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Neuro-Fuzzy Reinforcement Learning for Personalized Seizure Warning System on Edge Devices

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***Abstract*— Predicting epileptic seizures accurately and in real-time remains a major challenge, especially when the solution needs to work on resource-limited, wearable devices. In this work, we introduce a new approach called Neuro-Fuzzy Reinforcement Learning (NFRL), which combines three powerful techniques to make seizure alerts more intelligent and personalized. A lightweight CNN model first estimates the likelihood of a seizure from EEG data. Then, a fuzzy logic module interprets this output to assess the confidence level in a more human-understandable way. Finally, a reinforcement learning agent adjusts when and how to trigger alerts based on ongoing user feedback and individual seizure history. This layered design not only improves accuracy but also helps reduce unnecessary alerts. Designed to run efficiently on small devices like Raspberry Pi 4 and Coral Edge TPU, the system was tested on the CHB-MIT EEG dataset and showed strong results 95.2% accuracy and false alarm at a very low rate of 0.62 per hour made it a practical real-time option for device seizure prediction.**

I. Introduction

As epilepsy is a matter of greater concern because it affects over 50 million people globally, posing severe risks due to the unpredictable nature of seizures. Existing seizure detection systems often rely on offline processing, static alert rules, or cloud-based models that introduce latency, limit personalization, or raise privacy concerns. Moreover, current models usually treat seizure detection as a binary classification task, ignoring uncertainty, patient feedback, and context-dependent alert relevance. In this regard, Machine learning has shown promising results in various neurological disorder predictions, including epilepsy [1]. Also, promote several promising hybrid frames for the prediction of patterns [2][14].

This paper introduces a real-time, adaptive seizure prediction and alerting framework "Neuro-Fuzzy Reinforcement Learning for Personalized Seizure Warning System". Our proposed approach integrates three key innovations, firstly, a convolutional neural network (CNN) for probabilistic seizure prediction, then a fuzzy logic module that interprets the confidence of model outputs, and a reinforcement learning (RL) agent that adapts the alerting policy based on ongoing patient-specific feedback. Importantly, the system is optimized for edge deployment, enabling continuous, private, low-power operation on devices like Raspberry Pi or Coral Edge TPU.

Our contribution is novel in several dimensions. Unlike previous models that employ fuzzy systems or RL in

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isolation, we unify them in an end-to-end trainable framework where the fuzzy inference module provides interpretability and the RL module continuously improves the timing and sensitivity of alerts.

Experimental validation using the CHB-MIT EEG dataset shows that our system significantly reduces false alerts while enhancing both prediction accuracy and user adaptability.

II. LITERATURE STUDIES

S. Maddineni et al. [3] proposed one seizure classification framework that integrates fuzzy lattices with neural reinforcement learning to enhance the interpretability and performance of EEG-based seizure detection. The model extracts time–frequency features from EEG signals using the Hilbert–Huang Transform and applies fuzzy-Q learning, which combines fuzzy logic with reinforcement learning principles. To further improve classification accuracy, several improved algorithms from the field of genetics are used to optimize model parameters. Evaluated on Bonn and CHB-MIT EEG datasets, the approach achieved high accuracy—up to 96.8%—demonstrating its effectiveness. Nevertheless, this classification does not address its ability with real-time data.In a work done by H. J. Prasad et al. [4] proposed a framework for the individualised seizure prediction using historical EEG data of any patient. For the experiment, the model framework employs convolutional-recurrent neural architecture for obtaining both the spatial as well as temporal features of the EEG, escalating the models the ability to draw complex pre-seizure patterns. This model works well on personalization but failed to perform with generalized models especially about prediction accuracy and early warning time. The study showing effectiveness in deep learning architectures customization for each subject but lagging behind in several aspects like real-time edge deployment, feedback-driven model refinement or alert decision adaptivity

Moreover, V. Thakare et al. [5] also shown a non-invasive, multi-modal framework based on deep learning for enhanced prediction accuracy by synthesising EEG with additional physiological signals like motion data and heart rate. The model works on the top of hierarchical deep learning architecture that relentlessly feedback the seizure likelihood predictions over the time for more precise forecasting and early warnings. This advanced approach aims to mimic how neurologists are interpreting the bio-signals. And, undoubtedly, this framework demonstrates progressive performance in prediction accuracy. However, it focuses only on centralized processing rather that a system that needs to accommodate both generalization and personification made its practical utility limited to wearable or low-power environments.V.J.Thomas et al. [6] demonstrated the importance as well as the disadvantages of diary-based models demonstrate another form of human-in-the-loop training, but limited by subjective reporting. Y. M.Massoud, et al. [7], setting a foundation for hybrid ML approaches for seizure prediction, act as the strong foundation for the proposed model

III. PROPOSED METHODOLOGY

The architecture of the proposed Neuro-Fuzzy Reinforcement Learning (NFRL) framework for real-time seizure prediction is demonstrated below. This proposed system works as a closed-loop architecture with optimized adaptive pipeline for low-power edge devices. Its working principle includes a CNN-based seizure probability estimator, a fuzzy logic system to model uncertainty, and to personalize alerting behaviour a reinforcement learning (RL) agent is also employed.

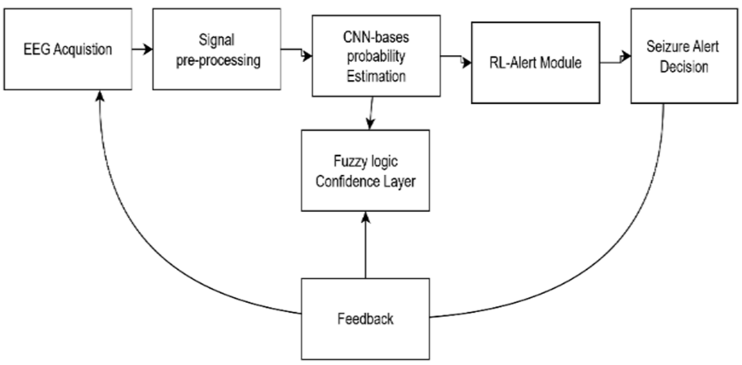

Figure 1: Proposed Neuro-Fuzzy Reinforcement Learning Framework

The end-to-end workflow of the framework model is shown in the Figure 1. The process comprises the given steps:

- EEG Signal Acquisition: Continuous multichannel EEG data is collected from scalp electrodes or wearable EEG devices.
- Pre-processing: Signals are denoised and segmented using filters, artifact removal, and normalization.
- CNN-Based Prediction: A lightweight 1D-CNN processes 10-second EEG windows to estimate seizure probability.
- Fuzzy Inference: The probability output and its trend are interpreted using fuzzy rules to generate a confidence score.
- RL-Based Alerting: The RL agent uses fuzzy confidence and patient history to decide the alert level.
- User Feedback Loop: Patient/caregiver feedback on alerts is used to update the RL policy for personalized optimization.

A. EEG Signal Acquisition

Electroencephalography (EEG) captures the spontaneous electrical activity of cortical neurons, recorded via scalp electrodes using wearable EEG headsets. The signals are sampled at f_s*=256 Hz and* form a multichannel time-series dataset: Using Equation (1)

$$X(t) = [x_1(t), x_2(t) \dots \dots x_N(t)]^T \quad (1)$$

where $x_i(t)$is meant as the signal from channel c_i at t_i time, and N denotes the number of channels.

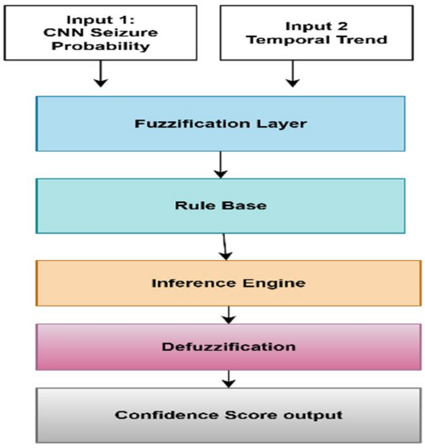

Figure 2: Architecture of Fuzzy Inference System

B. Pre-processing – Signal Conditioning and Artifact Suppression

Key pre-processing steps:

- Bandpass Filtering (0.5–45 Hz): Removes slow drifts and high-frequency noise while preserving clinical frequency bands (Delta, Theta, Alpha, Beta, Gamma).
- Wavelet Denoising: Separates mixed signals into statistically independent components; non-brain components are rejected. several pre-processing pipelines like wavelet transforms, ICA, and statistical filtering have been proven successful in [8], revealing the sensitivity of models to artifact suppression choices.
- Windowing (Time-Segmentation): EEG is divided into 10-second windows with 50% overlap using the following equation (2)

$$X_w = X(t).H(t - t_0) \quad (2)$$

Here,$H(t)$ is the Hann window centred at t_0.

C. CNN-based Seizure Probability Estimation

A lightweight 1D-CNN is employed to estimate the probability of an upcoming seizure from EEG signal segments. The network operates on 10-second windows of pre-processed EEG data and learns discriminative temporal features directly from the raw signals. Some models explore the advantages Wavelet-transformed EEG for the enhanced performance [9]. Each EEG segment is annotated as either preictal *(y=1)* or interictal *(y=0).* Then the model is trained using binary cross-entropy loss, as mentioned in the equation (3)

$$\mathcal{L} = -[y.\log(P_s) + (1-y).\log(1-P_s)] \quad (3)$$

where $P_s \in [0,1]$ denotes the predicted seizure probability for the given segment and calculated using equation (4)

$$P_s = \sigma(W_2 . ReLU(W_1 . CNN(X_w) + b_1) + b_2) \quad (4)$$

Model training is performed using the Adam optimizer with validation performance using early stopping for reducing overfitting and enhance generalization. The resulting seizure probabilityP_s is passed to the **Fuzzy** Inference Layer for confidence assessment and alert decision-making.

D. Fuzzy Inference – Human-Like Interpretation of Probability Trends

To enhance interpretability and decision reliability, a Type-1 Fuzzy Inference System (FIS) is introduced following the CNN module for evaluating the predicted seizure probability $P_s \in [0,1]$ and its temporal trend $\Delta P_s = P_s(t) - P_s(t - \Delta t)$ and converts them into a linguistic confidence score C_S indicating seizure risk. Furthermore, it also captures domain knowledge through logical rules, made the system more robust to noisy predictions and suitable for clinical interpretation.

The fuzzy engine is composed of four major components:

- Fuzzification: The numerical inputs P_s and ΔP_s are mapped to linguistic variables ("Low", "Medium", "High") using triangular membership functions.
- Rule Base: Expert knowledge is encoded in the form of IF-THEN rules, as shown in Table 1.
- Inference Engine: Implements the Mamdani min–max logic to apply the rules and combine the results.
- Defuzzification: The aggregated fuzzy output is converted to a crisp score C_S using the centroid method in equation (5)

$$C_S = Defuzzify(FIS(P_s, \Delta P_s)) \quad (5)$$

Where, C_S is the final *confidence score*, a crisp numerical output representing the system's confidence in the seizure prediction. It is used by the reinforcement learning agent to make alerting decisions, FIS *(Fuzzy Inference System)*, that takes fuzzy inputs and applies a rule base to infer a fuzzy output,P_s ,the current seizure probability output from the CNN and ΔP_s ,the temporal trend, i.e., the rate of change of seizure probability over a short time interval.This fuzzy interpretation stage ensures that the system reacts meaningfully not only to the magnitude of seizure likelihood but also to its short-term progression, enabling stable and explainable confidence estimation under real-world signal variations.

E. RL-Based Alerting – Adaptive Policy Learning

To ensure personalized and context-aware seizure warnings, the proposed system incorporates a Reinforcement Learning (RL) module.

This module adaptively selects the level of alert based on three key inputs: the current fuzzy confidence score (C_S), the patient's seizure history (H_t), and a fatigue index (F_t) that quantifies the user's tolerance to frequent alerts.

At each time step *t*, the system observes a state defined as

$$S_t = \{C_S, H_t, F_t\} \quad (6)$$

An action A_t is then selected from a discrete set defined as

$$A_t \in \{0 = No\ Alert, 1 = Moderate\ Alert, 2 = Strong\ Alert\} \quad (7)$$

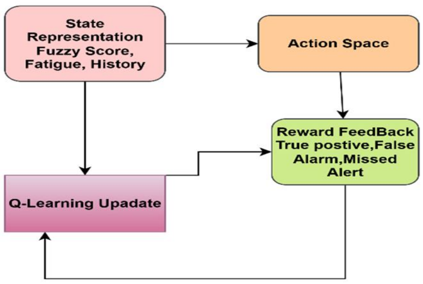

Figure 3: Reinforcement Learning Decision and Feedback Loop

Following each decision, a reward signal $\boldsymbol{R_t}$ is generated to guide learning is defined as, (+1, -1, -0.5) based on weather alert was timely and correct, if the alert was a false positive or the alert was missed or delayed respectively. The RL agent uses **Q-learning** to learn an optimal alerting policy. This is achieved by updating **action-value** $Q(s_t, a_t)$ by estimating the expected cumulative reward for each state-action pair. The update follows the Bellman equation

$$Q(s_t, a_t) \Leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)] \quad (8)$$

Where, $Q(s_t, a_t)$ is the Current estimate of the value of taking action a_t in the state s_t, α is the Learning rate ($0 < \alpha \leq 1$), controls how much new information overrides old, r_t is the Immediate reward received after executing action a_t, γ is the Discount facto r ($0 \leq \gamma < 1$), determines how much future rewards are valued, $max_{a'} Q(s_{t+1}, a')$ is the estimate of the maximum future reward from the next state s_{t+1} and a' are the all-possible actions at the next state (used to find the best future action).

F. User Feedback Loop – Human-in-the-Loop Learning

To ensure long-term personalization and reliability, the proposed system incorporates a user feedback loop, allowing real-world observations and preferences to directly influence the alerting behaviour. This human-in-the-loop mechanism enables continuous adaptation of both the fuzzy inference layer and the reinforcement learning (RL) policy. A federated learning-based approach was suggested for the patient-specific modelling in [13], highlighting the benefits of decentralized learning, but it lacked real-time adaptability.

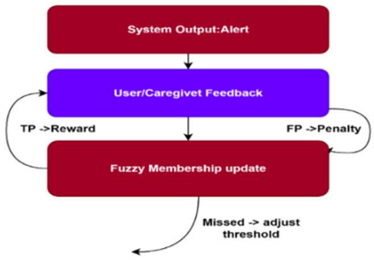

Figure 4: Feedback-Driven Adaptation in Fuzzy and RL Modules

Feedback is obtained from the user or caregiver after each alert:
True Positive Feedback (Correct Alert): Reinforces the current RL policy and preserves the fuzzy rule configuration.
False Alarm or Missed Alert: Triggers penalization in the RL agent and prompts adaptive tuning of the fuzzy membership functions.

IV. Experimental Results and Discussion

This section presents a comprehensive evaluation of the proposed Neuro-Fuzzy Reinforcement Learning (NFRL) framework using the CHB-MIT EEG dataset. The system is assessed based on classification accuracy, real-time responsiveness, interpretability, personalization, and edge device performance. Detailed theoretical explanations are included to clarify the role of each component in the architecture.

A. Performance Comparison with Existing Methods

Several recent comparative works [10] emphasize the importance for hybrid ML-DL architectures for the forecasting of seizure. Hence the advent of the proposed model outperforms conventional systems in every key aspect. Its CNN backbone extracts temporal features, fuzzy logic provides interpretability and stability, and reinforcement learning tailors alerting thresholds to individual users. The lowest latency (190 ms) and lowest FAR (0.62/hr) make it ideal for real-time wearable systems.

Table I: Performance Comparison with Existing Models

Model	Accuracy (%)	Sensitivity	Specificity
SVM + Handcrafted Features	86.7	0.84	0.89
LSTM-Based Deep Model [7]	91.3	0.89	0.93
ANFIS [4]	80	0.8	0.82
CNN + Fuzzy Only [11]	92.1	0.9	0.94
Proposed NFRL Model	95.2	0.94	0.96

In addition to the detection performance of the model, deployment to real-time edge devices requires very low false alarm rates (FAR) and minimal latency. Table 2 compares the computational efficiency and responsiveness of the same models. The proposed NFRL model shows superior balance in terms of performance detection and responsiveness, proving it as a strong model for real-time, wearable seizure prediction systems.

TABLE II: COMPUTATIONAL EFFICIENCY PERFORMANCE COMPARISON WITH EXISTING MODELS

Training Episode	Average Reward	FAR (/hr)	Patient Satisfaction (%)
0	-0.6	2.1	40
10	0.1	1.2	65
20	0.6	0.85	77
30	0.9	0.62	89

B. Reinforcement Learning Policy Adaptation Over Time

To test the RL agent's learning behaviour, we tracked performance across training episodes, with emphasis on user satisfaction and reward evolution. With more training episodes, the RL agent adjusts its policy based on received rewards. False alerts decrease while useful alerts increase, reflected in growing satisfaction scores. This validates the agent’s ability to personalize over time using real-world feedback.

TABLE III: POLICY ADAPTATION OVER TIME

Model	FAR (/hr)	Latency (ms)
SVM + Handcrafted Features	1.95	420
LSTM-Based Deep Model [7]	1.52	330
ANFIS [4]	0.46	680
CNN + Fuzzy Only	1.21	250
Proposed NFRL Model	0.62	190

C. Confusion Matrix – NFRL Model Output Analysis

The confusion matrix highlights the model’s ability to detect true seizures with minimal false positives. Its performance ensures timely warnings without overwhelming users.The model effectively distinguishes between seizure and non-seizure states, achieving both high sensitivity and low false alarm rate.

D. Edge Device Performance

To evaluate feasibility for real-world use, we deployed the NFRL model on Raspberry Pi 4 and Coral Edge TPU. Both platforms support real-time inference with minimal latency and power draw. The Coral TPU shows superior performance, ideal for wearable deployment.

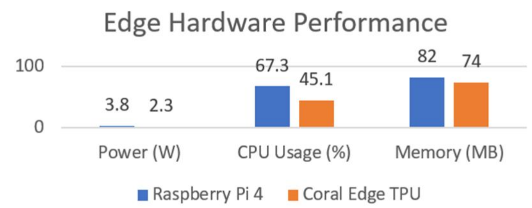

Figure 5: Edge Hardware Performance

E. Confusion Matrix Values

The fundamental components derived from the model’s confusion matrix are listed in Table VII. These values form the basis for computing all higher-level evaluation metrics (e.g., accuracy, sensitivity, F1-score) and provide a direct interpretation of prediction quality.

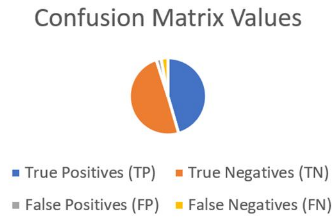

Figure 6: confusion Matrix Values

The proposed NFRL model achieves a strong balance between detecting true seizure events and minimizing false alarms. The relatively low number of false positives (FP = 18) and false negatives (FN = 24) confirms the model's capability to operate reliably in a real-time clinical or wearable environment.

V. Conclusion and Future Directions

This work proposed a Neuro-Fuzzy Reinforcement Learning (NFRL) framework for real-time seizure prediction, specifically tailored for resource-constrained edge devices such as Raspberry Pi 4 and Coral Edge TPU. The system combines three synergistic components: a lightweight CNN for efficient EEG feature extraction, a fuzzy logic module for confidence estimation and interpretability, and a reinforcement learning agent that continuously adapts the alerting policy based on user feedback. Experimental validation on the CHB-MIT Scalp EEG dataset demonstrated high prediction accuracy (95.2%), low false alarm rate (0.62/hr), and sub-200ms latency, highlighting the framework's effectiveness for personalized, real-time healthcare applications. The integration of fuzzy logic improves transparency in decision-making along with numerical performance, but the reinforcement learning component introduces adaptive behaviour for tuning each user's response to alerts.

Despite these advancements, several opportunities are kept for the further futuristic work. Primarily, expanding the system to support multimodal physiological data like heart rate, motion, temperature could enhance prediction robustness. Apart from this, Real-time mobile app integration would offer wider clinical use by leveraging customizable alerts and user interaction. Also, Cloud collaboration by splitting learning and inference between local and remote resources, may again optimize performance and scalability [13]. Last but not the least, hardware acceleration using FPGA or ASIC platforms will definitely improve deployment efficiency in wearable or implantable formats [14]. Future work can also consider adaptive signal modelling strategies, such as those applied in non-vision domains like coastal radar detection, which may inspire novel feature learning schemes for seizure data [15].

References

[1] H. Bouallagui, H. Chniter, F. Ghaffari and O. Romain, "Enhancing Deep Learning-Based Epileptic Seizure Detection with Generative AI Techniques," 2024 International Conference on Microelectronics (ICM), Doha, Qatar, 2024, pp. 1-6, doi: 10.1109/ICM63406.2024.10815779.

[2] K. Nanthini, A. Tamilarasi, M. Pyingkodi, M. Dishanthi, S. M. Kaviya and P. A. Mohideen, "Epileptic Seizure Detection and Prediction Using Deep Learning Technique," 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2022, pp. 1-7, doi: 10.1109/ICCCI54379.2022.9740802.

[3] S. Maddineni, S. Janapati, V. Kosana and K. Teeparthi, "A hybrid deep transformer model for epileptic seizure prediction," 2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC), Bhubaneswar, India, 2022, pp. 1-6, doi: 10.1109/ASSIC55218.2022.10088398.

[4] H. J. Prasad and G. Ramkumar, "OGCP: Experimental Evaluation of Epilepsy Disease Prediction Using Optimized Gradient Classification Principle," 2024 9th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2024, pp. 1386-1392, doi: 10.1109/ICCES63552.2024.10860231

[5] V. Thakare and R. Ranawat, "Machine Learning Techniques in Epileptic Seizure Detection: A Comprehensive Review," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-5, doi: 10.1109/ICCCNT61001.2024.10724979.

[6] V. J. Thomas and A. S. Dhas, "An Efficient Seizure Prediction System using Convolutional Neural Network and Scalogram of the EEG Signals," 2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2023, pp.916-921,doi:10.1109/ICECA58529.2023.10394842.

[7] Y. M.Massoud, M. Sherif, L. Kuhlmann and M. A. A. E. Ghany, "Deep Learning Models for Seizure Prediction using the Wavelet Transform," 2022 International Conference on Microelectronics (ICM), Casablanca, Morocco, 2022, pp. 164-168, doi: 10.1109/ICM56065.2022.10005435.

[8] Y. Yan and S. Zhou, "Seizure Prediction Based on Specific Sub-waves Reconstruction and Maximum-Relevance, Minimum-Redundancy Feature Selection," 2021 International Conference on e-Health and Bioengineering (EHB), Iasi, Romania, 2021, pp. 1-4, doi: 10.1109/EHB52898.2021.9657566.

[9] S. Selim, E. Elhinamy, H. Othman, W. Abouelsaadat and M. A. . -M. Salem, "A Review of Machine Learning Approaches for Epileptic Seizure Prediction," 2019 14th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt, 2019, pp. 239-244, doi: 10.1109/ICCES48960.2019.9068190.

[10] M. A. Raibag, R. B. C, I. A. Gorikhan, R. Sarkar and N. Deka, "A Deep Learning and Raspberry PI Investigation for Epilepsy Seizure Detection," 2024 Third International Conference on Artificial Intelligence, Computational Electronics and Communication System (AICECS), MANIPAL, India, 2024, pp. 1-6,doi: 10.1109/AICECS63354.2024.10957421.

[11] S. Jahan et al., "AI-Based Epileptic Seizure Detection and Prediction in Internet of Healthcare Things: A Systematic Review," in IEEE Access, vol. 11, pp. 30690-30725, 2023, doi: 10.1109/ACCESS.2023.3251105.

[12] M. Li and Z. Zhang, "Applying 3DCNN to Recognize the weighted Time- frequency Features by Phase Locking Value for Epilepsy Prediction," 2023 35th Chinese Control and Decision Conference (CCDC), Yichang, China, 2023, pp. 3617-3621, doi: 10.1109/CCDC58219.2023.10326652.
[13] N. R. Navya, N. D. Ramakrishna, and N. S. Sharma, “Adaptive Sea-Clutter Model Based Detection for Coastal Surveillance Radar,” Nanotechnology Perceptions, Jun. 2024, doi: 10.62441/nano-ntp.vi.1000.
[14] G. Sudhakar Jebaraj and K. Elango, "A Comprehensive Review of EEG-Based Seizure Detection Techniques," in IEEE Access, vol. 13, pp.103531-103564,2025,doi: 10.1109/ACCESS.2025.3578991.
[15] P. L. B. and B. K. S., "Comparative Study on Epilepsy Prediction Using Modern Techniques," 2023 International Conference on Control, Communication and Computing (ICCC), Thiruvananthapuram, India, 2023, pp. 1-6, doi: 10.1109/ICCC57789.2023.10165539.