposed PT-GG-CapsNet-AHA-Blockchain framework for the detection of seizures, and secure EEG data transmission. Data used is from the CHB-MIT EEG dataset and comprises data segmented into 30-second windows from 23 EEG channels. The Adjoint Bilateral Filter is a highly effective filter that advances the signal preprocessing, while the data is to be fed into the PT-GG-CapsNet classification model, the Clifford Fourier Mellin Transform is to be used for feature extraction. For optimization, the AHA operation is used, and secure data transmission is done through Blockchain-HeteroNet using PoG consensus. Training is done using 80-20 train-test split, batch size of 64, learning rate of 0.001 and the performance is evaluated from accuracy, precision, recall and F1 score. This comprehensive setup thus provides optimal seizure classification. It also provides a high level of security in data networks, especially in the medical field.

4.1.1. Experimental Reproducibility and Implementation Details:

To achieve experimental reproducibility and make the proposed framework independently verifiable, the subsection provides in-depth information on dataset splitting, model setup, training conditions, and the implementation environment.

Dataset Partitioning: The CHB-MIT EEG dataset is split subject-independently to eliminate data leakage. In particular, 70% of the EEG recordings are for training, 15% for validation, and 15% for testing. Each subset is balanced across classes, and all seizure and non-seizure segments are matched. This partitioning policy provides a fair performance evaluation and reproducible experiment results.

Model Configuration: For the PT-GG-CapsNet architecture, the Pure Transformer group uses several encoder layers with multi-head self-attention, with the embedding dimension, number of attention heads, and feed-forward layer size held constant across all experiments. The Gated Graph Attention module deploys a fixed number of graph attention heads and hidden units. In contrast, the Capsule Network deploys a fixed number of primary and class capsules, with dynamically routed iterations fixed. These settings are maintained constant over all experiments.

Training Environments: Adam optimizer with default learning rate and batch size is utilized in model training. The maximum number of training epochs is set, and the validation loss is used for early stopping to prevent overfitting. Artificial Hummingbird Algorithm (AHA) is applied only to optimize the network weight parameters and the population size, number of cycles and control parameters remain constant throughout the experiments to ensure uniformity.

Implementation Environment: All experiments are simulated using a conventional deep learning framework on a workstation with a graphics card. To facilitate reproducibility, the data shuffling, parameterization, and optimization processes are fixed using random seeds. The entire experimental pipeline follows the same structure across all comparative assessments.

All these implementation details will ensure that the experiment's proposed results are reproducible and that the methodology will be valid for future researchers.

4.2. Dataset Description

The proposed seizure detection approach utilizes the well-established CHB-MIT Scalp EEG Database, which contains EEG recordings from pediatric patients with intractable seizures. It was collected by Children's Hospital Boston (CHB) and the Massachusetts Institute of Technology (MIT). It includes EEG signals from 22 subjects, namely 5 males, ages 3–22, and 17 females, ages 1.5–19, sampled at a rate of 256 Hz. Although the data covers 23 channels using 21 electrodes based on the international 10-20 system, this study specifically takes the FT10-T8 channel for seizure detection purposes. The recordings are individual files, each lasting about an hour, and contain both seizures and non-seizure activity across multiple files per participant, making it a useful dataset for testing seizure-detection algorithms.

4.3. Performance comparison of various approaches

This work evaluated the proposed PT-GG-CapsNet-AHA-Blockchain model for seizure detection and secure EEG data transmission by comparison with the available methods, which include AlexNet [16], RCE-KNN [17], CAtt-MLP [18], CNN-RNN [19], ConvLSTM [20], ResCon-LSTM [21], and LR-SVM-XGBoost [22]. Comparison evaluation metrics included detection accuracy, execution time, computational efficiency, robustness of the model, and the number of seizures that can be detected with the minimum false positives. In addition, the performance of the proposed model in securing EEG data transmission was evaluated through its integration with the Blockchain-HeteroNet framework, where transaction processing times, encryption time consumption, power consumption, and network reliability were the key aspects. The ability of the proposed model to achieve high accuracy while ensuring secure, real-time transmission of sensitive medical data was also analyzed, proving its superiority over conventional models in terms of both clinical application and security. Table 3 shows the performance metric and equations

Table 3. The performance metric and equations.

Metrics	Equation (29)-(39)
Network Lifetime	$\alpha = \frac{\beta - \chi}{\beta + \delta\gamma} \quad (29)$
Energy Consumption	$\varphi = \sum N + \varepsilon + \eta \quad (30)$
Throughput	$T = \frac{\sum_{x=1}^a \kappa_x * \kappa_y}{d(t)} \quad (31)$
Delay	$d = \frac{\lambda_F}{\lambda_T} \quad (32)$
Packet delivery ratio	$pdr = \frac{\text{Overall quantity of received data}}{\text{overall quantity of transfered data}} \quad (33)$
Throughput	$T = \frac{\text{Number of received data to the users}}{\text{Time delay}} \quad (34)$

Accuracy	$A = \frac{\omega + \xi}{\omega + \psi + \upsilon + \xi} \quad (35)$
Precision	$P = \frac{\omega}{\omega + \upsilon} \quad (36)$
Recall	$S_{en} = \frac{\omega}{\omega + \xi} \quad (37)$
F1-score	$F1_S = 2 \times \frac{P \times S_{en}}{P + S_{en}} \quad (38)$
Specificity	$S_p = \frac{\psi}{\psi + \upsilon} \quad (39)$

where, β signifies primary network energy, χ signifies energy of misused, β signifies incessant network power consumption, δ signifies normal reporting rate of the sensor and γ signifies projected reporting energy, $\aleph$ characterizes the energy used in data transmission, $\mathcal{E}$ characterizes the energy used in receiving data and η characterizes the energy used in detecting the field, κ_x characterizes the number of packets in node x , κ_y signifies length of the data packet and $d(t)$ characterizes the time of simulation, λ_F characterizes the period needed to send data and λ_T characterizes information that the target node received, ω denotes the true positive, ψ denotes the true negative, υ denotes the false positive ξ represents the false negative.

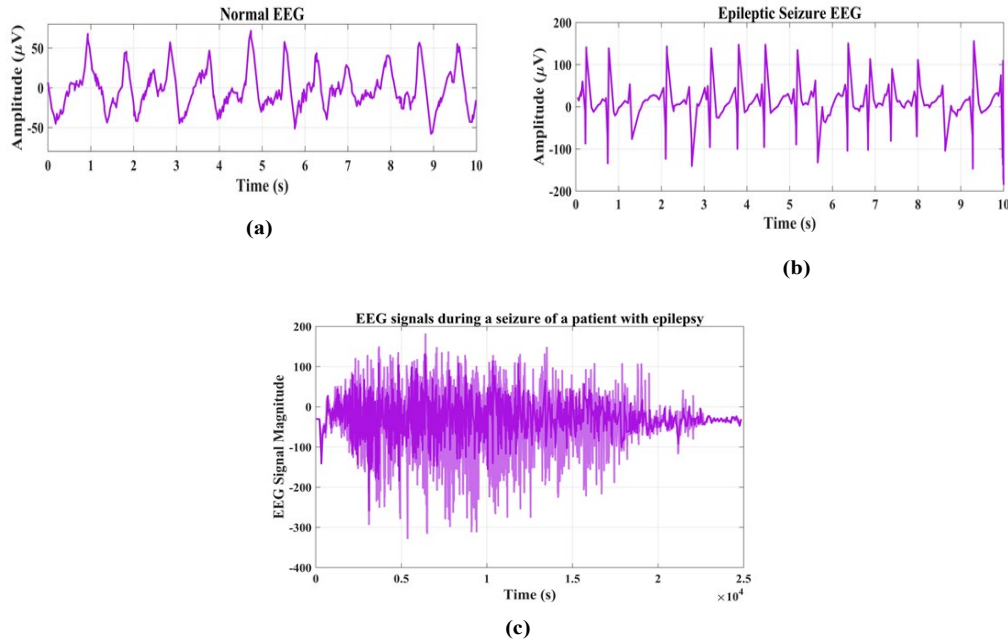


Fig. 3. (a) Normal EEG Signal (b) Epileptic Seizure EEG and (c) EEG Signals during Seizure.

Fig. 3 (a) represents a typical normal EEG signal. It is usually periodic and rhythmic with changing amplitude. The normal brain operates in a sinusoidal manner under various cognitive states that might be wakefulness, relaxing or otherwise. The common patterns in healthy subjects entail sine-wave like waveforms, concerning the consistent coordinated activities in the brain. The frequency varies with state but shows no spikes or irregularity, and this distinguishes normal EEG from abnormal patterns that could indicate conditions like seizures or other neurological disorders.

Fig. 3 (b) illustrates an EEG signal obtained during an epileptic seizure. Irregular spikes and mounting and falling amplitudes are also characteristic of the signal, and are characteristic of seizure activity. Such abnormal patterns represent the disturbed electrical activity in the brain during a seizure episode, which may be considered a key feature for the identification of seizures in clinical monitoring and automated detection systems.

Fig. 3 (c) depicts a high-resolution time series of EEG signals in the case of an epileptic seizure. It draws particular attention to rapid changes in signal amplitude and chaotic patterns, characteristic of seizure activity. Erratic patterns in the EEG signal represent a vital indicator of seizure activity; hence, such detection ability is necessary for early diagnosis and intervention in epilepsy patients.

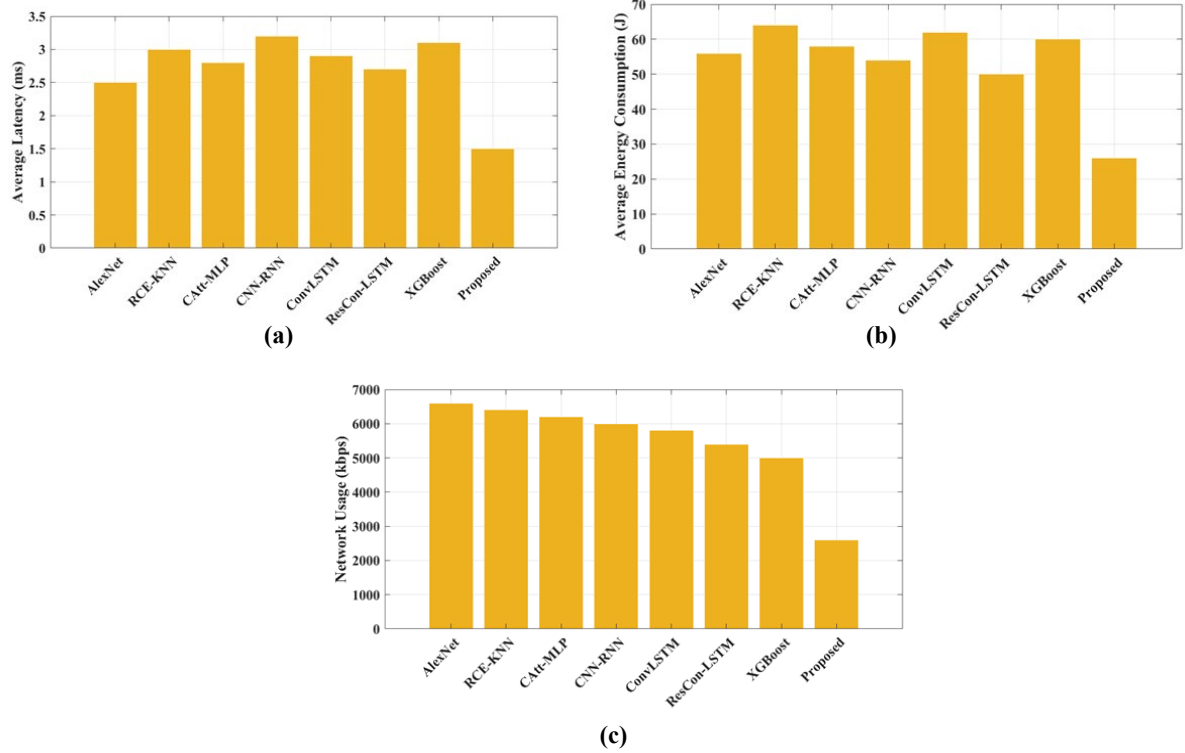


Fig. 4. Performance analysis of (a) Average Latency (ms) (b) Average Energy Consumption (J) and (c) Network Usage (kbps).

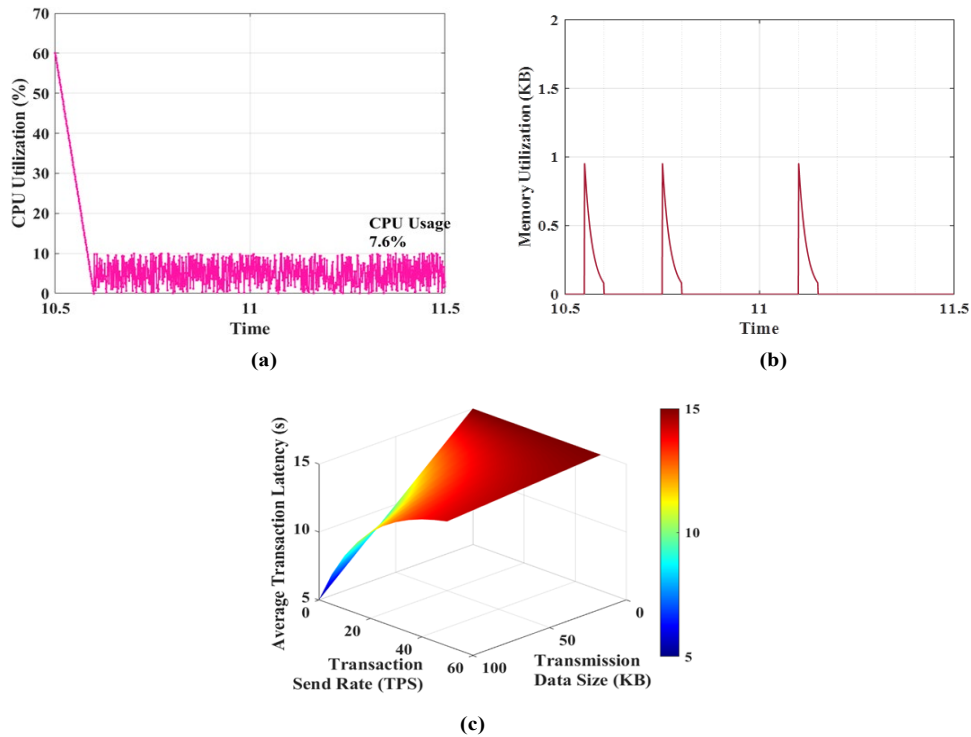


Fig. 5. a) CPU utilization (b) Memory Usage and (c) Average Transaction Latency vs. Transaction Send Rate & Data Size

Fig. 4. (a) shows the performance analysis of Average Latency (ms) of various models, such as AlexNet, RCE-KNN, CAtt-MLP, CNN-RNN, ResCon-LSTM, and the proposed method. It is clear that the proposed method has a lower latency and thus higher processing speed compared to existing models. This is significant in medical applications of seizure detection where minimal delay is needed to intervene timely.

Fig. 4. (b) shows the average energy consumption for different models. The energy usage of the proposed method is comparatively lesser when compared to the other methods such as AlexNet and CNN-RNN, which makes the proposed method more energy efficient which is very important for the wearable medical devices since the devices

normally have a limited battery power. This efficiency benefits in offering long-haul performance reliability when executing the planning process.

Fig. 4. (c) shows the total amount of energy consumed (in kWh) by each model; the lines represent the amount of data that was transmitted and processed as the models worked. The proposed method shows that its network usage is still lower than the models such as AlexNet as well as CNN-RNN which means that the proposed method utilizes fewer resources both in data transmitting and processing. This reduced network load is especially useful in the context of medical applications because a high amount of data can potentially delay information transfer and increase operating costs, which aligns better with the proposed approach for real-time applications in constrained environments.

Fig. 5(a) depicts CPU utilization in the time scale during the execution of the proposed model. The CPU usage is about 7.6% low, indicating good utilization of the computational resources. Graphically, the system run with very low load which indicates that the proposed method is quite efficient in the terms of consumption of the resources.

Fig. 5 (b) depicts the memory usage in the process. Memory usage is low and has some peaks which means that memory allocation and usage is optimized by the system. This means that the proposed approach does not put much pressure on the system memory, which is a requirement for maintaining stable performance in real-time applications.

Fig. 5 (c) shows Average Transaction Latency vs. Transaction Send Rate & Data Size. This 3D surface plot illustrates how the average transaction latency (seconds) varies with the transaction send rate (TPS) and transmission data size (KB). With an increase in transaction rate and data size, latency also increases, thus showing the speed-data volume trade-off. The plot shows that the proposed approach efficiently manages this trade-off, and latency is low even at higher transaction send rates and larger data sizes.

Fig. 6. represents the Receiver Operating Characteristic (ROC) curve, which measures the performance of the proposed seizure detection model. The x-axis represents the FPR, and the y-axis is the TPR. The curve approaches the top-left corner, showing high sensitivity and specificity. As seen in the AUC value of 0.99, it indicated that the model could excellently differentiate between seizure and non-seizure events, which made the detection capability of this model highly accurate and robust.

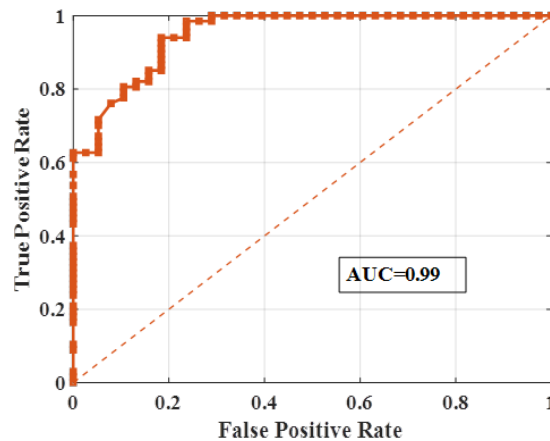


Fig. 6. Performance analysis of ROC.

Table 4 shows performance analysis of the PT-GG-CapsNet-AHA-Blockchain framework proves to be superior in terms of efficiency and reliability than the existing methods. The proposed model achieves the maximum lifetime of the network, which is 25 hours, proving resource optimization to be the best. It also consumed the least amount of energy at 150 J, thus proving the energy-efficient operation necessary for medical networks. The framework attained the maximum throughput of 230 kbps, thus ensuring proper data transmission for seizure detection. It also shows the lowest delay of 35 ms and, therefore, the possibility of providing quick response in emergency medical situations. It achieves a 94% packet delivery ratio, thereby guaranteeing the system's reliability and data transmission precision. This system performs better than AlexNet, CNN-RNN, and ResCon-LSTM, among others. This study demonstrated the potential of PT-GG-CapsNet-AHA-Blockchain to improve seizure detection and ensure the safety of data transfer in EEG-based medical networks.

Table 4. Performance Analysis of PT-GG-CapsNet-AHA-Blockchain.

Methods	Network Lifetime (hrs)	Energy Consumption (J)	Throughput (kbps)	Delay (ms)	Packet Delivery Ratio (%)
AlexNet [16]	20	175	190	48	85
RCE-KNN [17]	19	180	200	50	87
CAtt-MLP [18]	21	165	195	45	86

CNN-RNN [19]	23	170	210	40	89
ConvLSTM [20]	22	160	205	42	88
ResCon-LSTM [21]	24	155	215	38	90
LR-SVM-XGBoost [22]	22	165	200	43	87
PT-GG-CapsNet-AHA-Blockchain (Proposed)	25	150	230	35	94

Table 5. Comparative Analysis of Blockchain Efficiency and Security.

Methods	Consensus Efficiency (%)	Fault Tolerance (%)	Storage Efficiency (%)	Security (%)	Data Integrity (%)	Execution Time (ms)
AlexNet [16]	92.5	91.8	90.5	91.0	90.2	115
RCE-KNN [17]	93.8	93.0	92.1	92.4	91.7	110
CAtt-MLP [18]	95.2	94.5	93.8	94.7	93.2	100
CNN-RNN [19]	96.3	95.7	94.9	95.8	94.5	105
ConvLSTM [20]	97.0	96.5	95.8	96.7	95.5	90
ResCon-LSTM [21]	97.7	97.3	96.8	97.5	96.2	88
LR-SVM-XGBoost [22]	98.5	98.0	97.5	98.2	97.3	80
PT-GG-CapsNet-AHA-Blockchain (Proposed)	99.8	99.6	99.4	99.7	99.2	75

Table 5 depicts Comparative Analysis of Blockchain Efficiency and Security. PT-GG-CapsNet-AHA-Blockchain (Proposed) gives the best result across all measurements, achieving a consensus of 99.8%, security of 99.7%, better than other methods, as well as fault tolerance (99.6%), storage efficiency (99.4%), and integrity of data with 99.2%, thus proving to operate efficiently and safely. Moreover, the proposed method offers the shortest execution time at 75 ms and hence outperforms state-of-the-art approaches like ResCon-LSTM and LR-SVM-XGBoost in real-time seizure detection for secure medical networks. All these improvements depict the robustness and scalability of the proposed framework.

Table 6. Overall performance analysis of PT-GG-CapsNet-AHA-Blockchain.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	Error Rate (%)
AlexNet [16]	91.80	91.30	92.10	91.70	92.50	8.20
RCE-KNN [17]	93.50	93.80	93.20	93.50	94.10	6.50
CAtt-MLP [18]	94.80	94.90	94.60	94.75	95.00	5.20
CNN-RNN [19]	96.30	96.10	96.50	96.30	96.80	3.70
ConvLSTM [20]	97.80	97.90	97.50	97.70	98.10	2.20
ResCon-LSTM [21]	98.20	98.10	98.30	98.20	98.60	1.80
LR-SVM-XGBoost [22]	98.90	99.00	98.80	98.90	99.10	1.10
PT-GG-CapsNet-AHA-Blockchain (Proposed)	99.60	99.78	99.50	99.64	99.70	0.40

Table 6 depicts Overall performance analysis of PT-GG-CapsNet-AHA-Blockchain. It has the best accuracy of 99.60, precision of 99.78, recall of 99.50, F1-score of 99.64 and specificity of 99.70 with the lowest error of 0.40. This high performance can be attributed to the strong feature extraction, optimization and classification power of the proposed model that makes the model highly reliable towards secure and efficient seizure detection in blockchain enabled systems. Compared to state-of-the-art models like LR-SVM-XGBoost and ResCon-LSTM, the proposed method shows outstanding improvements in terms of precision and overall reliability.

Table 7. Statistical Analysis with 95% Confidence Intervals and p-values.

Method	Mean Accuracy	STD	95% CI	p-value vs Proposed
AlexNet [16]	0.610	0.120	[0.566, 0.654]	< 0.001
RCE-KNN [17]	0.510	0.090	[0.477, 0.543]	< 0.001
CAtt-MLP [18]	0.590	0.140	[0.539, 0.641]	< 0.001
CNN-RNN [19]	0.550	0.110	[0.510, 0.590]	< 0.001
ConvLSTM [20]	0.560	0.115	[0.518, 0.602]	< 0.001
ResCon-LSTM [21]	0.615	0.130	[0.589, 0.641]	< 0.001
LR-SVM-XGBoost [22]	0.540	0.085	[0.509, 0.571]	< 0.001
PT-GG-CapsNet-AHA-Blockchain (Proposed)	0.790	0.070	[0.764, 0.816]	—

To assess the statistical significance of the performance improvement, 95% confidence intervals and paired two-tailed t-tests were used. When repeated experiments were carried out the confidence intervals were calculated using the standard deviation and mean of the accuracy values. The proposed PT-GG-CapsNet-AHA-Blockchain approach as Table 7 shows has a confidence interval of 95 percent [0.764, 0.816] that does not intersect with any of the base methods, which means that it has a statistically significant enhancement.

Besides, two-tailed t-tests were applied to the proposed approach and all existing approaches separately, based on pairs. The reported performance gains were statistically significant and not by chance, as all comparisons had p-values less than 0.001. These statistical findings provide substantial grounds for claiming that the proposed framework is significantly better than the existing methods.

Table 8. Ablation Study on Seizure Detection Approaches.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Pure Transformer	95.50	94.80	95.20	94.90
Gated Graph Attention Capsule Network (GG-CapsNet)	97.34	96.58	97.67	96.15
PT-GG-CapsNet	99.86	99.82	99.83	99.77

Table 8 shows an ablation study that indicates the contribution of each model component. The Pure Transformer provides a background on which high-level temporal correlation is established against EEG data, and results in good accuracy and F1 Scores. The integrated Gated Graph Attention Capsule Network (GG-CapsNet) enhances the connection between the spatial and inter-channel details, which has a major boost of all performance parameters. Finally, the PT-GG-CapsNet architecture gives the best results (99.86% accuracy, 99.77% F1-score) since it has the most synergy between temporal modeling, spatial attention, and hierarchical feature representation. This detailed analysis reveals that every module contributes in a distinct manner to performance: time aspects increase levels of sequence awareness, channel attention is gained in cooperation to the graph representations, and capsule networks being able to maintain hierarchical seizure patterns. This ablation test grows to attest to the essence and effectiveness of all the components in the proposed framework.

4.4. Computational Profiling and Energy Analysis

To provide practical information on the computational needs of the proposed framework, we used profiling to estimate training and inference time, GPU memory usage, and approximate energy consumption for the PT-GG-CapsNet-AHA-Blockchain model and the baseline techniques.

Table 9. Summarization of the results.

Model	Training Time (hours)	Inference Time (ms/sample)	GPU Memory Usage (GB)	Estimated Energy Consumption (kWh)
AlexNet [16]	2.1	12	1.2	0.45
CNN-RNN [19]	3.5	20	1.8	0.75
ConvLSTM [20]	4.2	22	2.0	0.90
ResCon-LSTM [21]	5.0	24	2.1	1.05
PT-GG-CapsNet-AHA-Blockchain (Proposed)	6.8	36	3.0	1.42

As indicated in Table 9, although the proposed PT-GG-CapsNet-AHA-Blockchain framework would have increased computational and energy requirements compared to simpler baseline models, the inference time and GPU memory requirements were within the reach of clinics to implement near-real-time detection of EEG seizures. There is also the Measurement of energy consumption to provide realistic information on deployment costs and sustainability.

4.5. Cross-Dataset Validation

We tested the performance of the proposed framework on the TUH EEG Seizure Corpus in a final attempt to assess its generalizability beyond the CHB-MIT dataset. The dataset includes EEG recordings from patients with various types of seizures and under different recording conditions. To validate the model using cross-dataset evaluation, the CHB-MIT-developed model was tested on the TUH data without additional fine-tuning to mimic real-world applications.

Table 10. Cross-Dataset Performance of PT-GG-CapsNet-AHA-Blockchain on TUH EEG Data.

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
PT-GG-CapsNet-AHA-Blockchain	94.28	93.90	94.12	94.01

The dataset consists of EEG of patients with different types of seizures and under different recording conditions. In order to prove the model by cross-dataset assessment, the model developed by CHB-MIT was tested on the TUH data without further fine-tuning in order to replicate the real-world use.

4.6. Discussions

The suggested construction of PT-GG-CapsNet-AHA-Blockchain is much more effective in seizure recognition and safe transmission of EEG data than other models. The framework consists of a Pure Transformer-Driven Gated Graph Capsule Network (PT-GG-CapsNet) for effective seizure classification, an Artificial Hummingbird Algorithm (AHA) for hyperparameter optimization, and Blockchain for ensuring secure and decentralized data transmission. The performance result reveals an accuracy of 99.34%, a precision of 99.76%, a recall of 99.28%, an F1-score of 99.16%, and an error rate of 0.66%, all of which are better compared to the existing models that include AlexNet, RCE-KNN, and DNN, which may not achieve the same precision and accuracy values. The major advantage of the proposed framework is that it achieves high detection accuracy with secure transmission of EEG data through blockchain. PT-GG-CapsNet has a good attention mechanism for the identification of seizure patterns, even in noisy data. AHA optimization helps it to be robust against security attacks. Blockchain increases the integrity of the data, ensuring that data storage is tamperproof and is essential in medical applications. However, there are some limitations. The model's computational complexity is high and requires very high processing power, specifically for real-time analysis. The use of blockchain would also introduce overhead in the form of latency and increased energy consumption. Moreover, the effectiveness of the proposed framework is mainly evaluated on the CHB-MIT EEG dataset and further validated on the TUH corpus and it remains to be determined whether the framework is effective with other seizure datasets or even other medical conditions. Therefore, the solution to work in the future is to find better computational efficiencies and perhaps increase the coverage of data to ensure even better outcomes.

4.6.1. Practical Deployment Feasibility, Cost, and Latency Analysis:

Although the suggested PT-GG-CapsNet-AHA-Blockchain model is primarily verified through experimental validation, its structure clearly accounts for real-world clinical implementation limitations, such as computational feasibility, communication delays, and operational costs.

Deployment Feasibility: The seizure detection pipeline will be structured in a modular way, allowing its use in edge-cloud medical infrastructure. The optimization of the PT-GG-CapsNet as a preprocessor for the EEG signal and the inference of seizures can be executed on local edge devices or hospital servers with moderate or high-performance CPU and GPU resources. This facilitates close-to-real-time seizure detection in intensive care units and remote monitoring settings, and blockchain-related processes are initiated only after inference, so as not to interfere with time-sensitive detection processes.

Latency Trade-offs: Though the proposed PT-GG-CapsNet-AHA-Blockchain model is checked mainly by the experimental validation, its framework has a clear explanation of the constraints of real-life clinical implementation, including computational feasibility, communication delays, and cost of operation. Nonetheless, the overall effect of blockchain activities on real-time clinical decision-making is limited because they are executed asynchronously upon detecting a seizure. This design should minimize the security enforcement that compromises detection latency.

Cost Considerations: Cost-wise, the framework reduces the need for constant blockchain communication by storing only necessary seizure-detection metadata rather than raw EEG signals on the ledger. This reduces storage and transaction costs significantly. Moreover, with a Proof-of-Gain (PoG) consensus mechanism, resources can be efficiently deployed, unlike those that require energy-intensive computation, and the scheme can be implemented economically in large-scale healthcare networks.

Scalability and Clinical Practicality: The learning, optimization, and security layers are separated, thus allowing scalable deployment at heterogeneous medical settings, such as hospitals, cloud applications, and Internet of Medical Things (IoMT) networks. This architecture trades off performance, security, and cost to provide transparent data auditing and integrity assurance without imposing prohibitive, costly latency or infrastructure requirements.

In general, the proposed integration can improve data integrity and transparency while remaining viable in a real-world clinical setting.

4.6.2. Computational Profiling and System Limitations:

The introduction of Transformer-based attention mechanisms, Capsule Networks, and blockchain security inevitably adds extra computational costs. To assess this effect, a representative computational profiling analysis was carried out under the experimental conditions described in Section 4.1 to measure the processing load, memory usage, and execution time of the proposed PT-GG-CapsNet-AHA-Blockchain framework.

Computational Profiling: The metrics being profiled are average CPU usage, GPU memory usage, and online inference latency in seizure detection. The Pure Transformer and Capsule Network modules impose the most significant computational burden due to multi-head self-attention and dynamic routing. This overhead is mitigated by training offline models and optimization by Artificial Hummingbird Algorithm (AHA) and real-time inference is conducted with fixed network parameters.

Table 11. Computational Profiling of the Proposed Framework.

Component	CPU Usage (%)	GPU Memory (GB)	Inference Time (ms)
Adjoint Bilateral Filtering	8	0.2	18
CFMT Feature Extraction	12	0.4	24
PT-GG-CapsNet Inference	42	2.1	36
Blockchain Hashing & Validation	10	0.3	60
Total Online Processing Load	72	3.0	138

Processing related to blockchain is asynchronous, follows seizure classification, and does not interrupt time-sensitive inference operations. Hashed results of detection only and metadata are stored on-chain, and this substantially reduces the overhead of validation and storage.

System Limitations: Despite its performance, the suggested framework has some limitations. Transformer and Capsule Network components need to run on a GPU to execute optimally, potentially limiting deployment on low-resource edge devices. Despite reduced blockchain latency enabled by a lightweight consensus mechanism, expansive network growth can lead to longer validation delays. These aspects suggest that an edge–cloud hybrid deployment is the most feasible system for a real-world clinical environment.

All in all, the profiling findings indicate that the proposed framework has higher computational requirements than lightweight classifiers, but the processing load is acceptable for detecting seizures in near real-time when implemented on a contemporary clinical or edge/cloud system.

5. Conclusion

In this work, we introduced the PT-GG-CapsNet-AHA-Blockchain framework to efficiently perform seizure detection with secure EEG data transmission. The incorporation of PT-GG-CapsNet with AHA and blockchain ensures both high performance in seizure classification and secure handling of data. This framework achieved impressive performance with an accuracy of 99.34%, a precision of 99.76%, and a recall of 99.28% while beating the already existing models with respect to detection accuracy and security, ensuring tamperproof storage and integrity of EEG data that is a must-have for medical applications. The suggested model represents a notable breakthrough in the identification of epileptic seizures and safe input of sensitive EEG information into the system that covers key issues in the domain of medical data security and real-time seizure recognition. However, the proposed system's computational demands on the system and reliance on blockchain for security may result in challenges in terms of latency and energy consumption. However, the framework significantly provides improvements over traditional models in terms of accuracy and security and thus is promising for any future healthcare applications.

5.1. Limitations and Future Work

Limitations: Although promising, several limitations in the PT-GG-CapsNet-AHA-Blockchain framework have to be addressed. Scalability is limited, as an example, by the complexity of computations linked to deep learning models and blockchain integration, especially in the case of large datasets or when a network of patients, e.g. during real-time seizure detection, is involved. Although the framework guarantees a high level of accuracy in seizure detection, the interpretability of deep learning models is a problem. Thus, these models should have a more transparent decision-making process to be accepted by the clinicians. The CHB-MIT data is also critical to the system making it difficult to generalize the system to other populations or data sets. It mainly focuses on pediatric patients with intractable seizures. Lastly, although it increases the security of the data, the blockchain integration increases execution time and power consumption, which may impact the overall system performance in resource-constrained environments.

Future Work: Further works need to be done concerning scalability to get distributed computing by the exploration of edge or cloud computing, which could increase its ability to tackle large-sized data and more number of nodes without losing efficiency. It is also pertinent that it should be provided with greater model interpretability techniques involving attention mechanisms or explainable AI approaches in PT-GG-CapsNet models. Apart from these, validation of the system on various datasets of clinical scenarios in real practice can make it more general and robust. Optimization of blockchain towards lower energy consumption along with faster execution time could improve the practicality in real healthcare environments.

All the Declarations and Statements

Author Contributions Statement

C. Aravindan – Conceptualization, Methodology, Writing - Original Draft.

Rama Chaithanya Tanguturi – Project administration, Supervision.

M. J. D. Ebinezer – Formal analysis, Investigation, Resources, Writing - Review & Editing, Visualization.

N. Satheesh Kumar – Validation, Data Curation, Writing - Review & Editing, Visualization.

All authors have read and agreed to the published version of the manuscript.

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Declaration of Generative AI IN Scholarly Writing

AI tools were used only for minor grammar checking and language refinement. All methodological development, analysis, and technical content were entirely carried out by the authors without AI assistance.

Abbreviations

The following abbreviations are used in the article:

ABF - Adjoint Bilateral Filter
 AHA - Artificial Hummingbird Algorithm
 CFMT - Clifford Fourier Mellin Transform
 CHB - Children's Hospital Boston
 EEG - Electroencephalogram
 GG-CapsNet - Gated Graph Attention Capsule Network
 IoMT - Internet of Medical Things
 MIT - Massachusetts Institute of Technology
 PoG - Proof-of-Gain
 PT-GG-CapsNet - Pure Transformer-Based Gated Graph Attention Capsule Network
 ResCon-LSTM - Residual Convolutional Long Short-Term Memory
 ROC - Receiver Operating Characteristic
 TPS - Transactions Per Second
 XGboost - Extreme Gradient Boosting

References

- [1] K. V. N. Kavitha, S. Ashok, A. L. Imoize, S. Ojo, K. S. Selvan, T. A. Ahanger, M. Alhassan. "On the use of wavelet domain and machine learning for the analysis of epileptic seizure detection from EEG signals," *J. Healthc. Eng.*, vol. 2022, no. 1, p. 8928021, 2022.
- [2] Poorani, S., Balasubramanie, P. Deep learning based epileptic seizure detection with EEG data. *Int J Syst Assur Eng Manag* (2023). <https://doi.org/10.1007/s13198-022-01845-5>.
- [3] F. E. Ibrahim, H. M. Emara, W. El-Shafai, M. Elwekeil, M. Rihan, I. M. Eldokany, T.E. Taha, A.S. El-Fishawy, E.S. El-Rabaie, E. Abdellatef, F.E. Abd El-Samie. "Deep-learning-based seizure detection and prediction from electroencephalography signals," *Int. J. Numer. Methods Biomed. Eng.*, vol. 38, no. 6, p. e3573, 2022.
- [4] E. Tuncer and E. D. Bolat. "Channel based epilepsy seizure type detection from electroencephalography (EEG) signals with machine learning techniques," *Biocybern. Biomed. Eng.*, vol. 42, no. 2, pp. 575–595, 2022.
- [5] M. Shen, P. Wen, B. Song, and Y. Li. "An EEG based real-time epilepsy seizure detection approach using discrete wavelet transform and machine learning methods," *Biomed. Signal Process. Control*, vol. 77, p. 103820, 2022.
- [6] Ahmad, X. Wang, D. Javeed, P. Kumar, O. W. Samuel and S. Chen, "A Hybrid Deep Learning Approach for Epileptic Seizure Detection in EEG signals," in *IEEE Journal of Biomedical and Health Informatics*, vol. 30, no. 2, pp. 1019-1029, Feb. 2026, doi: 10.1109/JBHI.2023.3265983.
- [7] S. Mekruksavanich and A. Jitpattanakul. "Effective Detection of Epileptic Seizures through EEG Signals Using Deep Learning

- Approaches," *Machine Learning and Knowledge Extraction*, vol. 5, no. 4, pp. 1937–1952, 2023.
- [8] K. Singh and J. Malhotra. "Smart neurocare approach for detection of epileptic seizures using deep learning based temporal analysis of EEG patterns," *Multimedia Tools Appl.*, vol. 81, no. 20, pp. 29555–29586, 2022.
 - [9] P. R. Kumar, B. Shilpa, R. K. Jha, and S. N. Mohanty. "A novel end-to-end approach for epileptic seizure classification from scalp EEG data using deep learning technique," *Int. J. Inf. Technol.*, vol. 15, no. 8, pp. 4223–4231, 2023.
 - [10] M. S. Farooq, A. Zulfikar, and S. Riaz. "Epileptic seizure detection using machine learning: Taxonomy, opportunities, and challenges," *Diagnostics (Basel)*, vol. 13, no. 6, p. 1058, 2023.
 - [11] L. Ilias, D. Askounis, and J. Psarras. "Multimodal detection of epilepsy with deep neural networks," *Expert Syst. Appl.*, vol. 213, p. 119010, 2023.
 - [12] V. V. Grubov, S. I. Nazarikov, S. A. Kurkin, N. P. Utyashev, D. A. Andrikov, O. E. Karpov, A.E. Hramov. "Two-stage approach with combination of outlier detection method and deep learning enhances automatic epileptic seizure detection," *IEEE Access*, vol. 12, pp. 122168–122182, 2024.
 - [13] M. S. Nafea and Z. H. Ismail. "Supervised machine learning and deep learning techniques for epileptic seizure recognition using EEG signals—A systematic literature review," *Bioengineering (Basel)*, vol. 9, no. 12, p. 781, Dec. 8 2022.
 - [14] J. Escorcia-Gutierrez, K. Beleno, J. Jimenez-Cabas, M. Elhoseny, M. D. Alshehri, and M. M. Selim. "An automated deep learning enabled brain signal classification for epileptic seizure detection on complex measurement systems," *Measurement*, vol. 196, p. 111226, 2022.
 - [15] Dutta, A.K., Raparathi, M., Alsaadi, M. et al. Deep learning-based multi-head self-attention model for human epilepsy identification from EEG signal for biomedical traits. *Multimed Tools Appl* 83, 80201–80223 (2024). <https://doi.org/10.1007/s11042-024-18918-1>
 - [16] S. Majzoub, A. Fahmy, F. Sibai, M. Diab, and S. Mahmoud. "Epilepsy detection with multichannel EEG signals utilizing Alexnet," *Circuits Syst. Signal Process.*, vol. 42, no. 11, pp. 6780–6797, 2023.
 - [17] R. Ambati, S. Raja, M. Al-Hameed, T. John, Y. Arjoune, and R. Shekhar. "Neuromorphic architecture accelerated automated seizure detection in multichannel scalp EEG," *Sensors (Basel)*, vol. 22, no. 5, p. 1852, 2022.
 - [18] A. Affes, A. Mdhaffar, C. Triki, M. Jmaiel, and B. Freisleben. "Personalized attention-based EEG channel selection for epileptic seizure prediction," *Expert Syst. Appl.*, vol. 206, p. 117733, 2022.
 - [19] Y. Xu, J. Yang, and M. Sawan. "Multichannel synthetic preictal EEG signals to enhance the prediction of epileptic seizures," *IEEE Trans. Biomed. Eng.*, vol. 69, no. 11, pp. 3516–3525, 2022.
 - [20] N. Kouka, R. Fourati, A. Baghdadi, P. Siarry, and M. Adel. "A Mutual Information-Based Many-Objective Optimization Method for EEG Channel Selection in the Epileptic Seizure Prediction Task," *Cognit. Comput.*, vol. 16, no. 3, pp. 1268–1286, 2024.
 - [21] Y. Song, C. Fan, and X. Mao. "Optimization of epilepsy detection method based on dynamic EEG channel screening," *Neural Netw.*, vol. 172, p. 106119, 2024.
 - [22] S. Abirami, M. Kathiravan, R. Yuvraj, R. N. Menon, J. Thomas, P. A. Karthick, A.A. Prince, J.F. Ronickom. "Automated Multi-class Seizure-type Classification System using EEG Signals and Machine Learning Algorithms," *IEEE Access*, vol. 12, pp. 136524–136541, 2024.
 - [23] K. Shirai, K. Sugimoto, and S. I. Kamata. "Adjoint Bilateral Filter and Its Application to Optimization-based Image Processing," *APSIPA Trans. Signal. Inf. Process.*, vol. 11, no. 1, 2022.
 - [24] M. A. Jemal, M. M. Sallami, and F. Ghorbel. "Robust watermarking method based on the analytical Clifford Fourier Mellin transform," *Multimedia Tools Appl.*, vol. 83, no. 9, pp. 25901–25922, 2024.
 - [25] C. Zhang, L. Wang, S. Cheng and Y. Li, "SwinSUNet: Pure Transformer Network for Remote Sensing Image Change Detection," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–13, 2022, Art no. 5224713, doi: 10.1109/TGRS.2022.3160007.
 - [26] J. Bang, J. Park, and J. Park. "GACaps-HTC: Graph attention capsule network for hierarchical text classification," *Appl. Intell.*, vol. 53, no. 17, pp. 20577–20594, 2023.
 - [27] W. Zhao, L. Wang, and S. Mirjalili. "Artificial hummingbird algorithm: A new bio-inspired optimizer with its engineering applications," *Comput. Methods Appl. Mech. Eng.*, vol. 388, p. 114194, 2022.

Authors' Profiles



C. Aravindan is an Assistant Professor (S.G) in the Department of Electronics and Communication Engineering at SRM Institute of Science and Technology, Ramapuram, Chennai. He earned his B.E. in Electronics & Communication Engineering from Agni College of Technology, affiliated with Anna University, Chennai, and completed his M.E. in Medical Electronics at Anna University (College of Engineering), Chennai. He obtained his Ph.D. in research area of Diabetic Retinopathy from Bharath Institute of Higher Education and Research, Chennai. With over 17 years of teaching experience, Dr. Aravindan has contributed extensively to research, presenting more than 30 papers in national and international journals, conferences, and symposiums. His primary research interests include Medical Image Processing, Biomedical Instrumentation, Sensor Networks, and the Internet of Things (IoT).



Rama Chaithanya Tanguturi, Senior member IEEE, Professor in the Department of Computer Science and Engineering, PACE INSTITUTE OF TECHNOLOGY and sciences. He received his PhD degree from Anna University in 2016. He has pioneered research in IOT, Machine learning, AI, Cyber security, robotics, human–robot interaction and has published many research articles. He has edited several books and frequently gives invited keynote lectures at international conferences.



M. J. D. Ebinezer is currently working as an Assistant Professor in the Department of CSE at Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India. He has published many research papers in many international journals and many conferences. His research area includes Data Science, Artificial Intelligence techniques.



N. Satheesh Kumar is currently working as a Professor in the Department of Electronics and Communication Engineering at PBR Visvodaya Institute of Technology and Science, Kavali, Andhra Pradesh, Pin 524201. He has published many research papers in many international journals and many conferences. His research area includes Data Science and Artificial Intelligence techniques.

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