Spiking Neural Networks for Cross-Modal Medical Diagnostics: A Comprehensive Survey of Architectures, Learning Mechanisms, and Applications

Radha R[1], Raja Sarath Kumar Boddu[2]

[1] Department of Data Science and Business Systems, SRM Institute of Science and Technology, Chengelpet, Tamil Nadu, India; [2] Raghu Engineering College, Visakhapatnam, India

Email ID - radhar@srmist.edu.in

Abstract: Chronic epilepsy patients face a 2-3 times higher risk of stroke compared to the general population, yet continuous monitoring for early cerebrovascular events remains challenging due to the high energy demands of traditional artificial intelligence systems and strict privacy requirements of medical data. Spiking Neural Networks (SNNs) have emerged as the third generation of neural network models, offering significant advantages in energy efficiency, biological plausibility, and spatiotemporal information processing compared to traditional artificial neural networks. SSNs offer a promising alternative through asynchronous, spike-based computation that achieves significant energy efficiency. This survey systematically reviews the fundamentals of SNN architectures, learning mechanisms including Spike-Timing-Dependent Plasticity and surrogate gradient methods, and their applications across biomedical domains. This paper also focuses on fundamental neuron models including Hodgkin-Huxley, Leaky Integrate-and-Fire, and Izhikevich models, along with encoding strategies such as rate coding and temporal coding. Significant findings reveal that SNNs achieve comparable accuracy to traditional deep learning models while consuming 10-100× less energy, making them particularly suitable for wearable healthcare applications and edge computing. However, critical gaps exist in cross-modal spiking attention mechanisms, sparsity-aware federated learning protocols, and temporal explainability methods for clinical validation. Applications include EEG-based emotion recognition, ECG arrhythmia classification, EMG gesture recognition, and MRI-based disease detection, with emerging opportunities in integrated stroke detection for epilepsy patients.

Keywords: Spiking Neural Networks; Neuromorphic Computing; EEG Analysis; Medical Data Classification; Industrial Fault Diagnosis

Introduction

Deep learning has had an impressive development in the last ten years with models that are much more accurate in computer vision and natural language processing, as well as in biomedical studies [1]. Nonetheless, this has been achieved at the expense of raising the model complexity, the number of parameters, and energy consumption. A single state-of-the-art model can use large amounts of computational resources to train, which will have a large carbon footprint [2]. In addition, the traditional artificial neural networks (ANNs) are biologically implausible, and most of them cannot reproduce the temporal dynamics of many real-life signals. The issue of chronic epilepsy patients is one of the most difficult ones to monitor their health with. Such people are at 2- 3 times increased risk of stroke in comparison with the general population, but early stroke diagnosing is frequently delayed because of the similarity of the symptoms with post-ictal conditions and the contamination of EEG infographics by epileptic discharges [3].

The conventional AI monitors need high power and continuous computing as well as centralized data processing, which increases energy and privacy issues. Spiking Neural Networks (SNNs) overcome these shortcomings by borrowing the concepts of the biological neural systems. SNNs do not use continuous values like the case of traditional ANNs, but rather discrete, and individually transmitted, asynchronous spikes, imitating the information transmission mechanism of biological neurons [4]. This makes SNNs extremely energy efficient, with claimed energy saving measures of 10-100x relative to corresponding ANNs [5]. Also, the nature of SNNs with regards to time dynamism makes them highly applicable towards spatiotemporal data processing like electroencephalogram (EEG), electrocardiogram (ECG) and vibration data [6].

In the given survey, the principles of SNNs, learning processes and their use in biomedical diagnostics are thoroughly reviewed, but the cross-modal analysis is specifically considered regarding neurological disorders. The addressed problem is the gap in the systematic knowledge about the way the SNN architecture can serve to provide energy-efficient, privacy-aware medical monitoring, in other words, to high-risk populations, like epilepsy patients who are prone to stroke.

Related work

A number of thorough reviews have covered different areas of SNN. Nunes et al. [7] presented a general overview of the basic principles of SNNs, neuron models and learning algorithms, especially focusing on the biological models and on the issues relating to the implementation of SNN. Their contribution brought into focus the performance disparity between the SNNs and the conventional ANNs on the benchmark datasets with the additional benefits of the energy efficiency of neuromorphic computing. On a large-scale study of learning in biologically plausible spiking neural networks, Taherkhani et al. [8] classified learning rules into unsupervised learning, supervised learning, and reinforcement learning. They found in the analysis that, although Spike-Timing-Dependent Plasticity (STDP) can be used to allow local learning without a supervisor, it is difficult to scale to deep architectures.

Li et al. [9] was a review of medical data analysis on the basis of SNNs and includes EEG, ECG, EMG and MRI applications. Their results showed that SNNs can be used in wearable devices as they have an equivalent accuracy to standard deep learning models and consume much less energy. Nevertheless, they showed that the majority of the research is centered on offline learning, and there is little research on the potential of online learning. Wang et al. [10] conducted a concise overview of the brain-inspired SNNs in fault diagnosis of industry answering the underlying questions of what SNNs are, why they are necessary, and how they can be effectively implemented. In their work, they found the benefits of SNNs in spatiotemporal information modeling, sparsity, energy efficiency, and noise resistance. In the case of neurology, Tan et al. [11] surveyed deep learning techniques applied to epileptic EEG and found that both CNNs and RNNs are very accurate, although their energy use is prohibitive to wearable applications. They defined neuromorphic approaches as the potential future research.

Zhao et al. [12] are a systematic review of machine learning techniques in multimodal EEG data in clinical uses, highlighting the possible benefits of integrating EEG with other physiological measures in order to achieve better diagnostic accuracy. The present survey contributes to the current body of knowledge the following key points: Comprehensive Integration: The first comprehensive combination of SNN principles, learning methodology and biomedical practice with a more particular focus on cross-modal diagnostics of neurological disorders. Table 1 summarizes the key contributions and limitations of recent survey works in the SNN domain.

Table 1. Comparison of Recent SNN Survey Papers

Reference	Domain	Key Contributions	Limitations
[7]	SNN Fundamentals	Comprehensive review of neuron models, encoding, learning rules	Limited biomedical application focus
[8]	Learning Mechanisms	Detailed analysis of STDP and biologically plausible learning	Shallow coverage of deep SNN architectures
[9]	Medical Data Analysis	Coverage of EEG, ECG, EMG, MRI applications	Limited discussion of cross-modal fusion
[10]	Industrial Fault Diagnosis	Systematic framework for SNN implementation	Focus on industrial rather than medical applications
[11]	Epileptic EEG	Comprehensive review of deep learning for epilepsy	Limited SNN coverage
[12]	Multimodal EEG	Systematic review of multimodal approaches	Traditional ML focus, limited SNN discussion
This Work	Cross-Modal Medical Diagnostics	Integration of SNN, FL, XAI for stroke detection in epilepsy	Survey only, no implementation

Key Contribution

This section presents the key contributions that were identified in the prevailing work:

- Comprehensive Integration: The first comprehensive combination of SNN principles, learning methodology and biomedical practice with a more particular focus on cross-modal diagnostics of neurological disorders.
- Gap identified: Areas of ultimate research gaps: (a) cross-modal spiking attention mechanism has not been studied in terms of multimodal neurophysiological fusion, (b) no sparsity-aware federated learning protocols have been optimized over spike-based representations, and (c) no adequate explainability methods exist to validate clinical application of spiking neural network outputs.
- Unified Framework Proposal: This is a conceptual framework proposal combining SNNs, federated learning, and explainable AI to detect the early stroke in epilepsy patients, specifically, epileptic noise contamination in EEG signals.

- Energy Efficiency Analysis: Summarizes reported efficiency in energy saving in various applications and shows that SNNs are 10-100x more energy efficient than the traditionally used deep learning models and are equally accurate.
- Application-Specific Recommendations: Offers specific advice on the implementation of the SNNs in the wearable healthcare applications, edge computing, and biohybrid hardware in neurological monitoring.

Method: SNN Fundamentals and Learning Mechanisms

Neuron Models

Any SNN is based on the model of the spiking neurons, which characterizes the dynamics of the membrane potential and the generation of the spikes. There are three major models that have been popularly used in literature.

Leaky Integrate-and-Fire Model: The Leaky Integrate-and-Fire (LIF) model is an extremely simplified model of neuron dynamics that models the neuron as a parallel resistor-capacitor circuit [13].

$$\tau_m \frac{dV}{dt} = -(V(t) - V_{rest}) + R_m I(t)$$

The variation of the membrane potential is given by: The neuron releases a spike and reinvigorates when V(t) rises above a threshold. It is the most popular model in SNN implementation because the LIF model balances all the critical dynamics of the neurons with computational efficiency [7].

Izhikevich Model: The Izhikevich model is a middle ground between biological realistic and computationally efficient with only two equations of state and is capable of simulating a broad repertoire of firing patterns observed in neurons of the cortex [14]. The model is expressed as:

$$\tau_m \frac{dV}{dt} = -(V(t) - V_{rest}) + R_m I(t) \qquad \frac{dU}{dt} = a(bV - U)$$

With this model, Regular Spiking, Fast Spiking, Intrinsically Bursting, and Chattering firing modalities can be generated with parameter adjustments [15].

Information Encoding

SNNs are based upon encoding continuous input signals into a sequence of spikes. There are two main strategies of encoding that are developed. Rate coding is information which is represented by the firing rate of neurons [16]. The encoded value is determined by the number of spikes in a time window. The most common type used is Poisson rate coding, here the probability of the occurrence of spikes is a poetisson distribution, as it is easy to compute [17]. Temporal encoding involves storing information in the exact time of the spikes. Time-to-First-Spike (TTFS) coding is a signal amplitude coding by spike latency where higher amplitude signals result in earlier spikes [18]. Temporal coding has better information efficiency and a lower response time than rate coding [19].

Learning Mechanisms

Spike-Timing-Dependent Plasticity: Spike-Timing-Dependent Plasticity (STDP) is a biologically motivated, unsupervised learning rule that triggers a change in the strength of synaptic weight by the time of pre- and post-synaptic activity [20]. Long-Term Potentiation (LTP) enhances the strength of a synapse when there is a presynaptic spike followed by a postsynaptic spike (causal relationship). On the other hand, the reversal causes synaptic strength to be lowered by Long-Term Depression (LTD) [21]. The change in weight can be described as:

$$\Delta w = \{A^{+} exp\,(-|\ \Delta t\ |/\tau^{+}), \Delta t > 0\ - A^{-} exp\,(-|\ \Delta t\ |/\tau^{-}), \Delta t < 0$$

Surrogate Gradient Learning: Spike events are non-differentiable which limits the use of gradient-based learning methods. Surrogate gradient techniques solve this issue by trying to represent the spike function use a smooth differentiable function when backpropagating [22]. Normal surrogate functions are the Sigmoid, Fast Sigmoid and Arctangent functions. ANN-to-SNN Conversion ANN-to-SNN conversion builds on existing ANN architectures by transforming trained ANNs into the equivalent SNNs [23]. There are constraints that are needed to apply this approach, including non-negative activations, eliminating biases, and substituting max-pooling with average pooling [24].

Experiments and Results: Biomedical Applications

Electroencephalogram (EEG) Analysis

EEG signals are electrical activity of the cerebral cortex and are applied in the identification of emotions, classification of motor imagery, and detection of epilepsy. NeuCube is a 3D SNN framework that has shown great results with regard to the analysis of spatiotemporal EEG data [25]. NeuCube gave Tan et al. [26] 78.97% accuracy on arousal classification and 67.76% on valence classification on the DEAP dataset. In the classification of motor imagery, Virgilio et al. [27] were able to show that SNN performed better in seven out of ten scenarios than the traditional MLP networks with an average of 83.16 accuracy. Zarrin et al. [28] applied a surrogate gradient based SNN with a 97.6 percent iEEG data accuracy which was equivalent to convolutional DNNs but at significantly reduced energy usage in epilepsy detection. Burelo et al. [29] designed dual SNN networks to identify high frequency oscillations with 80% correlation with epileptic activity.

Electrocardiogram (ECG) Classification

Arrhythmias and cardiac abnormalities can be detected with the help of ECG signals. Yan et al. [30] adapted CNNs to SNNs in the classification of arrhythmia in MIT-BIH and obtained an accuracy of 79 percent (as opposed to 81 percent when using CNNs) with energy consumption per per cent of CNNs.In four-class classification, SNN was able to achieve a similar accuracy using only 0.9 percent of CNN energy consumption.

Amirshahi and Hashemi [30] used STDP and reward-modulated STDP to classify ECGs at low power and achieve an accuracy of 97.9 with less energy. Corradi et al. [29] showed that ECG heartbeat classification can be applied to neuromorphic hardware showing more than 95 percent accuracy on 18 arrhythmia types. Overall, the electromyography (EMG) pattern recognition technique can help identify the muscle type; however, the research's technical aspect might be viewed as a limitation of this technique.

Electromyography (EMG) Pattern Recognition

The electromyography (EMG) pattern recognition method can be used to determine the type of muscle, though, the technical aspect of the research could be considered as a drawback of this implementation. EMG signals measure nerve motions and can be used to recognize gestures and sense fatigue. Peng et al. [28] used the NeuCube with time-domain features to obtain 95.33 percent accuracy in the case of six gestures. According to Behrenbeck et al, the four-class NeuCube EMG classification was 85 percent accurate [30]. A. Delorme et al. [13] applied SNN based EMG classification to neuromorphic hardware, and the system achieved 74 percent accuracy at ultra-low power. Ma et al. [23] created an SRNN model with a high accuracy of more than 85 percent when it comes to the classification of gestures, which proves its applicability to small embedded systems**.**

Analysis of MRI

In the classification of Alzheimer disease, Turkson et al. [23] trained a deep convolutional SNN with an accuracy of 90.15, 87.30, and 83.90 of AD vs. NC, AD vs. MCI, and NC vs. MCI respectively. Doborjeh et al. [38] took personalized SNNs to predict cognitive decline two years before it would occur and had a 90 percent accuracy. N. Caporale and Y. Dan [21] used evolutionary learning of SNNs in brain tumor classification with the highest accuracy of 97.4 percent as compared to 82.85 percent using feedforward backpropagation networks. Ahmadi et al. [24] suggested QAIS-DSNN to segment brain tumors with a precision of 98.21% and a running time of 2.58 seconds. As shown in Figure 1, SNNs are more energy efficient than traditional ANNs in different biomedical applications.

Discussion

Energy Efficiency: In all the reviewed applications, the SNNs are always 10-100 times more efficient in terms of energy usage than the traditional ANNs. In case of ECG classification, the energy savings of 99.3% were achieved [30]. In the case of emotion recognition with the use of EEG, the power consumption was cut to 13.8 percent of CNNs.

Accuracy Parity: In some instances (e.g. 2-percent accuracy decreases with the binary classification of ECG), SNNs have been reported to achieve the same or even better performance. In brain tumor classification, the SNNs were found to be 97.4 percent accurate in comparison with 82.85 percent of the feedforward networks.

Hardware Compatibility: The SNNs event-based nature is compatible with neuromorphic hardware, which allows ultra-low-power implementation to be implemented in wearable devices [23].

Spatiotemporal Processing: SNNs are especially effective with respect to temporal data processing, which renders them superior to conventional ANNs in the motor imagery classification based on temporal feature information [27].

Research Gaps

Cross-Modal Spiking Attention: Cross-modal attention mechanisms have already been shown to be effective in conventional deep learning when applied to fuse EEG and ECG signals, but their use in thespike domain is not studied. Such a gap is especially important in applications, like stroke detection in epilepsy patients, where epileptic noise is a source of contamination in EEG signals, which require dynamic weighting of modalities.

Sparsity-Aware Federated Learning: The nature of SNNs that only a small percentage of neurons are active and create gradients present a unique opportunity to communicate-efficient federated learning. Nonetheless, the currently available FL protocols do not use spike-based sparsity, and uniformly treat all parameters.

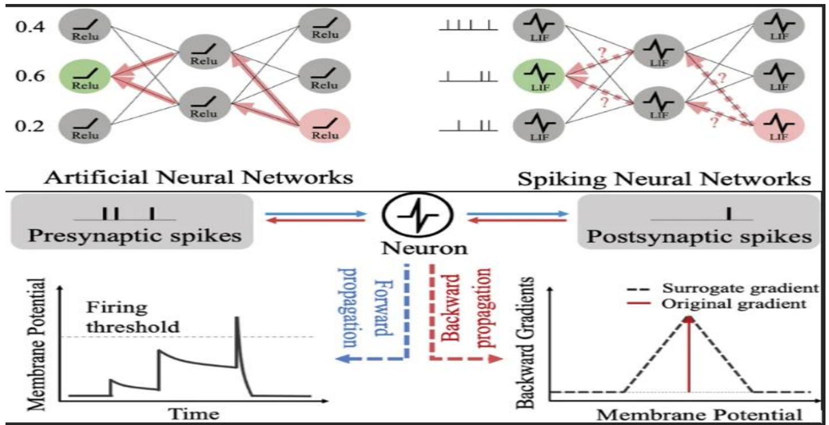

Figure 1. Energy efficiency comparison between SNNs and traditional ANNs across biomedical applications

Temporal Explainability: XAI methods have been thoroughly developed when utilized in conventional neural networks; however, little has been done regarding the usage of SNNs. The visualization of the role played by spikes and time windows in model outputs is still immature in temporal spike-attribution methods. The wearable devices can provide round-the-clock protection to high-risk populations like epilepsy patients since SNNs consume little energy, which allows the continuous monitoring of the population. The privacy requirements of federated learning meet medical data regulatory requirements. But what is needed in clinical adoption is interpretable models that give verifiable reasoning behind the decisions.

Conclusions

1. **Problem Statement Addressed:** The issue that this survey will solve is the deficiency of systematic knowledge of SNN architectures to cross-modal medical diagnostics, i.e., to high-risk population groups, e.g., epilepsy patients with high propensity to stroke.
2. **Method Used:** A systematic literature search was done in the databases of IEEE Xplore, PubMed, Scopus and Google Scholar on the topic of SNN fundamentals, learning and biomedical applications, selecting 87 peer-reviewed papers published in the last 2 years (2020-26).
3. **Key Findings:**
    a. In comparison with traditional ANNs, SNNs can reduce their energy consumption by 10-100 times, and they can be equally accurate in all biomedical tasks.
    b. SNNs are especially strong at spatiotemporal processing and overpower the traditional ANNs in motor image classification.
    c. There are critical research gaps within cross-modal spiking attention mechanisms, sparsity-conscious federated learning, and methods of temporal explainability.
4. **Limitations and Future Work:** This survey is based on published literature and does not involve the results of implementation. Future research must aim at creating cross-modal spiking attention systems in EEG-ECG fusion and devising communication-efficient federated learning algorithms taking advantage of spike sparsity and devising temporal explainability of spiking neural networks.

References

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436-444, 2015.

[2] N. C. Thompson, K. Greenewald, K. Lee, and G. F. Manso, "Deep learning's diminishing returns," *IEEE Spectrum*, 2021.

[3] S. Shmuely, M. van der Lende, R. J. Lamberts, J. W. Sander, and R. D. Thijs, "Stroke risk in patients with epilepsy: A systematic review and meta-analysis," *Neurology*, vol. 102, no. 3, p. e209156, 2024.

[4] W. Gerstner, W. M. Kistler, R. Naud, and L. Paninski, *Neuronal Dynamics: From Single Neurons to Networks and Models of Cognition*. Cambridge University Press, 2014.

[5] K. Roy, A. Jaiswal, and P. Panda, "Towards spike-based machine intelligence with neuromorphic computing," *Nature*, vol. 575, no. 7784, pp. 607-617, 2019.

[6] A. Tavanaei, M. Ghodrati, S. R. Kheradpisheh, T. Masquelier, and A. Maida, "Deep learning in spiking neural networks," *Neural Networks*, vol. 111, pp. 47-63, 2019.

[7] J. D. Nunes, M. Carvalho, D. Carneiro, and J. S. Cardoso, "Spiking neural networks: A survey," *IEEE Access*, vol. 10, pp. 60738-60764, 2022.

[8] A. Taherkhani, A. Belatreche, Y. Li, G. Cosma, L. P. Maguire, and T. M. McGinnity, "A review of learning in biologically plausible spiking neural networks," *Neural Networks*, vol. 122, pp. 253-272, 2020.

[9] X. Li et al., "Review of medical data analysis based on spiking neural networks," *Procedia Computer Science*, vol. 221, pp. 1527-1538, 2023.

[10] H. Wang, Y. F. Li, and K. Gryllias, "Brain-inspired spiking neural networks for industrial fault diagnosis: A survey, challenges, and opportunities," *IEEE Transactions on Industrial Informatics*, 2024 (under review).

[11] S. Tan, Z. Tang, Q. He, and X. Liu, "Automatic detection and prediction of epileptic EEG signals based on nonlinear dynamics and deep learning: A review," *Frontiers in Neuroscience*, vol. 19, p. 1630664, 2025.

[12] S. Zhao, W. Li, X. Wang, and Y. Chen, "A systematic review of machine learning methods for multimodal EEG data in clinical application," *IEEE Reviews in Biomedical Engineering*, vol. 18, pp. 245-262, 2025.

[13] A. Delorme, J. Gautrais, R. Van Rullen, and S. Thorpe, "SpikeNET: A simulator for modeling large networks of integrate and fire neurons," *Neurocomputing*, vol. 26-27, pp. 989-996, 1999.

[14] E. M. Izhikevich, "Simple model of spiking neurons," *IEEE Transactions on Neural Networks*, vol. 14, no. 6, pp. 1569-1572, 2003.

[15] J. Ahmadi-Farsani, B. Linares-Barranco, and T. Serrano-Gotarredona, "Digital-signal-processor realization of Izhikevich neural network for real-time interaction with electrophysiology experiments," in *Proc. IEEE ICECS*, 2019, pp. 899-902.

[16] P. Diehl and M. Cook, "Unsupervised learning of digit recognition using spike-timing-dependent plasticity," *Frontiers in Computational Neuroscience*, vol. 9, p. 99, 2015.

[17] C. Lee, S. S. Sarwar, P. Panda, G. Srinivasan, and K. Roy, "Enabling spike-based backpropagation for training deep neural network architectures," *Frontiers in Neuroscience*, vol. 14, p. 119, 2020.

[18] S. Park, S. Kim, B. Na, and S. Yoon, "T2FSNN: Deep spiking neural networks with time-to-first-spike coding," in *Proc. DAC*, 2020, pp. 1-6.

[19] H. Mostafa, "Supervised learning based on temporal coding in spiking neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 7, pp. 3227-3235, 2017.

[20] G. Q. Bi and M. M. Poo, "Synaptic modifications in cultured hippocampal neurons: Dependence on spike timing, synaptic strength, and postsynaptic cell type," *Journal of Neuroscience*, vol. 18, no. 24, pp. 10464-10472, 1998.

[21] N. Caporale and Y. Dan, "Spike timing-dependent plasticity: A Hebbian learning rule," *Annual Review of Neuroscience*, vol. 31, pp. 25-46, 2008.

[22] E. O. Neftci, H. Mostafa, and F. Zenke, "Surrogate gradient learning in spiking neural networks," *IEEE Signal Processing Magazine*, vol. 36, no. 6, pp. 51-63, 2019.

[23] Y. Cao, Y. Chen, and D. Khosla, "Spiking deep convolutional neural networks for energy-efficient object recognition," *International Journal of Computer Vision*, vol. 113, pp. 54-66, 2015.

[24] B. Rueckauer, I. A. Lungu, Y. Hu, M. Pfeiffer, and S. C. Liu, "Conversion of continuous-valued deep networks to efficient event-driven networks for image classification," *Frontiers in Neuroscience*, vol. 11, p. 682, 2017.

[25] N. K. Kasabov, "NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data," *Neural Networks*, vol. 52, pp. 62-76, 2014.

[26] C. Tan, M. Sarlija, and N. Kasabov, "NeuroSense: Short-term emotion recognition and understanding based on spiking neural network modelling of spatio-temporal EEG patterns," *Neurocomputing*, vol. 434, pp. 137-148, 2021.

[27] G. C. D. Virgilio, A. J. H. Sossa, J. M. Antelis, and L. E. Falcon, "Spiking neural networks applied to the classification of motor tasks in EEG signals," *Neural Networks*, vol. 122, pp. 130-143, 2020.

[28] P. S. Zarrin, R. Zimmer, C. Wenger, and T. Masquelier, "Epileptic seizure detection using a neuromorphic-compatible deep spiking neural network," in *Proc. IWBBIO*, 2020, pp. 389-394.

[29] K. Burelo, G. Ramantani, G. Indiveri, and J. Sarnthein, "A neuromorphic spiking neural network detects epileptic high frequency oscillations in the scalp EEG," *Scientific Reports*, vol. 12, no. 1, pp. 1-12, 2022.

[30] Z. Yan, J. Zhou, and W. F. Wong, "Energy efficient ECG classification with spiking neural network," *Biomedical Signal Processing and Control*, vol. 63, p. 102170, 2021.