IoT-enabled EEG-based Epilepsy Detection using Multilayer Deep Learning and the Evolutionary Algorithm Approach

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Received: 30 June 2024 | Revised: 26 July 2024 | Accepted: 3 August 2024

 DOI: https://doi.org/10.48084/etasr.8270

ABSTRACT

Abnormal signals of brain activity can predict epilepsy, which can be effectively detected with the use of IoT-enabled Electro-Encephalo-Gram (EEG) devices. In this process, wearable devices can collect relevant data and transmit them to health providers for analysis. These data can be assessed for epilepsy using Deep Learning (DL) algorithms. DL and evolutionary algorithms are combined to detect epilepsy detection with optimized performance. This study proposed a system with multiple objectives. First, EEG signals were obtained using IoT from subjects in healthy conditions and with epilepsy. In preprocessing, the EEG signal is filtered using finite impulse response. Features were extracted from preprocessed signals, including wavelet coefficients, signal entropy, spectral power, coherence, and frequency bands. An optimal structure was selected from the extracted features through a newly designed hybrid optimization model, called the alpha bat customized squirrel optimizer, with a combination of standard jellyfish search algorithm with particle swarm optimization. Finally, a multimodal deep learning framework, including Long Short-Term Memory Network (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Network (CNN), detects epilepsy. The results show that the proposed multilayer DL-based approach outperforms existing methods in terms of accuracy, precision, sensitivity, False Negative Rate (FNR), and specificity.

Keywords-deep learning; LSTM ; GRU; CNN ; jellyfish search algorithm

I. INTRODUCTION

Recently, the field of ECG and EEG biometrics research has grown tremendously and many researchers are working to improve recognition performance. In [1], the efficacy of Seismo Cardio Graph (SCG) and fusion-based predictions was determined against traditional ECG-based methods. This study reflects a difference between how SCG and fusion-based projections work compared to the traditionally used EEG-based method in CCTA gating. The Internet of Things (IoT) has become a ubiquitous innovation in e-health, changing how healthcare services are offered from traditional facilities to homes and workplaces [2]. IoT devices support the quick generation and sharing of data over the Internet, improving the monitoring and management of wireless medical devices. Today, Coronary Heart Disease (CHD) and heart attacks cannot be fully treated but can be managed to some extent through proper monitoring and timely medications. Deficiencies in the EEG signals obtained are used to diagnose cardiac abnormalities [3].

Various IoT devices are used to analyze ECG signals at home and assist remote cardiac patient monitoring systems. However, how they influence consumer OGS adoption in developing countries remains largely unexplored. The study in [4] aimed to bridge this knowledge gap, helping to update the understanding of online retail strategies for dynamic environments. EEG-based biometric developments have focused on improving recognition performance. Comparative studies of SCG and fusion-based predictions versus traditional ECG methods in CCTA highlight possible improvements in predictive accuracy and reliability [5]. IoT has revolutionized health by redistricting services to the periphery, being one of the vital e-health innovations that allow rapid data establishment and sharing over the Internet, helping to better monitor and manage wireless medical devices [6]. In [7], a visualization display was created for a 10-second segment of the EEG signal encoding amplitudes of the brain wave signal, the so-called steady-state brain activity, for an IoT-enabled EEG device for epilepsy prediction. This is in agreement with a focus on IoT EEG devices and DL algorithms that can put meaningful steady-state EEG analysis into practice to detect abnormal brain activity patterns indicative of epilepsy [8].

The Short-Time Fourier Transform (STFT) of the EEG signal describes all changes in the frequency content over time. For a 10-second signal, the STFT is very uniform, showing a consistent pattern of frequency over time. This stability in the distribution of frequencies could mean that the brain activity of the subject was perhaps constant during this period and that this might represent phases of sleep or relaxation without sudden changes, as seen in states such as epileptic seizures or sleep spindles. The proposed system captures EEG signals from the IoT-enabled Emotiv EPOC X, a continuous brain activity monitoring device. This device captures EEG signals through electrodes attached to the scalp and records them using microcontrollers connected to laptops via microUSB cables for real-time transmission to health providers. Continuous monitoring by such IoT-enabled devices is of prime importance for the early detection and timely intervention of epileptic events. In contrast to traditional approaches that are mediated by episodic or manual data collection, IoT devices can support remote monitoring and improve patient convenience by minimizing the frequency of hospital visits. Moreover, continuous data acquisition supplies a complete dataset to enhance the accuracy of DL algorithms used in anomaly detection. Real-time data processing and advanced algorithms integrated with IoT-enabled EEG devices significantly increase the effectiveness of epilepsy detection and treatment for prompt medical decisions, improving patient outcomes. Wearable IoT EEG devices have electrodes attached to the scalp, connected with physical leads to the EEG equipment. These devices use a microcontroller interfaced with a laptop PC through a micro-USB cable and run various signal-processing software for real-time data acquisition and processing. Continuous monitoring by IoT EEG devices can help in terms of early diagnosis and management of epilepsy, improving patient outcomes. Although epilepsy cannot be completely treated, continuous monitoring and preventive measures are highly necessary to treat such neurological disorders.

Abnormal EEG signals could indicate problems such as epilepsy. In this case, IoT devices are essential for signal interpretation at home and support the development of remote patient monitoring systems. However, more understanding is needed about the adoption of IoT-enabled health monitoring systems in emerging countries. This study attempts to fill this gap and allow the development of effective e-health strategies for rapidly evolving environments. As shown in Figure 1, the architecture was designed so that IoT-enabled EEG devices are integrated with multilayer deep learning supported by evolutionary algorithms to improve epilepsy detection. This integration provides real-time data processing and ascertains early identification of the trends leading to epilepsy, improving overall disease management and eventually the quality of patients' lives. The primary technical contributions of this study are:

- Feature extraction: Extract features of mutual information based on EEG signals to improve prediction accuracy, and use sophisticated signal processing techniques to recognize relevant patterns and characteristics that indicate epilepsy.
- Feature selection: This process is carried out through a fusion of the Jellyfish Search Algorithm and Particle Swarm Optimization (PSO), to effectively balance the exploration and exploitation involved in identifying the most informative features.
- Deep multilayer framework: This study uses a new DL framework that integrates CNN, GRU, and LSTM.

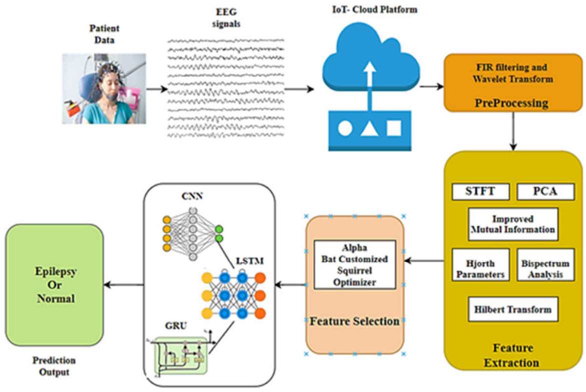

Fig. 1. System architecture.

In [10], early detection of arrhythmia was proposed, showing that IoT has enormous potential for remote and noninvasive monitoring of cardiac arrhythmias, modernization in the healthcare sector, acquisition, processing, and triggering alerts for doctors in emergencies. In [11], the growing demand for low-latency applications, such as health monitoring and surveillance systems, was addressed by proposing edge and cloud computing paradigms to efficiently solve the data processing problem by bringing resources closer to the user, as traditional centralized storage in cloud databases suffers from degraded performance. In [12], the data flow in health systems was explained. Providers collect patient data, forwarding them to different authorized medical facilities and life insurance and pharmaceutical companies. This study raised warnings about the security risks involved in the process, especially breaches during synchronization or cloud transfers. In [13], problems in data quality from wearable technology and non-professional users that make feature extraction complex and reduce detection accuracy were addressed, proposing new techniques to improve detection accuracy using raw ECG data in wireless healthcare systems. In [14], SaaS solutions were investigated, coupled with smart device insights to simplify monetization in vertical domains. This study described the concept of a machine economy, where effective data commercialization is an advantage in the digital market. In [15], a one-dimensional deep CNN method was proposed to classify cardiac conditions. Empirical mode decomposition reflects a technique that preprocesses EEG signals in advance and feeds the modified signal into the network.

In [16], various methods and their main features were discussed to support ES detection. In [17], feature extraction techniques were described along with the results of automated identification methods in different stages of epilepsy, highlighting their efficiency. Performance evaluation of feature extraction methods and classification algorithms assessed the practical feasibility of seizure detection techniques for real-world applications. Reviews of new strategies in classification methods and feature selection on BCI have also been reported, including DL approaches and classifying brain signals. The impact of ambiguity in EEG data on classifier efficiency has been estimated by investigating different classification algorithms. Models have been proposed for the segmentation of EEG signals into sub-bands using different transformations, such as DCT and DWT [18-20]. In [21], common ML approaches to epilepsy prediction models were critically reviewed, underlining the challenges that ML methods face in this domain.

In [22], a literature review on different ML techniques to detect ES was presented, with studies using black-box and non-black-box methods and, where appropriate, several statistical features. In [23], the need for early ES detection and the use of DL or ML techniques for prediction was underlined [23]. In [24], several ML classification techniques were used for ES detection, with experiments showing that RF was the most efficient classifier. In [25], various DL techniques for ES detection were reviewed, highlighting the pros and cons of each model. This study addresses the challenge of accurately and efficiently detecting epilepsy using IoT-enabled EEG devices in conjunction with DL algorithms. While EEG-based biometric recognition and IoT healthcare solutions have seen considerable development, existing methods have significant gaps and limitations.

A. Problem Statement

- Current limitations: Traditional epilepsy detection using EEG signals has many drawbacks, such as difficulty in real-time processing and poor accuracy of the results. However, most approaches underutilized the power of IoT and state-of-the-art DL techniques for monitoring and analysis.
- IoT-device integration with advanced algorithms: The integration of IoT-enabled devices with advanced algorithms to ensure real-time, accurate, and secure data transmission and analysis remains relatively unexplored.
- Feature extraction and selection: Many existing methods lack strong feature extraction and selection modules, which are very important and extremely influential on predictive performance.

B. Significance of this Study

- Improved performance: With the aid of IoT-enabled EEG devices, the proposed method ensures that it is continuous and will remain real-time, improving the quality and comprehensiveness of the data to be collected and resulting in fine-tuned predictions and earlier detection of epilepsy.
- Advanced signal processing: Preprocessing involves FIR filtering. It also incorporates a hybrid optimization model for feature selection, the Alpha Bat Customized Squirrel Optimizer (ABCSO), to ensure that the most relevant features are effectively utilized to improve the overall accuracy and efficiency of the detection model.
- DL framework: A multilayer integration of a DL framework provides a robust and sophisticated way to analyze EEG signals for superior performance compared to traditional ML models.
- Comprehensive evaluation: The proposed approach was evaluated based on several performance metrics, including accuracy, sensitivity, specificity, precision, recall, FPR, and FNR to clearly understand its strengths and weaknesses.
- Scalability and practical applications: A method deployed in MATLAB is intended to be both scalable and practical, so its applications run efficiently in real-world scenarios. This underscores how vitally critical secure data transmission and processing are for any IoT-enabled health monitoring system.
- Contribution to e-health innovations: This study offers a novel solution, contributing significantly to the developing area of e-health in the management and monitoring of epilepsy - an issue whose management is tricky in developing countries where access to continuous healthcare remains a challenge.

II. PROPOSED METHOD

A. Preprocessing using Hybrid Wavelet Transform

Wavelet transform is one of the essential preprocessing techniques that is applied to a large extent in EEG signal analysis. While FIR filters are designed essentially for stationary signals, wavelet transformation can capture transient features and non-stationarities inherent in EEG data. This technique decomposes the signal at different scales into different frequency components, improving the representation of EEG signals. Wavelet transform is very useful, particularly in applications such as epilepsy detection and brain activity monitoring. FIR filters are applied to the EEG signal to remove noise or unwanted frequency components. FIR filters can improve signal quality by providing selective attenuation or amplification of specific frequency ranges. The output of FIR filtering can be modeled as:

$$y[n] = \sum_{k=0}^{M-1} b[k] \cdot x[n-k] \quad (1)$$

where $x[n]$is the input, $b[k]$ denotes the FIR filter coefficients, and $M-1$ is the filter length. Wavelet transform is then performed on the preprocessed EEG signal to decompose it into time-frequency components. Equation (2) represents both time-localized and globally averaged frequency features of the wavelet transform that may be very helpful in detecting transient features and non-stationarities of EEG signals.

$$CWT_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \quad (2)$$

Let $x[n]$ be the original EEG signal. The combined preprocessing step before wavelet transform, represented as $y[n]$, can be expressed as one in which FIR filtering is applied.

$$z[n] = CWT_y(a,b) \quad (3)$$

where $CWT_y(a,b)$ denotes the wavelet transform applied to the FIR-filtered signal $z[n]$ containing valuable information in both time and frequency domains, especially for feature extraction. This approach ensures that an EEG signal is processed for its informational content while retaining relevant transient and nonstationary features of paramount importance to make an accurate inference on epilepsy detection.

B. Feature Extraction

1) PQ-Segment Analysis

The PQ segment, as shown in (4), denotes the time elapsed from the beginning of the P-wave to the onset of the QRS complex in an EEG signal. This measure reflects the delay between the depolarization of the atria and that of the ventricles. The PQ time interval is essential for EEG-based epilepsy detection, as it provides information about the heart's electrical activity and possible aberrations. The exact matching of this interval improves epilepsy detection by providing critical insights into the cardiac and neural activities under study through these advanced DL and evolutionary algorithms.

$$PQ_{duration} = t_{QRSonset} - t_{Ponset} \quad (4)$$

where $t_{QRSSonset}$ is the onset of the QRS complex, and t_{Ponset} is the onset of the P-wave.

2) Short-Time Fourier Transform (STFT)

STFT can be applied to analyze changes in the signal's frequency content with time. Notably, this will show the time-varying pattern of the EEG signal. Hence, it can detect some transient events or frequency shifts that might give a clue about cardiac abnormalities. STFT is given by:

$$STFT(x[n], \tau, \omega) = \sum_{n=-\infty}^{\infty} x[n] \cdot w[n-\tau] \cdot e^{-j\omega n} \quad (5)$$

where $x[n]$ is the EEG signal, $w[n]$ is a window function (e.g., Hamming window), τ is the window shift parameter, and ω is the frequency parameter.

3) Principal Component Analysis (PCA)

PCA is a mathematical technique to decrease the dimensions within datasets while retaining their principal structure. The original features are transformed into new, equally sized variables, called principal components, which are linearly uncorrelated with each other. These principal components explain the maximum possible variance among all linear transformations in the original data. Thus, their representation will be succinct and effective for analysis. PCA can be used as one of the preprocessing aspects to enhance the performance of a model on EEG data by reducing noise and leading to better computational efficiency. Equation (6) represents the matrix decomposition, where Y captures the component score by projecting X onto the component W.

$$\mathrm{Y} = \mathrm{X} \cdot \mathrm{W} \quad (6)$$

where X represents the matrix of all relevant features of EEG signals, and W is the matrix of principal components.

4) Hilbert Transform

The Hilbert transform, represented in (7), is a mathematical tool that aids in retrieving the complex analytic representation of a signal. An analytic signal represents both the amplitude and information of the phase of an original signal, which is very useful for signals whose frequency changes over time, as can be seen in the case of EEG signals exhibiting complex dynamics.

$$H(x(t)) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \quad (7)$$

where $x(\tau)$ is the original EEG signal and $z(\tau)$ is the analytic signal obtained through the Hilbert transform.

5) Improved Mutual Information (IMI)

IMI is one of the methods to assess the statistical dependencies between variables in EEG signals. It aims to select the optimal features by considering both information content and signal variability. IMI with Standard Deviation (SD) weighting is given by:

$$IMI(\mathrm{X}, \mathrm{Y}) = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{1}{\sigma_X^2} \cdot (x_i - \bar{x}) \cdot (y_i - \bar{y}) \right) \quad (8)$$

where $\mathrm{X} = \{x_1, x_2, \ldots, x_N\}$ and $\mathrm{Y} = \{y_1, y_2, \ldots, y_N\}$ are sets of EEG signal data points, σ_X is the SD of X, $\bar{x}$ and $\bar{y}$ are the mean values of X and Y, respectively.

6) Hjorth Parameters

Equations (9) and (10) represent the Hjorth parameters that describe EEG signals with activity and mobility. The time and frequency domains of the signal are provided, which helps in discriminating different brain states and abnormalities.

$$Activity = \frac{1}{T} \sum_{i-1}^{N} x_i^2 \quad (9)$$

where x_i are the EEG signal samples and T is the total duration of the signal.

$$Mobility = \sqrt{\frac{\sum_{i-2}^{N} (x_i - x_{i1})^2}{(N-1) \cdot T}} \quad (10)$$

7) Bispectrum Analysis

Bispectrum analysis accounts for the nonlinear interoperability of the various frequency components of an EEG signal. This means that it can identify phase coupling and non-Gaussianity related to neural mechanisms and abnormalities. The bispectrum $B(f_1, f_2)$ of a signal $x(t)$ is computed using the third-order moment as in:

$$B(f_1, f_2) = \lim_{T \to \infty} \frac{1}{T} \int_0^T x(t) e^{-j2\pi f_1 t} x(t+\tau) e^{-j2\pi f_2 t} x (t + 2\tau) dt \quad (11)$$

where f_1 and f_2 are frequency components and τ is the lag parameter.

C. Feature Selection via Alpha Bat Customized Squirrel Optimizer

This study used a hybrid optimization algorithm based on ABCSO for feature selection. This is a variant of the standard jellyfish search algorithm with specific strategies added from PSO. This algorithm can achieve a better search for the optimal feature subset by balancing exploration and exploitation and improving the convergence speed to the best solution, since it uses the strategies of both jellyfish search and PSO. Most currently available methods produce a search-utilization equilibrium, lack resilience, experience early settlement, and need more expandability. Motivated by these challenging issues, this study focuses on developing a hybrid optimization technique. The need to create ABCSO is realized due to the limitations posed by the traditional approaches in offering proper exploration-exploitation trade-offs, strong robustness, rapid convergence speeds, and flexibility in dealing with different problems. The fitness function is designed to maximize the accuracy obtained from the selected features

(12). The optimization algorithm determines which feature subset gives maximum accuracy for classification or prediction tasks. By maximizing accuracy, this approach helps to improve the efficiency of the selected features and provides better results for feature selection.

First, IoT-based EEG signals are obtained for persons both healthy and with epilepsy. Afterward, they are preprocessed using FIR filtering. Wavelet coefficients, signal entropy, spectral power, coherence, and frequency bands are extracted from these preprocessed signals as features. The ABCSO filters them for the most relevant features. This model aims to find the best feature subset that provides maximum accuracy, improving the performance of deep models.

$$Fitness = \max(accuracy) \quad (12)$$

The position update in the jellyfish search algorithm is given by:

$$X_i(t+1) = X_i\ (t) + J_i\ (t)\ .\ X_{best}(t) - \ X_i(t) \quad (13)$$

where $X_i(t)$ is the position of the i-th feature at iteration t, $J_i(t)$ is the movement step size influenced by the jellyfish search dynamics, and $X_{best}(t)$ is the position of the best feature so far. The position update in PSO is defined as:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1\big(p_i - X_i(t)\big) + c_2 r_2\big(g - X_i(t)\big)$$

$$X_i(t+1) = X_i(t) + v_i(t+1)$$

where $v_i(t)$ is the velocity of the i-th feature at iteration t, ω represents a momentum factor, c_1 and c_2 include individual and collective parameters, correspondingly, r_1 and r_2 are stochastic values ranging from zero to one, p_i is the individual optimal location of the i-th characteristic, and g is the overall optimal location among all characteristics. The jellyfish search and PSO updates are taken according to a control parameter α as in:

$$\begin{cases} X_i(t) + J_i(t) \cdot \Big(X_{\text{best}}\ (t) - X_i(t)\Big), \text{ if } \alpha < \alpha_{\text{threshold}} \\ X_i(t) + \omega v_i(t) + c_1 r_1\big(p_i - X_i(t)\big) + c_2 r_2\big(g - X_i(t)\big)\ otherwise \end{cases} \quad (15)$$

where α determines the switch between jellyfish search and PSO, and $\alpha_{\text{threshold}}$ is a predefined threshold value. This study uses the maximum accuracy achieved as the fitness function. The optimization model aims to identify the optimal subset of features for better classification accuracy.

D. Epilepsy Detection

1) Convolutional Neural Networks (CNN)

CNNs are used due to their ability to extract spatial features directly from the input, such as EEG signals. CNNs are made up of several layers: a convolutional layer, an activation function, and a pooling layer.

a) Convolutional Layer

The convolutional layer convolves the input signal for feature extraction. Unlike traditional neural networks that use matrix multiplication to process data, CNNs process data via convolution. Mathematically, this operation is expressed as shown in (16). The convolutional layer identifies the patterns and anomalies of EEG signals. Through convolutional operations, it manages to perfectly capture spatial hierarchies within the data, which in turn makes DL techniques more accurate and robust for epilepsy detection.

$$y(i,j) = (x * w)(i,j) = \sum_m \sum_m x(m,n) w(i-m, j-n) \quad (16)$$

where w is the weight of the convolutional kernel at position (i,j), x is the pixel value of the input image at position (m,n), and y is the output feature map.

b) Activation Function

CNNs often use the nonlinear ReLU activation function to increase non-linearity in the model and speed up training. ReLU is defined as:

$$f(x) = \max(0, x) \quad (17)$$

c) Pooling Layer

The pooling layer reduces the spatial dimensions of the input feature map, thus reducing computational load and emphasizing only the most important features and their information. Max-pooling is defined as:

$$y(i,j) = \max_{m,n} x(i \cdot s + m, j \cdot s + n) \quad (18)$$

where s is the stride, and m,n are the dimensions of the pooling kernel.

2) Long Short-Term Memory Networks (LSTM)

LSTM is a recurrent neural network that aims to capture and learn the long-term dependencies existing in the data. LSTMs are instrumental in handling sequential information and making forecasts, since they can keep the memory of previous inputs for very long periods. This study uses LSTMs to analyze EEG signal sequences. Since LSTMs can retain information that is valid for a more extended period, they are ideal for detecting epilepsy-associated patterns and anomalies, enhancing the accuracy and reliability of the approach using multi-layer DL and evolutionary algorithms. An LTSM cell is defined by:

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \quad (19a)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (19b)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (19c)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (19d)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (19e)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (19f\_$$

where f_t is the forget gate, i_t is the input gate, o_t is the output gate, $\tilde{C}_t$ is the cell state candidate, C_t is the cell state, and h_t is the hidden state.

3) Gated Recurrent Units (GRU)

GRUs merge the forget and input gates into a single update gate, simplifying the architecture. They maintain the efficiency and performance of LSTMs while reducing the overall complexity of the model. GRUs offer a powerful solution for handling sequential EEG data. Due to their simplified structures and faster computations, along with less resourceintensive training, they are critical in performing real-time epilepsy detection guided by DL and evolutionary algorithms. A GRU is defined by:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (20a)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (20b)$$

$$\tilde{h_t} = \tanh(W_h \cdot [r_t \cdot h_{t-1}, x_t] + b_h) \quad (20c)$$

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \quad (20d)$$

where z_t is the update gate, r_t is the reset gate, h_{t-1} is the candidate hidden state, and $\tilde{h}_t$ is the hidden state.

III. RESULTS AND DISCUSSION

A. Dataset Description

This study utilized two key databases: the CHB-MIT Scalp EEG Database and the TUH EEG Seizure Corpus. These datasets contain all forms of multivariate EEG time series data needed to test the effectiveness of the proposed method in epilepsy diagnosis.

1) CHB-MIT Scalp EEG Database

- Source: Contains EEG recordings taken from pediatric subjects who have intractable seizures.
- Subjects: 24 subjects on the dataset.
- Duration: Contains over 900 hours of EEG recordings.
- Sampling Rate: Recordings are sampled at a rate of 256 Hz.
- Context: Contains different EEG channels, meaning that there are multiple channels in which brain activity is recorded.
- Annotations: Each recording is annotated with seizure events, including their presence and duration.

2) TUH EEG Seizure Corpus

- Source: Consists of multichannel EEG data obtained from a significantly large number of subjects that account for diverse features.
- Significance: Is notable for its extensive size and detailed seizure event annotations.
- Data type: Contains EEG recordings with detailed annotations regarding seizure events.
- Preprocessing: The received signal is preprocessed using an FIR filter to remove noise and artifacts.
- Features are extracted from the preprocessed signals to improve seizure detection accuracy.

B. Results

Table I provides the performance evaluation of the proposed model for epilepsy detection over simple models. Figure 2 compares the four deep learning models: CNN, RNN, DNN, and the proposed multilayer framework integrating LSTM, GRU, and CNN architectures. In all metrics, the multilayer framework achieved better performance with an accuracy of 95%, a precision of 91%, a recall of 93%, and an FNR of 8%. CNN achieved 90% accuracy, 85% precision, 88% recall, and 12% FNR, RNN achieved 88% accuracy, 82% precision, 86% recall, and 14% FNR, and DNN achieved 92% accuracy, 87% precision, 90% recall, and 10% FNR. These results show that the proposed multilayer framework worked better in classifying EEG signals related to epileptic detection than single models.

TABLE I. PERFORMANCE EVALUATION OF EPILEPSY DETECTION MODELS

Methods	30%	50%	70%	90%
CNN	0.896	0.891	0.894	0.898
RNN	0.902	0.903	0.909	0.911
DNN	0.911	0.915	0.916	0.934
Multilayer framework	0.936	0.945	0.954	0.968

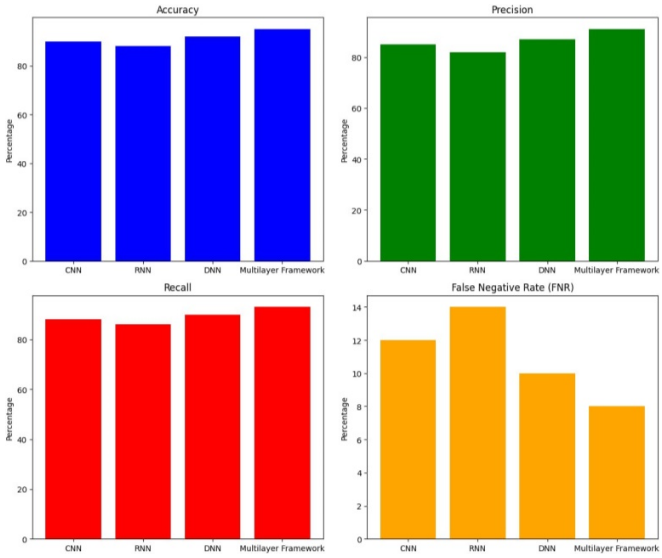

Fig. 2. Comparative performance analysis of DL models for EEG-based epilepsy detection.

Figure 3 shows the (a) accuracy, sensitivity, specificity, (b) precision, recall, and (c) FNR of the four models for raw data without feature selection. This graph shows that although the proposed multilayer framework is, in general, time-consuming compared to CNN, RNN, and DNN, its performance was consistently better than the other models in all metrics. The results show that the proposed model had better epileptic detection capabilities, achieving higher accuracy, sensitivity, specificity, precision, and recall while obtaining a lower FNR rate. From the visualization, it is evident that even though it is more computationally expensive, the proposed multilayer framework is better at discriminating a person with epilepsy from non-epileptic EEG signals. Table II presents the obtained performance metrics for four different techniques used in epilepsy detection from EEG signals without feature selection. In all the metrics, the proposed multilayer framework presents a superior performance, attaining an increased accuracy of 90.2%, sensitivity of 85.56%, specificity of 92.8%, precision of 88.6%, recall of 88.78%, and a low FNR of 15.4%.

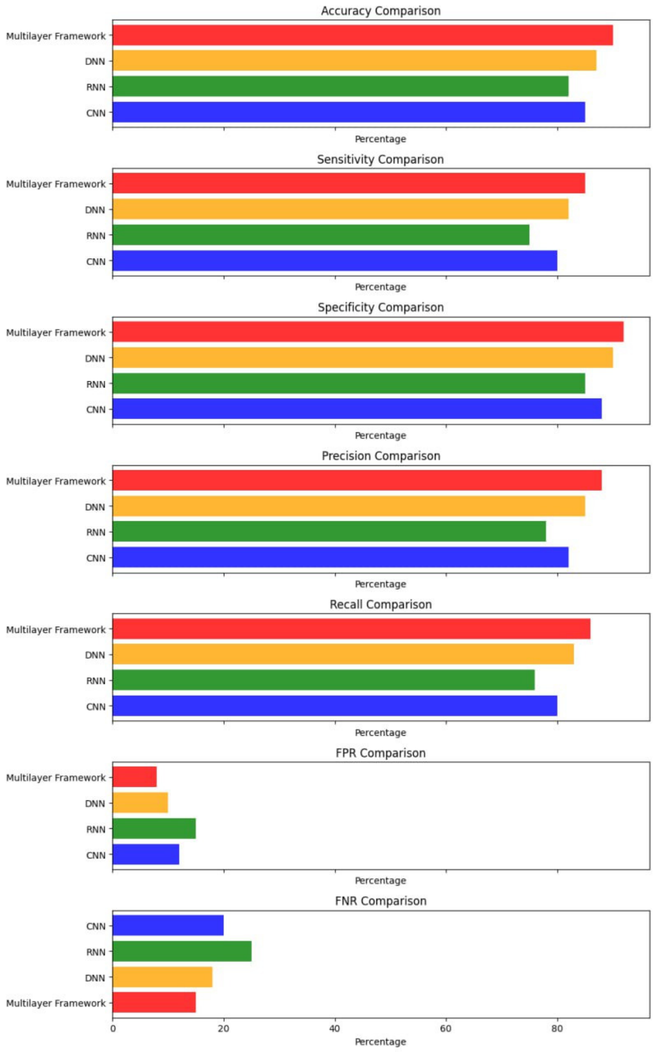

Fig. 3. Performance metrics of DL models.

TABLE II. COMPARISON OF DL FRAMEWORKS FOR EEG-BASED EPILEPSY DETECTION WITHOUT FEATURE SELECTION

Method	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**Recall**	**FNR**
CNN	85.02	80.23	88.23	82.9	78.7	20.6
RNN	82.23	75.62	85.02	76.09	80.56	25.7
DNN	87.26	82.23	90.65	83.45	85.34	18.6
MLF	90.2	85.56	92.8	88.6	88.78	15.4

Some critical aspects form the basis for choosing an optimized method. The method should ensure continuous real-time monitoring of EEG signals, which is a vital component of timely detection and intervention in the management of epilepsy. Accurate preprocessing using FIR filtering removes noise and artifacts satisfactorily compared to more straightforward techniques. This study extracted advanced features, including wavelet coefficients, signal entropy, spectral power, coherence, and frequency bands. All of them constitute one complete feature set that is very informative and improves the performance of the model. Furthermore, efficient feature selection is ensured, since this is achieved by a hybrid optimization model where the ABCSO combines the jellyfish search algorithm with PSO for better relevance of features. CNN, LSTM, and RNN models are combined to achieve superior performance in epilepsy detection over single or simpler ML models.

The results show the excellent effectiveness of the proposed multilayered framework for the precise detection of epileptic events while keeping the occurrence of both false positives and negatives at a minimum level, as required for clinical applications. Therefore, these findings support the efficacy of the proposed approach in the research related to epilepsy detection using EEG-based methods. Table III illustrates a comparative analysis highlighting the advantages of the proposed compared to the existing methods.

TABLE III. COMPARATIVE ANALYSIS OF THE PROPOSED OVER EXISTING MODELS

Aspect	**Proposed Method**	**Existing Methods**	**Advantages**
Data acquisition and real-time monitoring	Collects and monitors the data of IoT-based EEG devices in real time.	Frequently rely on episodic data collection, manual EEG recordings, or offline analysis.	Continuous monitoring can provide a complete dataset than other methods, allowing improved prediction and early detection of epilepsy.
Preprocessing techniques	Uses FIR filtering to preprocess EEG signals.	Use less efficient or more straightforward preprocessing techniques.	FIR filtering removes noise and artifacts in an input data stream, improving its quality before analysis.
Feature extraction	Extracts advanced features, such as wavelet coefficients, signal entropy, spectral power, coherence, and frequency bands.	Often rely on basic statistical features or fewer types of features.	More rich and diversified feature sets have more relevant information captured from EEG signals, enhancing model performance.
Feature selection	Uses a hybrid optimization model, the alpha bat customized squirrel optimizer, which assimilates the power of the basic jellyfish search algorithm and PSO.	Use traditional feature selection methods, which are often not as effective.	The proposed hybrid optimization model is better at selecting only the most relevant features, achieving higher model accuracy and efficiency.
DL models	Integrates a multi-layer framework of CNNs, LTSM, and RNNs.	Often, only simpler ML algorithms or single neural network types are used.	Combining CNN with LSTM and RNN provides an establishment that is more accurate and robust in detection.
Performance metrics	Performance was evaluated with a complete set of metrics: accuracy, sensitivity, specificity, precision, recall, false positive and false negative rates.	Report fewer metrics or mainly focus on accuracy.	Detailed performance evaluation allows for a more profound comprehension of the strengths and weaknesses of the method, ensuring reliability and robustness.
Implementation	Implementation in MATLAB.	Various platforms are used but not constantly optimized.	MATLAB provides many tools and libraries in signal processing and DL, making development efficient.

Although the proposed technique is on the cutting edge, it has some limitations. Computational complexity and extensive resource usage make it less feasible for comprehensive practice. Challenges related to real-time processing and the need for secure data transmission cast doubt over the practicality and privacy of data. Furthermore, high-quality training datasets are required. Finally, the lack of model interpretability affects generalization and thus clinical acceptance.

IV. CONCLUSION

This study presented an advanced IoT-enabled ECG-based system for the detection of epilepsy, applying a multilayer hybrid DL algorithm to analyze EEG signals. The process involved capturing EEG signals from both healthy and individuals suffering from epilepsy using IoT-enabled devices, which relay the captured data to health analysis units. The preprocessing stage involves FIR filtering to clean the signals, while feature extraction identifies wavelet coefficients, signal entropy, spectral power, coherence, and frequency bands. The proposed hybrid optimization method was introduced to select features. This model integrates the standard jellyfish search algorithm in combination with the PSO to ensure that the most relevant features are selected for accurate prediction. The last stage is epilepsy detection, which is achieved through the sophisticated multilayer DL framework that incorporates CNN, GRU, and LSTM. The comparative analysis of the results showed that the proposed multilayer framework was highly superior to several conventional methods, such as CNN, RNN, and DNN. The results obtained show that the proposed framework had the highest accuracy, sensitivity, specificity, precision, recall, and FNR of 90.2, 85.56, 92.8, 88.6, 88.78, and 15.4%, respectively. This method is a novel approach to the detection and prediction of epilepsy by integrating IoT, using advanced feature selection techniques and multilayer DL frameworks for improved results. Future work should investigate the development of data collection in a diverse population with real-time monitoring, advanced wearable devices that enable the continuous non-intrusive monitoring of EEG signals, and adaptive learning algorithms to facilitate personalized medicine. Emphasis should also be placed on cloud-based and edge computing to enable efficient processing of large volumes of EEG data and accelerate analysis for timely interventions.

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