

Spiking Neural Networks for the Analysis of Physiological Signals

Alexander Brady and Hisham Daoud * 

School of Computer and Cyber Sciences, Augusta University, Augusta, GA 30912, USA; abrady@augusta.edu

* Correspondence: hdaoud@augusta.edu

Abstract

Physiological signals, such as electroencephalograms (EEG), electrocardiograms (ECG), and electromyograms (EMG) play a critical role in modern clinical diagnosis, monitoring, and rehabilitation. While deep artificial neural networks (ANNs) have achieved strong performance in analyzing these signals, their high computational cost and energy demands limit deployment in real-time, wearable, and edge-based healthcare systems. Spiking Neural Networks (SNNs), inspired by biological neural computation, offer an event-driven alternative that naturally captures temporal dynamics and enables energy-efficient inference. This article provides a comprehensive review of SNN-based methods for physiological signal analysis across EEG, ECG, and EMG modalities. We survey neuron models, network architectures, encoding schemes, and training methodologies, and systematically review recent state-of-the-art applications in medical diagnosis and rehabilitation. Through analysis, we identify recurring architectural and methodological trends that indicate the dominance of convolution-based spiking architectures, the critical role of encoding strategies in determining energy efficiency, and the task-dependent nature of SNN training approaches. Despite demonstrating performance comparable to conventional deep learning models, often at significantly reduced computational cost, SNN research remains challenged by inconsistent evaluation protocols, limited benchmark standardization, and restricted clinical validation. We conclude by outlining key open challenges and future research directions, emphasizing the need for standardized benchmarks, encoding-aware training, and hybrid ANN–SNN systems. As neuromorphic hardware and event-driven learning methods continue to mature, SNNs are well-positioned to introduce scalable, low-power physiological signal processing for next-generation intelligent healthcare systems.

Keywords: architectures; ECG; EEG; EMG; encoding schemes; learning rules; neuron models; physiological signals; Spiking Neural Network



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1. Introduction

Physiological signals provide non-invasive measurements of underlying biological processes and form the foundation of modern clinical diagnosis, monitoring, and disease prediction. Signals such as electroencephalograms (EEG), electrocardiograms (ECG), electromyograms (EMG), and other signals are routinely used to assess neurological, cardiovascular, and neuromuscular function across a wide range of clinical settings. These signals are inherently temporal, non-stationary, and often noisy, exhibiting complex interactions between normal physiological activity and pathological states. Accurate and efficient analysis of physiological time-series data is therefore critical for early disease detection, long-term patient monitoring, and the deployment of personalized and wearable healthcare technologies.

In recent years, machine learning and artificial intelligence approaches, such as deep Artificial Neural Networks (ANNs), have demonstrated strong performance in physiological signal analysis. However, many state-of-the-art ANN-based models rely on continuous-valued computation and high computational resources, which can limit their suitability for real-time, low-power clinical applications. These constraints are especially relevant in wearable and edge-based systems, where energy efficiency, latency, and on-device processing are essential. As a result, there is growing interest in alternative computational paradigms that can better align with the temporal nature of physiological signals while operating under strict resource constraints.

Spiking Neural Networks (SNNs), often regarded as the third generation of neural networks, offer a biologically inspired framework for processing time-dependent data using event-driven computation. By representing information through discrete spikes, SNNs have the potential to reduce computational overhead while preserving the ability to model complex temporal patterns. These properties make SNNs an increasingly attractive approach for physiological signal analysis, particularly in applications involving continuous monitoring, real-time inference, and power-efficient wearable devices.

This review provides a comprehensive overview of the explicit role SNNs play in physiological signal modalities, as well as addresses their performance in diagnostic challenges associated with their analysis. This review builds upon existing surveys by providing a consolidated perspective across EEG, ECG, and EMG modalities, while emphasizing the relationships between encoding strategies, model design, and deployment considerations in SNN-based physiological signal analysis. Additionally, we highlight the current challenges of using SNNs for the analysis of physiological signals and provide recommendations and future directions to overcome those challenges that could guide new researchers in the field. We first characterize the physiological signals considered in this work and outline the key challenges they present. We then review SNN models, encoding schemes, neuron dynamics, and training methodologies relevant to physiological data. Finally, we survey recent state-of-the-art applications of SNNs across multiple physiological domains, discuss current limitations, and highlight promising directions for future research.

Search Strategy

To acquire the articles presented within this review, we used the following search strings and their combinations:

- “EEG”, “ECG”, “EMG”, and “Physiological signals”;
- “Spiking”, “Spiking Neural Network”, and “SNN”;
- “Architectures”, “Encoding schemes”, “Learning rules”, and “Neuron models”;
- “Time-series”.

while the searches were conducted on the following academic research databases:

- Google Scholar;
- IEEE Xplore;
- MDPI;
- ResearchGate;
- Scopus.

2. Physiological Signals and Their Significance

Physiological signals such as electroencephalograms (EEG), electrocardiograms (ECG), and electromyograms (EMG) provide non-invasive measurements of underlying biological processes and play a central role in the diagnosis, monitoring, and prediction of a wide range of neurological, cardiovascular, and neuromuscular disorders. These signals are inherently temporal, exhibiting complex, non-stationary dynamics that reflect both normal

physiological function and pathological states. Accurate analysis of physiological time-series data is therefore critical for early disease detection, long-term patient monitoring, and the development of personalized and wearable healthcare technologies. In the following section, we characterize the physiological signals considered in this review and outline the key diagnostic challenges they present.

2.1. Electroencephalogram (EEG)

Electroencephalograms (EEG) record the electrical activity of the brain by measuring voltage fluctuations along the cerebral cortex. These recordings provide clinically relevant information for the diagnosis of neurological disorders (e.g., epilepsy, Alzheimer's disease), often manifested as transient abnormalities characterized by abrupt spiking activity or amplitude variations. EEG signals are typically low in amplitude and are predominantly composed of rhythmic oscillatory patterns (Figure 1), which are commonly categorized into five primary frequency bands:

- Delta 0.5–4 Hz, associated with deep sleep;
- Theta 4–8 Hz, associated with light sleep or meditative states;
- Alpha 8–12 Hz, associated with relaxed wakefulness;
- Beta 12–30 Hz, associated with active cognition and alertness;
- Gamma > 30 Hz, associated with memory processing and perception.

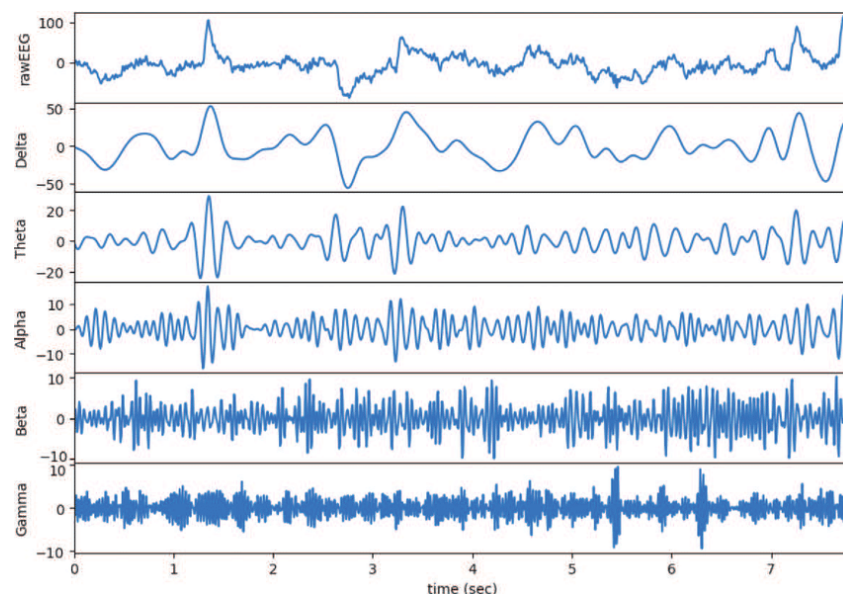


Figure 1. EEG Wavelets for different brain states [1].

While SNNs have been explored across diverse EEG signal analysis tasks, including emotion recognition and motor control, diagnostic applications (e.g., epileptic seizure detection and prediction) serve as a central focus for EEG-based analysis within this review. Nevertheless, many of the discussed models and methods are broadly applicable to other neurological conditions and EEG-based analysis tasks.

2.2. Electrocardiogram (ECG)

Electrocardiograms (ECG) capture the electrical activity generated by the heart. In comparison to EEG, ECG signals typically exhibit higher amplitudes and are acquired using multiple electrode leads placed at standardized locations. The ECG waveform (Figure 2) is composed of three primary components:

- P-wave, representing atrial depolarization;

- QRS complex, representing ventricular depolarization;
- T-wave, representing ventricular repolarization.

ECGs are primarily used to capture rhythmic activity and detect cardiovascular anomalies, such as arrhythmia, ischemia and myocardial infarction.

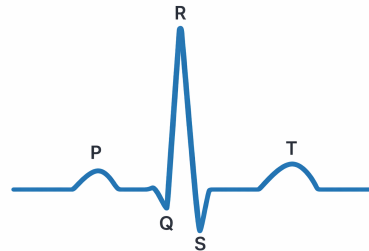


Figure 2. ECG waveform illustrating P-wave, QRS complex, and T-wave.

2.3. Electromyogram (EMG)

Electromyograms (EMG) quantify muscular activity by recording the electrical potentials generated during muscle contraction. Compared to EEG and ECG, EMG signals present unique analytical challenges, as they are highly susceptible to motion artifacts and cross-talk from adjacent muscles. In addition, even minor variations in electrode placement (i.e., electrode shift) can significantly impact signal quality and recording reliability. Despite these challenges, EMG signals play a critical role in the diagnosis of neuromuscular disorders, as well as in the control of prosthetic and assistive devices. The amplitude and frequency characteristics (Figure 3) of EMG signals vary depending on the specific muscle group and level of activation:

- Amplitude, μV to mV depending on muscle and activation level;
- Frequency, 10–500 Hz.

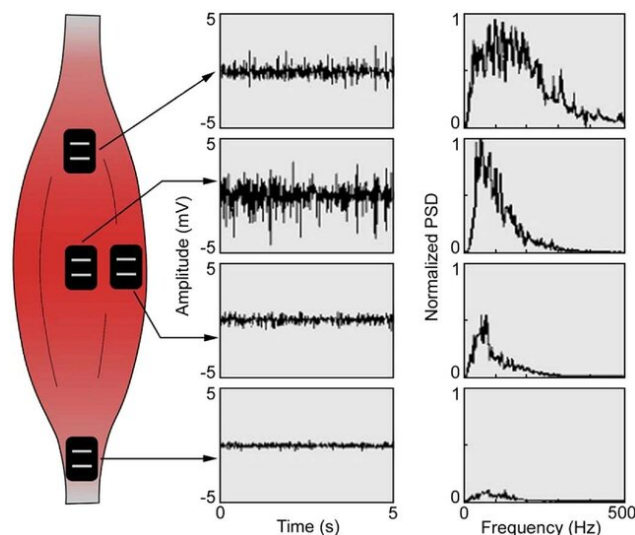


Figure 3. The amplitude and spectrum of EMG signals as a function of electrode location, with respect to the muscle [2].

At this time, the body of literature investigating SNN-based approaches for diagnostic applications using EMG signals remains limited, making comprehensive comparative evaluation difficult. In contrast, SNNs have been extensively applied to EMG classification tasks within myoelectric control systems. Such systems have demonstrated significant clinical value, such as in the rehabilitation of individuals with neuromuscular disorders and limb amputations.

3. Spiking Neural Networks

Spiking Neural Networks (SNNs) are a class of neural networks inspired by the event-driven communication mechanisms of biological neural systems, where information is transmitted through discrete spikes rather than continuous signals. This spike-based formulation enables SNNs to naturally process temporal information and operate in an event-driven manner, which can significantly reduce computational overhead while still preserving expressive temporal modeling capabilities [3]. These properties make SNNs particularly well-suited for physiological time-series data, where relevant information is often sparse and distributed across time. Ongoing advances in neuron models, network architectures, encoding schemes, and training methods continue to improve the accuracy, efficiency, and scalability of SNNs, helping to further expand their applicability. As a result, SNNs have emerged as competitive candidates for medical applications that require low computational cost and high accuracy, including edge computing deployments on neuromorphic hardware such as wearable EEG and ECG sensors [4]. Important note: A common postulate underlying the evaluation of spiking neural networks is that their energy efficiency is realized under deployment on neuromorphic hardware. While SNNs can be simulated on conventional von Neumann architectures, such platforms do not inherently exploit the event-driven and sparse computational paradigm that enables their efficiency advantages.

In this section, we review key SNN methodologies employed in the literature for physiological diagnosis.

3.1. Neuron Models

SNNs are inspired by the biological processes of the human nervous system and brain, where information is processed and transmitted through networks of interconnected neurons. In biological neural systems, neurons act as information-processing units, communicating with one another through synapses by emitting discrete electrical events, commonly referred to as spikes. This spike-based mode of communication enables the efficient transmission of information over time and forms the conceptual foundation of spiking neural computation [5].

Similarly, SNNs propagate information through networks of artificial neurons using discrete spikes, with overall network behavior emerging from the collective dynamics of individual neuron models. The choice of neuron model plays a critical role in determining the computational properties of an SNN. While conductance-based neuron models, such as the Hodgkin–Huxley and FitzHugh–Nagumo formulations, provide biologically accurate representations of neuronal membrane dynamics, their high dimensionality and computational complexity limit their practical use in large-scale or resource-constrained SNN applications. As a result, simplified neuron models are more commonly employed in modern SNN-based physiological signal analysis [5].

Threshold-based spiking neuron models, on the other hand, provide a favorable balance between biological plausibility and computational efficiency by abstracting neuronal dynamics to membrane potential integration and spike generation governed by fixed or adaptive thresholds. Models such as the Leaky Integrate-and-Fire (LIF), Exponential Integrate-and-Fire (EIF), and Adaptive Exponential Integrate-and-Fire (AdEx) reduce the dimensionality and computational overhead associated with conductance-based formulations, while still preserving key temporal characteristics of neuronal firing. Owing to their event-driven operation and efficient temporal integration, these models are widely adopted in practical SNN implementations for processing time-series biomedical data. As highlighted in the literature, threshold-based neuron models form the backbone of many SNN architectures applied to physiological signal analysis, thus helping to enable

effective modeling of temporal dynamics in signals such as EEG, ECG, and EMG under resource-constrained and real-time settings [6].

In this section, we summarize the neuron models most commonly adopted in the SNN literature. This discussion is not intended to provide an exhaustive survey of all existing spiking neuron formulations, but rather to focus on those models that are most frequently applied in the context of physiological signal analysis and diagnostic applications.

3.1.1. Izhikevich

The Izhikevich neuron model, conceptually rooted in the Hodgkin–Huxley (HH) framework, originates from conductance-based formulations but reduces their dimensional complexity. It is specifically designed to retain much of the biological realism of the HH model while approaching the computational efficiency of the Leaky Integrate-and-Fire (LIF) model. This balance is achieved through a simplified system of coupled differential equations [7]:

$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I, \quad (1)$$

$$\frac{du}{dt} = a(bv - u). \quad (2)$$

where

- v is the membrane potential of the neuron;
- u is the membrane recovery variable;
- a, b, c, d are dimensionless parameters that define neuron type and firing behavior;
- I is the input current.

After the neuron fires ($v \geq 30$ mV), it resets with respect to:

$$v \leftarrow c, \quad u \leftarrow u + d. \quad (3)$$

This means that after the spike occurs, the values v and u are updated to, or assigned the values of c and $u + d$, respectively.

3.1.2. Integrate-and-Fire (IF)

The Integrate-and-Fire (IF) neuron represents the simplest form of a threshold-based spiking neuron model. It offers an abstracted description of biological neuronal behavior by accumulating incoming input currents over time.

The membrane potential dynamics of the IF neuron are governed by:

$$\frac{dV}{dt} = \frac{R}{\tau_m} I(t). \quad (4)$$

where

- V is the membrane potential;
- τ_m is the membrane time constant;
- R is the membrane resistance;
- $I(t)$ is the input current.

When the membrane potential, V , reaches a predefined threshold, V_T , the neuron emits a spike and the membrane potential is reset to V_{reset} [5].

3.1.3. Leaky Integrate-and-Fire (LIF)

The Leaky Integrate-and-Fire (LIF) neuron extends the standard threshold-based IF model by incorporating membrane leakage dynamics. While the IF model provides a simplified abstraction of neuronal behavior by integrating incoming inputs until a threshold

is reached, the LIF model introduces a decay term that models the gradual loss of membrane potential over time.

The membrane potential dynamics of the LIF neuron are governed by:

$$\frac{dV}{dt} = -\frac{1}{\tau_m}(V - E_m) + \frac{R}{\tau_m}I(t). \quad (5)$$

where

- V is the membrane potential;
- τ_m is the membrane time constant;
- E_m is the resting membrane potential;
- R is the membrane resistance;
- $I(t)$ is the input current.

When the membrane potential V reaches a predefined threshold V_T , the neuron emits a spike and the membrane potential is reset to a lower value V_{reset} .

Due to its balance between biological plausibility and computational efficiency, the LIF neuron is the most widely adopted model in practical SNN implementations [8,9]. By accounting for the passive leakage of charge across the neuronal membrane, without explicitly modeling ion-channel conductance dynamics, the LIF formulation serves as an intermediate representation between fully conductance-based models and the basic IF model [5,10].

3.1.4. Exponential Integrate-and-Fire (EIF)

A variation of the LIF model, Exponential Integrate-and-Fire, incorporates exponential spike generation. The exponential component in this model causes the membrane potential of the neuron to shoot up quickly just before the spike threshold, explained by the following formula [5]:

$$\frac{dV}{dt} - \frac{R}{\tau_m}I(t) = \frac{1}{\tau_m}[E_m - V + \Delta_T \exp(\frac{V - V_T}{\Delta_T})]. \quad (6)$$

where

- V_T is the spike initiation threshold;
- τ_m is the membrane time constant;
- E_m is the resting potential;
- Δ_T is the sharpness of action potential initiation.

EIF is a more biologically plausible implementation than the standard LIF model, because it more closely mimics the biological neuron's membrane voltage spiking prior to the neuron firing [11,12]. This makes this model more suited for simulations that require more accurate spiking dynamics.

3.1.5. Adaptive Exponential Integrate-and-Fire (AdEx)

The Adaptive Exponential Integrate-and-Fire (AdEx) model further enhances the biological realism of the EIF formulation by incorporating spike-frequency adaptation mechanisms [13,14]. Specifically, it introduces an adaptation variable w , which increases following each spike event, reflecting the biological tendency of neurons to reduce their firing rate after rapid successive activations. This feature makes the AdEx model particularly suitable for simulating neuronal populations that exhibit adaptive firing behavior, such as those involved in sensory processing. The membrane potential dynamics of the AdEx neuron are governed by the following equation [5]:

$$\tau_m \frac{dV}{dt} = -(V - E_L) + \Delta_T \exp(\frac{V - V_T}{\Delta_T}) - w + RI(t). \quad (7)$$

where

- V_T is the spike initiation threshold;
- τ_m is the membrane time constant;
- E_L is the resting potential;
- Δ_T is the slope factor (how quickly the voltage grows near the threshold);
- w is the adaptation variable;
- $RI(t)$ is the input current scaled by the membrane resistance R .

The first term of the right-hand side of the equation, $-(V - E_L)$, models the leak; the tendency of the membrane voltage to decay to its resting state. The other terms represent the spiking behavior of the neuron, including the exponential component, $\Delta_T \exp(\frac{V-V_T}{\Delta_T})$, the integration of the input current, $RI(t)$, and the adaptation component, $-w$, which slows down the firing rate if the neuron has spiked recently. The temporal dynamics of the adaptation variable, w , can be modeled with the following equation:

$$\tau_w \frac{dw}{dt} = a(V - E_L) - w. \quad (8)$$

where

- τ_w is the time constant;
- a is the level of threshold adaptation.

and the adaptation variable w is increased at each spike.

3.2. SNN Architectures

SNNs consist of interconnected neurons that communicate through synapses using discrete, event-driven spikes rather than continuous-valued activations. This spike-based computation enables biologically inspired temporal processing, while still offering potential gains in computational efficiency. Similar to traditional artificial neural networks (ANNs), SNNs adopt a wide range of architectural paradigms, such as recurrent and convolutional structures, which are adapted from ANN counterparts. This section highlights SNN architectures that are most relevant to recent work on physiological signal analysis.

3.2.1. Recurrent Spiking Neural Networks (RSNN)

Recurrent spiking neural networks (RSNNs) incorporate feedback connections that allow spikes from previous time steps to influence current network states, and thus enable temporal memory and sequential processing [15,16]. These properties make RSNNs well-suited for time-series tasks, such as epileptic seizure detection, where long-term temporal dependencies are critical [17]. However, RSNNs often suffer from training difficulties, including vanishing gradients, which can limit scalability in deeper architectures.

3.2.2. Convolutional Spiking Neural Networks (CSNN)

Convolutional spiking neural networks (CSNNs) extend convolutional neural network principles to the spiking domain, bringing spatio-temporal feature extraction. This is particularly beneficial for physiological signals such as EEG, ECG, and EMG, which contain both spatial structure and temporal dynamics [18]. By operating on discrete spikes, CSNNs support asynchronous, event-driven computation, making them well-suited for low-power, real-time applications [19]. CSNNs are among the most widely adopted SNN architectures in physiological signal analysis [17,20,21].

3.2.3. Neucube

Neucube is a three-dimensional SNN architecture designed for spatio-temporal data modeling, with neurons spatially organized to reflect biological brain structures [22]. Time-

series inputs are encoded into spike trains and then processed through a reservoir-based learning framework, followed by supervised classification [23]. While effective at capturing complex temporal dependencies, Neucube models typically incur higher computational cost and require careful parameter tuning.

3.2.4. Spiking Variable Projection Neural Networks (VPSNN)

Spiking Variable Projection Neural Networks (VPSNNs) integrate variable projection layers with SNNs to perform compact, interpretable feature extraction. Input signals are projected into a latent space and then encoded as spike trains, allowing for energy-efficient classification of physiological data such as ECG signals [24]. Several variants, including convolutional and temporal VPSNNs, have been proposed to extend this framework.

3.2.5. Binarized Spiking Neural Networks (BSNN)

Binarized spiking neural networks (BSNNs) reduce computational and memory costs by using binary-valued weights and activations [25–27]. This design choice makes BSNNs attractive for deployment on resource-constrained neuromorphic hardware.

3.2.6. Multi-Spiking Neural Networks (MuSpiNN)

Multi-Spiking Neural Networks (MuSpiNNs) allow multiple synaptic connections between neuron pairs, enabling neurons to emit multiple output spikes in response to presynaptic activity. This structure enhances representational capacity and preserves fully connected architecture [28,29].

3.2.7. Hybrid Configurations

Hybrid SNN architectures combine spiking networks with complementary models, such as support vector machines or recurrent-convolutional structures to leverage the strengths of multiple paradigms. These hybrid approaches are typically explored in order to improve robustness and performance in physiological signal classification tasks [17,30,31].

3.3. Encoding Schemes

Physiological signals such as EEG, ECG, and EMG are inherently temporal and continuous, requiring efficient encoding strategies to convert them into discrete spike trains suitable for spiking neural networks. Commonly used approaches include Poisson encoding, delta modulation, and rank-based methods, which broadly fall into two categories: rate coding and temporal coding. This section summarizes encoding schemes that have been widely adopted in physiological signal analysis.

3.3.1. Rate Coding

Rate coding represents input intensity through spike frequency, reflecting the biological principle that stronger stimuli elicit higher firing rates [10]. This encoding scheme is well-suited for continuous-valued physiological signals such as EEG and ECG. Variants of rate coding include spike count, spike density, and population rate representations [32]. Additional rate-based approaches include phase coding, in which spikes are generated relative to the phase of an oscillatory reference signal. Phase-based methods can be particularly useful for EEG analysis, where rhythmic oscillatory activity across frequency bands plays a central role in representing neurological states.

A widely used form of rate coding is Poisson encoding, where spikes are generated probabilistically with a firing rate proportional to the input amplitude. This stochastic formulation is effective at handling noisy signals, and has also been applied to EEG-based seizure detection and prediction tasks [31,33].

Rate coding approaches are generally straightforward to implement and often exhibit stable training behavior, making them attractive for continuous-valued physiological signals. However, because information is represented through spike frequency accumulated over time, these methods may require larger numbers of spikes and longer observation windows, potentially increasing latency and reducing energy efficiency compared to sparse temporal encoding schemes.

3.3.2. Temporal Coding

Temporal coding encodes information with precise timing of spikes, rather than their firing rate [10]. Spike timing can be represented relative to absolute time references or through inter-spike relationships, thus resulting in encoding schemes such as time-to-first-spike (TTFS), interspike interval (ISI), and latency coding [32]. Temporal coding strategies are particularly useful for event-driven physiological signals, where diagnostically relevant information may be contained within transient temporal dynamics rather than sustained amplitude variations. For example, TTFS encoding can support rapid inference by allowing stronger stimuli to generate earlier spikes, while ISI-based representations can capture rhythmic and oscillatory characteristics commonly observed in EEG and ECG signals.

A prominent temporal encoding method is delta modulation, in which spikes are generated only when the input signal exceeds a predefined change threshold. This event-driven strategy reduces redundant spikes and improves energy efficiency. For example, Corradi et al. employed delta modulation for real-time ECG heartbeat classification on neuromorphic hardware and demonstrated accurate processing with reduced power consumption [34].

More specialized temporal encoding strategies have also been proposed. Tian et al. introduced a temporal Gaussian random sparse encoding scheme for EEG-based seizure prediction, which transforms continuous signals into time-dependent binary spike sequences while maintaining essential temporal dynamics [21]. Additionally, Banerjee et al. proposed Spiking Hamilton (SH) encoding, a spike-domain adaptation of the Hamilton ECG peak detection algorithm that leverages adaptive-threshold IF neuron dynamics [35,36].

Because temporal coding methods often generate sparse spike activity, they can significantly improve energy efficiency and reduce redundant computation in neuromorphic systems. However, these approaches are typically more sensitive to noise and timing perturbations and may require more precise parameter tuning and synchronization than conventional rate-based methods.

3.3.3. Hybrid Coding

Hybrid encoding approaches combine elements of both rate and temporal coding in order to exploit their complementary strengths [10]. Hybrid coding approaches may be particularly beneficial for physiological signals that contain both long-term amplitude characteristics and short-duration temporal events. By combining rate-based and timing-based information, these methods can improve robustness in noisy biomedical environments, while still preserving temporal sensitivity. For instance, Zarrin et al. employed a hybrid encoding scheme for EEG-based seizure detection, achieving improved classification performance by joining rate-based and temporal features [37]. Similarly, Mehrabi et al. combined Delta-Sigma and rate-based encoding strategies for EEG seizure detection, demonstrating that hybrid spike representations can effectively capture both transient and sustained signal characteristics [38].

Although hybrid methods may improve representational flexibility and classification performance, they often introduce additional architectural complexity and computational overhead due to the simultaneous processing of multiple spike representations.

Overall, the selection of an encoding strategy is highly task-dependent and can substantially influence model sparsity, latency, energy efficiency, and classification performance. Consequently, encoding should be viewed as an integral component of SNN design rather than a simple preprocessing step.

3.4. Learning Rules and Training Methods

Training SNNs remains a central challenge due to the non-differentiability of spike events, which prevents the direct application of conventional backpropagation [10]. To address this limitation, a range of biologically-inspired, gradient-based learning rules have been proposed. These include local plasticity mechanisms, surrogate-gradient approaches, temporal backpropagation techniques, and ANN-to-SNN conversion strategies. This section summarizes training methods that are most relevant to SNN-based physiological signal analysis.

3.4.1. Spike-Timing Dependent Plasticity (STDP)

Spike-timing dependent plasticity (STDP) is a biologically-inspired local learning rule that updates synaptic weights based on the relative timing of pre- and post-synaptic spikes [10,39]. Synapses are strengthened through long-term potentiation when pre-synaptic spikes precede post-synaptic spikes, and weakened through long-term depression when the firing order is reversed [3].

3.4.2. Backpropagation-Based Methods

Several adaptations of backpropagation have been developed for training SNNs. Backpropagation through time (BPTT) treats neuronal membrane potentials as differentiable state variables, thus allowing gradient-based optimization across temporal sequences [10,40]. Building on this idea, spatio-temporal backpropagation (STBP) introduces surrogate derivatives for spike activity, further allowing gradients to be propagated through both spatial and temporal dimensions of SNNs. STBP has demonstrated strong performance on benchmark datasets, such as MNIST and N-MNIST, outperforming competing SNN training approaches [20,41].

3.4.3. Surrogate Gradient Descent (SGD)

Surrogate gradient descent addresses the non-differentiability of spike functions by replacing them with smooth, differentiable approximations during training [10,42]. This enables standard gradient descent techniques to be applied while still preserving the spike-based forward dynamics. Surrogate-gradient methods have been shown to effectively train SNNs on complex spatio-temporal tasks involving physiological signal classification [43].

3.4.4. Spike-Based Implicit Differentiation (SPIDE)

Spike-Based Implicit Differentiation on the Equilibrium State (SPIDE) extends implicit differentiation methods to spiking neural networks by operating directly on spike events during both forward and backward passes. Using equilibrium-state formulations and modified reset dynamics, SPIDE allows for fully event-driven training with reduced approximation error and fewer simulation steps, which helps to improve training efficiency for feedback SNNs [30,44].

3.4.5. SpikeProp and Multi-SpikeProp

SpikeProp is an early supervised learning algorithm that adjusts spike timing using gradient descent in order to minimize errors between the actual and the target spike times [45]. Multi-SpikeProp extends this framework by allowing neurons to emit multiple

spikes, thus increasing representational capacity and improving classification performance in temporal tasks, such as epileptic seizure detection [28].

3.4.6. Direct Conversion Methods

Direct ANN-to-SNN conversion provides an alternative training strategy by mapping pre-trained artificial neural networks to spiking equivalents, typically using threshold-based neuron models [46,47]. Synaptic weights are transferred directly, followed by optional fine-tuning using SNN-specific learning rules, such as STDP or surrogate-gradient methods, in order to adapt the network to spike-based computation [20].

4. Evaluation Metrics and Validation Protocols

The evaluation of SNNs for physiological signal analysis commonly relies on performance metrics such as accuracy, sensitivity, specificity, F1-score, and the area under the receiver operating characteristic curve (AUROC).

Accuracy provides an overall measure of classification performance, while sensitivity and specificity quantify a model's ability to correctly identify positive and negative classes, respectively. Because many physiological signal analysis tasks involve class imbalance, particularly in applications such as epileptic seizure prediction and arrhythmia detection, additional metrics, such as F1-score and AUROC, are frequently reported in order to provide a more comprehensive assessment of model performance. Consequently, comparisons between studies should consider multiple evaluation metrics rather than relying solely on overall accuracy.

In addition to performance metrics, differences in validation protocols can substantially influence reported results. Many studies use patient-specific evaluation, in which training and testing data originate from the same subject. While this approach is useful for assessing personalized diagnostic systems, it often benefits from reduced inter-subject variability and therefore may produce higher classification performance. In contrast, cross-patient evaluation requires models to generalize across multiple unseen subjects and is generally considered a more challenging and realistic assessment of deployment performance. As a result, direct comparison between patient-specific and cross-patient studies should be approached with caution.

Further variability arises from differences in dataset selection, preprocessing methodologies, and experimental design. Studies frequently utilize different benchmark datasets, recording durations, signal acquisition protocols, and preprocessing pipelines, all of which can influence classification performance. In seizure prediction applications, additional factors such as the definition of preictal intervals, prediction horizons, seizure occurrence periods, and post-processing methods may further affect reported results. Consequently, performance metrics reported across different studies do not always reflect equivalent experimental conditions.

With these considerations in mind, Section 5 reviews recent SNN-based approaches for EEG, ECG, and EMG analysis.

5. Recent Work & Comparative Analyses for SNN Methods in Addressing Problems for Physiological Signals

5.1. Problems and Recent Work with EEG

We now examine recent advances in SNN-based EEG signal classification, with particular emphasis on applications in medical diagnosis and rehabilitation. A comparative analysis of state-of-the-art SNN approaches, evaluated on common datasets and identical task formulations, enables a more equitable assessment of performance across methodologies.

5.1.1. Epileptic Seizure Detection

In the context of epileptic seizure detection, research primarily focuses on a model's capacity to differentiate between interictal (non-seizure) and ictal (seizure) phases of epileptiform activity. This task is particularly challenging due to the non-stationary characteristics of EEG signals, which exhibit substantial variability across these physiological states. To address this complexity, a range of spiking neural networks (SNNs), alongside conventional deep learning models, have been investigated.

Several benchmark EEG datasets are commonly employed to evaluate detection performance. The CHB-MIT Scalp EEG Database (<https://physionet.org/content/chbmit/1.0.0/> (accessed on 31 March 2026)), which contains surface EEG recordings from 22 patients with intractable epilepsy, remains one of the most widely used resources for seizure detection studies. Additional frequently utilized datasets include the Freiburg Seizure Prediction Project Database (<https://www.epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database> (accessed on 31 March 2026)), comprising invasive EEG recordings from 21 patients with medically refractory focal epilepsy, and the European Epilepsy Database, EPILEPSIAE (<https://www.epilepsy-database.eu/> (accessed on 31 March 2026)). The EPILEPSIAE dataset, which contains both invasive and surface EEG recordings from 250 patients, represents one of the largest collections of long-term EEG data available and is extensively used in SNN-based seizure detection research. Other notable datasets include the Bonn (<https://www.ukbonn.de/epileptologie/arbeitsgruppen/ag-lehnertz-neurophysik/downloads/> (accessed on 31 March 2026)) and PKU1st datasets.

These benchmark datasets provide a standardized basis for evaluating the robustness and generalization capability of SNN-based detection models. A comprehensive summary of relevant studies, including architectures, neuron models, learning rules, training methodologies, and reported performance metrics, is presented in Table 1.

In one study, Shan et al. proposed a fully connected SNN integrated with a Support Vector Machine (SVM) to discriminate between interictal and ictal EEG states [31]. Continuous EEG signals were first transformed into spike trains using Poisson rate encoding, enabling compatibility with the spiking framework. The SNN was trained using spike-based learning mechanisms, after which the learned feature representations were provided to an SVM for final classification. Among the evaluated configurations, the combination of spatio-temporal backpropagation (STBP) with SVM yielded the highest performance, achieving an accuracy of 95.07% on the CHB-MIT dataset.

Chen et al. proposed a Spiking Convolutional Transformer for epileptic seizure detection and prediction [17]. Their architecture combines spiking convolutional layers with spiking self-attention mechanisms, allowing for effective extraction of both local and long-range temporal features from raw EEG signals. In order to improve computational efficiency, but still preserve temporal fidelity, the model employs an approximate spike-triggered update mechanism within the spiking-based addition layers, which helps to reduce redundant computations. Experimental results on the CHB-MIT dataset demonstrated strong performance, achieving a sensitivity of 94.9% and a specificity of 99.3% for seizure detection.

Table 1. Summary of SNN-Based Methods for seizure detection and prediction using EEG signals. “N/A” indicates no reported value. “PS” and “CP” represent Patient-Specific and Cross-Patient evaluations, respectively. “Acc.”, “Sens.”, and “Spec.” represent Accuracy, Sensitivity, and Specificity, respectively. Entries taking the form of “(#/#)” and “(#/#/#)” represent Hold-Out Train/Test and Train/Validation/Test splits and ratios, respectively.

Task	Author(s)	Dataset	Model Architecture	Neuron Model	Encoding/Feature Extraction	Learning Rules	Validation Method	Evaluation	Acc. (%)	Sens. (%)	Spec. (%)
Seizure Detection	H. Shan et al. [31]	CHB-MIT	Fully-connected SNN + SVM	LIF	Poisson Frequency Encoding	STDP/STBP + SVM	5-Fold CV	PS	95.07	88.44	84.56
	Q. Chen et al. [17]	CHB-MIT	Spiking Convolutional Transformer	LIF	Raw EEG	Surrogate Gradient Backpropagation	10-Fold CV	CP	97.1	94.9	99.3
	Z. Zhang et al. [30]	CHB-MIT	Recurrent Convolutional SNN (EESNN)	LIF	EEG treated as input current	Implicit Differentiation on Equilibrium state (IDE), Surrogate Gradient + BPTT	LOOCV	CP	94.42	91.67	N/A
	Ghosh-Dastidar et al. [28]	Bonn	Multi-Spiking Neural Network (MuSpiNN)	LIF	STD, Correlation, Lyapunov	Gradient-based Backpropagation on Spike Timing	Hold-Out	PS	94.8	N/A	N/A
	K. Burelo et al. [48]	USZ-NCH	SNN	LIF	Asynchronous Delta Modulation	Fixed Weights	Clinical Validation	PS	80	71	100
Seizure Prediction	Q. Chen et al. [17]	CHB-MIT	Spiking Convolutional Transformer	LIF	Raw EEG	Surrogate Gradient Backpropagation	10-Fold CV	CP	93.1	96.8	89.5
	F. Tian et al. 2021 [21]	CHB-MIT	Spiking-CNN	LIF	Temporal Gaussian Random Sparse Encoding	Surrogate Gradient Backpropagation	Random Hold-Out	CP	91.4	95.1	99.2
	F. Tian et al. 2023 [49]	CHB-MIT	Spiking-CNN	LIF	Sparse Gaussian Spike Encoder	Surrogate Gradient Backpropagation	Random Hold-Out (80/20)	CP	91.4	92.7	N/A
	S. Zhu et al. [50]	CHB-MIT	Spiking-CNN	LIF	Level-Crossing (LC) Sampling	Surrogate Gradient Backpropagation	CV	PS	93.97	94.85	93.14
	Y. Al Musafir et al. [51]	CHB-MIT	GSNN	Sigma-Delta	STFT + MWV	Surrogate Gradient Backpropagation	Hold-Out (80/10/10)	CP	99.14	N/A	N/A

Zhang et al. proposed an EEG-based recurrent convolutional spiking neural network (EESNN). The proposed architecture integrates convolutional layers with recurrent spiking connections to better capture the temporal dynamics and biological characteristics of EEG signals. The model uses LIF neurons and is trained using surrogate-gradient-based backpropagation and implicit differentiation on equilibrium states. Using the CHB-MIT and PKU1st datasets, the authors achieved sensitivities, AUCs, GMeans, and RAccuracies of 91.67%, 0.9864, 94.38%, and 94.42% on CHB-MIT and 80.82%, 78.04%, 69.89%, and 70.63% on PKU1st, respectively [30].

Yang et al. proposed a deep spiking neural network incorporating a novel spiking ConvLSTM unit (SPCLU) for epileptic seizure detection [52]. The proposed architecture consists of three SPCLU layers followed by two dense layers, where membrane potential and synaptic current replace the hidden and cell states used in conventional ConvLSTM models. To address the non-differentiability of spike generation, the network is trained from scratch using surrogate gradient descent. The model was evaluated using leave-one-out cross-validation (LOOCV) on three public datasets, and achieved mean AUC scores of 89.0% on CHB-MIT, 92.7% on the Freiburg dataset, and 81.1% on the EPILEPSIAE dataset. In addition to competitive detection performance, the authors reported substantial reductions in memory footprint (2–5×) and energy consumption (up to four orders of magnitude) compared to non-spiking ConvLSTM baselines.

Ghosh-Dastidar et al. introduced a Multi-Spiking Neural Network (MuSpiNN) together with a novel Multi-SpikeProp supervised learning algorithm for epileptic seizure detection from EEG signals [28]. The proposed model employs LIF-based spiking neurons in a fully-connected, feedforward architecture, where information is transmitted via multiple spikes and synapses with distinct delays between presynaptic and postsynaptic neurons. The network was evaluated on the Bonn EEG dataset using a modular classification strategy and achieved EEG classification accuracies in the 90.7–94.8% range.

Burelo et al. introduced a custom spiking neural network (SNN) tailored for neuro-morphic hardware to detect interictal high-frequency oscillations (HFOs) from scalp EEG recordings [48]. The proposed system employs LIF neurons within a shallow two-layer SNN architecture augmented by global inhibitory and disinhibitory interneurons, as well as a parallel artifact-rejection SNN operating in the 500–900 Hz band. Continuous EEG signals were converted into spike trains using an asynchronous delta modulation (ADM) scheme that generates UP/DN events based on signal changes. The model was evaluated on 20 scalp EEG recordings from 11 pediatric focal lesional epilepsy patients and achieved 80% accuracy, 71% sensitivity, and 100% specificity in associating detected HFO rates with active epilepsy.

5.1.2. Epileptic Seizure Prediction

Similar to seizure detection, epileptic seizure prediction focuses on a model's ability to differentiate between distinct stages of epileptiform activity. However, unlike detection, which separates ictal from interictal periods, prediction requires distinguishing preictal states from interictal activity.

This task presents greater difficulty for SNN-based approaches, as the electrophysiological differences between preictal and interictal intervals are often more subtle and less distinct than the contrasts observed between ictal and interictal states.

A summary of seizure prediction studies, including the employed architectures, neuron models, learning rules, training methodologies, and reported performance metrics, is provided in Table 1.

Tian et al. (2021) proposed a spiking convolutional neural network (Spiking-CNN) for epileptic seizure prediction using the CHB-MIT EEG database [21]. Their approach

employs a temporal Gaussian random sparse encoding algorithm to convert raw EEG samples into spike sequences. A conventional CNN was first trained, after which its weights were directly mapped to a structurally equivalent Spiking-CNN, using ANN-to-SNN conversion. The resulting model consists of multiple convolutional and max-pooling layers implemented with integrate-and-fire (IF) neurons, along with dedicated spike encoding and spike-counting output layers. Evaluated on CHB-MIT EEG recordings, the model achieved a mean sensitivity of 95.1% and an AUC of 0.912, while significantly reducing computational complexity compared to the original CNN.

In a later work, Tian et al. (2023) proposed NeuroCARE, a generic neuromorphic edge computing framework evaluated across multiple biomedical signal processing tasks, including EEG-based epileptic seizure prediction [49]. NeuroCARE employs a sparse Gaussian spike encoder to transform raw biomedical signals into spike sequences and utilizes a spiking-CNN inference engine obtained via direct conversion from a pre-trained CNN using an adaptive, encoder-aware weight mapping strategy. The spiking network replaces ReLU activations with integrate-and-fire neurons while preserving the original CNN topology. For seizure prediction on the CHB-MIT dataset, the framework explicitly performs preictal versus interictal classification using a defined prediction horizon, achieving 91.4% accuracy, 92.7% sensitivity, and an F1 of 95.1%, while reducing computational complexity and energy consumption by over 80% compared to CNN baselines.

Chen et al. applied the same Spiking Conformer architecture and training methodology used in their seizure detection study to the seizure prediction task. Raw EEG signals were directly processed in an end-to-end framework, without intermediate feature engineering. For preictal versus interictal classification, the model achieved an average sensitivity of 96.8%, specificity of 89.5%, and overall accuracy of 93.1% [17].

Al Musafir and Mesbah introduced a graded spiking neural network (GSNN) framework for non-patient-specific epileptic seizure prediction, implemented on Intel's Loihi 2 neuromorphic processor. Unlike conventional binary SNNs, the proposed GSNN utilizes graded spike amplitudes to enhance the representation of subtle temporal features in EEG signals. The model incorporates preprocessing via short-time Fourier transform (STFT), channel selection for data reduction, and a multi-window voting (MWV) mechanism to improve robustness against noise and artifacts. Evaluated on the CHB-MIT dataset, the system achieved a prediction accuracy of 99.14%, along with improved sparsity characteristics and energy efficiency compared to traditional ANN-based approaches. The neuromorphic implementation demonstrated real-time capability, achieving a throughput of 21.6 EEG segments per second with an energy consumption of 25.104 mJ per input [51].

Zhu et al. proposed a neuromorphic seizure monitoring system based on a Dynamic Execution Latency Tuning through Adaptive Timestep SNN (DELTAT-SNN) framework. The approach integrates Level-Crossing (LC) sampling for direct spike-based encoding of EEG signals, which eliminates the need for conventional recoding and reduces computational overhead. The proposed adaptive timestep optimization dynamically reduces the number of simulation steps during training, resulting in improved efficiency and reduced inference latency. Additionally, the system supports multifunctional operation by combining seizure detection and prediction within a unified architecture, with hardware implementation validated on FPGA. Evaluated on the CHB-MIT dataset, the method achieved a 60.27% reduction in training time and up to 90% reduction in timestep, with hardware measurements reporting a latency of 5.77 ms and power consumption of 0.181 W, and 93.97% accuracy in seizure prediction [50].

5.1.3. Other Neurological Conditions

EEG classification for Alzheimer's Disease (AD) diagnosis using SNNs remains a niche research area; however, Capecchi et al. presented an early and influential study applying the NeuCube spiking neural network architecture to longitudinal EEG data for the analysis of Alzheimer's degeneration [53]. The study employed a biologically-inspired NeuCube model with LIF neurons, threshold-based spike encoding, and STDP-driven unsupervised learning, followed by supervised classification using a dynamic evolving SNN. Rather than reporting conventional diagnostic accuracy metrics, the authors analyzed changes in spatio-temporal neural activity across brain regions over time, demonstrating consistent reductions in neuronal connectivity, particularly within the α , β , δ , and θ bands between measurements at t_0 and t_1 . These findings aligned with established neurological observations of AD-related degeneration, including reduced β -band activity.

Another relatively underexplored application of spiking neural networks for EEG analysis is the diagnosis of Attention-Deficit Hyperactivity Disorder (ADHD) and its subtypes. Pedrollo et al. investigated this problem using the NeuCube spiking neural network architecture to perform both binary ADHD diagnosis and multi-class classification of ADHD subtypes from resting-state EEG signals [54]. The model used LIF neurons, threshold-based spike encoding, and STDP-driven unsupervised learning within the NeuCube reservoir, followed by supervised classification at the output layer. Multiple NeuCube configurations were evaluated, ranging from 125 to 8000 neurons, with results averaged across 20 randomized train-test splits. The highest binary classification accuracy of 72.0% was achieved using the 125-neuron configuration, while the best multi-class accuracy of 68.0% for distinguishing ADHD subtypes was obtained with 1000 neurons. Increasing the neuron count beyond these values resulted in slower models with reduced accuracy. Compared against classical machine learning baselines, the NeuCube-based SNN achieved the highest overall accuracy across both classification tasks, indicating the potential of SNN-based approaches for EEG-driven ADHD diagnosis and subtype differentiation.

Perhaps one of the more unconventional applications of spiking neural networks to physiological signal analysis is the use of EEG data to differentiate between addicted and non-addicted individuals during cognitive tasks. Doborjeh et al. applied a NeuCube spiking neural network architecture to EEG recordings collected during a GO/NOGO task from healthy control (CO), methadone maintenance treatment (MMT), and untreated opiate (OP) subjects [55]. The model consisted of a 3-D brain-inspired SNN cube with 1471 LIF neurons, and used threshold-based representation encoding to convert EEG signals into temporal spike trains. Synaptic weights were adapted using unsupervised STDP, followed by supervised classification using a dynamic, evolving spiking neural network, and evaluated via repeated random subsampling validation. For GO/NOGO classification, the model achieved accuracies of 90.91%, 83.87%, and 83.33% for CO, MMT, and OP subjects, respectively. Further group-wise comparisons yielded 100% accuracy in distinguishing MMT from OP subjects, and 85% accuracy for both OP versus CO and MMT versus CO.

5.2. Problems and Recent Work with ECG

We now turn to recent developments in SNN-based ECG signal classification, with emphasis on applications in medical diagnosis and rehabilitation. Conducting comparative evaluations of state-of-the-art SNN methods on shared datasets and equivalent task formulations allows for a more balanced and consistent assessment of performance across different approaches.

5.2.1. Arrhythmia Detection

Arrhythmia detection represents one of the most extensively investigated applications of SNNs in physiological signal analysis. The prominence of ECG-based research within the SNN literature is largely attributable to the relative practicality and stability of ECG signals. Compared to EEG, ECG recordings are generally less susceptible to noise, making them more straightforward to interpret both manually and through automated SNN-based approaches. Moreover, ECG acquisition avoids the electrode-shift challenges commonly encountered in EMG recordings, as standardized electrode placements are well established in clinical practice. For these reasons, ECG has become a primary modality in SNN research focused on arrhythmia and fetal arrhythmia detection [56,57].

Several benchmark ECG datasets are frequently employed to evaluate detection performance. The 2017 PhysioNet/CinC Challenge Dataset (<https://archive.physionet.org/challenge/2017/> (accessed on 31 March 2026)), which contains 8528 single-lead ECG recordings, is among the most widely used resources for arrhythmia-related classification tasks. Additional commonly utilized datasets include the MIT-BIH Arrhythmia (<https://physionet.org/content/mitdb/1.0.0/> (accessed on 31 March 2026)) database, comprising 48 half-hour excerpts of two-channel ambulatory ECG recordings from 47 subjects, and the UCR ECG (https://www.cs.ucr.edu/%7Eeamonn/time_series_data_2018/ (accessed on 31 March 2026)) repository, which includes multiple benchmark datasets ranging from ECG200 to ECG5000.

These datasets provide a standardized foundation for assessing the robustness and generalization of SNN-based arrhythmia detection models. A comprehensive summary of relevant studies, including architectures, neuron models, learning rules, training methodologies, and reported performance metrics, is presented in Table 2.

Feng et al. proposed a 14-layer deep convolutional spiking neural network (CSNN) for ECG classification, representing the deepest SNN applied to ECG-related tasks at the time of publication [58]. The model was constructed through direct ANN-to-SNN conversion, where a pre-trained deep CNN was transformed into an equivalent SNN by replacing all activation functions with LIF neurons while preserving the original convolutional, pooling, and nonlinear structure. Input ECG signals were converted into spike trains using Poisson-distributed rate encoding, and the resulting SNN was evaluated under a clock-driven simulation framework. Experiments were conducted using four activation functions in the source ANN—ReLU, Leaky ReLU, SELU, and GELU—to study their effect on post-conversion SNN performance. Using the PhysioNet/CinC 2017 dataset and a 90%/10% train–test split, the SNN converted from a ReLU-based ANN achieved the best overall results, with 84.4% accuracy, 70.7% F1 score, 94.5% ROC-AUC, and 67.2% recall, slightly exceeding the performance of the original ANN after sufficient simulation time.

Rana and Kim proposed an ANN-inspired spiking neural network framework for ECG classification by converting a twelve-layer ANN into a six-layer SNN augmented with an attention mechanism using LIF neurons. The model was implemented using the SpikingJelly framework within PyTorch and evaluated on the 2017 PhysioNet Challenge and MIT-BIH Arrhythmia databases, using a 70:30 training–testing split. The proposed SNN achieved overall classification accuracies of 85.8% and 93.8%, F1 scores of 70.4% and 85.4%, and precisions of 75.7% and 88.0% on the PhysioNet 2017 and MIT-BIH datasets, respectively [59].

Table 2. Summary of SNN-Based Methods for arrhythmia detection and sleep apnea detection using ECG signals. “N/A” indicates no reported value. “PS” and “CP” represent Patient-Specific and Cross-Patient evaluations, respectively. “Acc.” and “Sens.” represent Accuracy and Sensitivity, respectively. Entries taking the form of “(#/#)” and “(#/#/#)” represent Hold-Out Train/Test and Train/Validation/Test splits and ratios, respectively. “SVEB” stands for Supraventricular Ectopic Beats. “VEB” stands for Ventricular Ectopic Beats.

Task	Author(s)	Dataset	Model Architecture	Neuron Model	Encoding/Feature Extraction	Learning Rules	Validation Method	Evaluation	Acc. (%)	Sens. (%)	F1 (%)
Arrhythmia Detection	Y. Feng et al. [58]	PhysioNet 2017	Deep CSNN	LIF	Poisson-Distributed Rate-Based Spike Encoding	Adam Optimizer	Hold-Out (9/1)	CP	84.4	67.2	70.7
	A. Rana et al. [59]	MIT-BIH	Attention-Augmented SNN	LIF	Raw EEG	Gradient-based training in ANN stage	Hold-Out (70/30)	CP	93.8	N/A	85.4
	D. Banerjee et al. [35]	MIT-BIH	SNN	LIF	Spiking Hamilton	STDP	Hold-Out	CP	94.5	N/A	N/A
	H. Chu et al. [60]	MIT-BIH	Recurrent Spiking MLP (rMLP)	LIF	Level-Crossing Sampling, Native Temporal Spike Encoding	Hardware-Aware STBP	Hold-Out (80/20)	CP	98.22	N/A	N/A
	Y. Xing et al. [19]	MIT-BIH	CSNN + CAM	LIF	Direct Processing of Segmented ECG Beats	Surrogate-Gradient Backpropagation	Hold-Out (70/30)	CP	98.26	94.75	89.09
	P. Kovacs et al. [24]	MIT-BIH	Variable Projection + SNN (VPSNN)	LIF	Variable Projection	Surrogate-Gradient Backpropagation	Hold-Out (60/40)	CP	97.16	94.72	N/A
	A. Amirshahi et al. [56]	MIT-BIH	SNN	LIF	Poisson Spike Encoding Proportional to ECG Amplitude	STDP, R-STDP	Hold-Out	PS	97.9	80.2	88
	F. Tian et al. 2023 [49]	MIT-BIH	Spiking-CNN	LIF	Sparse Gaussian Spike Encoder	N/A	Hold-Out (80/20)	CP	86.5	96.7	98.2
	K. Buettner et al. [61]	MIT-BIH	CNN-to-SNN	IF	Rate-Based Encoding	Direct Conversion	Hold-Out (90/10)	CP	97.8	N/A	87.9
Sleep Apnea Detection	Z. Yan et al. [62]	MIT-BIH	CNN-to-SNN	IF	Rate-Based Encoding	Weight Transfer	Hold-Out	CP	90	67 (SVEB) & 77 (VEB)	N/A
	S. Salam and R. Rafi [63]	PhysioNet Apnea-ECG	Fully-Connected SNN	LIF	Image-Based Encoding	STDP	Hold-Out (90/10)	CP	89.2	87.27	87.96
	DT Pham et al. [64]	PhysioNet Apnea-ECG	Spiking-Transformer	N/A	R-Peak Detection + Median Filtering	Surrogate Gradient Backpropagation	5-Fold CV	CP	95.0	93.3	93.5
	L. Werthen-Brabants [65]	Custom Dataset	Spiking-RNN	LIF	STFT	Surrogate Gradient Backpropagation	Hold-Out (17/8/8) + 4-Fold CV	CP	83	83	N/A

Utilizing the BindsNET [66] GPU-based SNN simulator, Banerjee et al. investigated two spiking neural network architectures—reservoir-based and feed-forward—for ECG classification in the context of atrial fibrillation detection [36]. Extending their prior work on ECG encoding, the authors used LIF neurons together with a novel Spiking Hamilton (SH) encoder, which converts ECG morphology into sparse spike trains based on peak timing. Both architectures were evaluated on five benchmark datasets: ECG200, ECG5000, ECGFiveDays, PhysioNet 2017, and MIT-BIH, and their performance was compared against multiple encoding schemes and existing state-of-the-art approaches. Across all datasets, the SH encoder consistently outperformed alternative spike encoders and significantly narrowed the accuracy gap with non-spiking state-of-the-art models, while requiring substantially fewer synaptic operations. The SH-Reservoir configuration achieved accuracies of 80.0%, 93.5%, 86.4%, 78.5%, and 93.7%, while the SH-Feed-Forward configuration achieved 82.0%, 92.8%, 89.2%, 77.0%, and 94.5% on ECG200, ECG5000, ECGFiveDays, PhysioNet 2017, and MIT-BIH datasets, respectively.

Yan et al. proposed an energy-efficient ECG classification framework based on a CNN-to-SNN conversion pipeline, targeting deployment on wearable and resource-constrained platforms [62]. The approach employs a two-stage convolutional architecture, where a binary normal/abnormal classifier is followed by a multi-class heartbeat classifier, and both stages are subsequently converted into spiking neural networks using IF neurons. Raw ECG signals from the MIT-BIH Arrhythmia database were encoded using rate-based spike encoding, and the trained CNN weights were transferred directly to the SNN while preserving the original network structure. The converted SNN achieved an average inter-patient classification accuracy of approximately 90%, with competitive sensitivity and positive predictivity across major heartbeat classes, while reducing power consumption to less than 1% of the original CNN.

Chu et al. introduced a low-power neuromorphic processing system for real-time ECG classification based on a spike-driven spiking recurrent multilayer perceptron (rMLP), implemented with LIF neurons [60]. The system integrates level-crossing (LC) sampling, which directly converts ECG signals into single-bit spike events, eliminating conventional spike encoding overhead and achieving native temporal coding. A hardware-aware spatio-temporal backpropagation (STBP) training scheme was used in order to jointly optimize classification accuracy, firing rate, synaptic sparsity, and fixed-point precision. Evaluated on the MIT-BIH arrhythmia database for five-class classification, the proposed system achieved 98.22% accuracy while consuming only 0.75 μ J per classification.

Xing et al. proposed a lightweight CSNN integrated with a channel-wise attentional mechanism (CAM) for real-time ECG heartbeat classification on portable, low-power devices [19]. The model uses LIF neurons and incorporates the CAM between two SNN layers in order to enhance temporal, morphological, and multi-channel feature extraction, while still maintaining low computational complexity. Evaluated on the MIT-BIH arrhythmia database, their evaluation method of 70:30 Train/Test split (which produced the highest accuracy) achieved an overall classification accuracy of 98.26%, sensitivity of 94.75%, and F1 score of 89.09%. The system demonstrated strong real-time capability with a runtime of 1.37 ms per heartbeat and high energy efficiency, consuming 346.33 μ J per beat.

Kovács and Samiee proposed a multiple hybrid Variable Projection–Spiking Neural Networks (VPSNNs) architecture for efficient ECG classification, combining a trainable Variable Projection (VP) layer with spiking neural networks using LIF neurons [24]. The VP layer acts as both a feature extractor and spike encoder, learning clinically interpretable parameters corresponding to the location and width of ECG waveforms (e.g., QRS complexes), while subsequent spiking layers perform temporal classification. Evaluated on ventricular ectopic beat (VEB) detection using the PhysioNet MIT-BIH Arrhythmia Database, the

proposed best-performing VPSNN variant (VPTSNN) achieved an accuracy of 97.16%, specificity of 99.60%, and sensitivity of 94.72% with a highly compact topology consisting of only 242 trainable parameters.

Amirshahi and Hashemi introduced a low-power spiking neural network for real-time ECG classification, targeting wearable arrhythmia detection systems. Their approach uses a fully spike-domain pipeline composed of spike encoding, unsupervised STDP-based feature extraction with inhibitory competition, and supervised classification using Reward-Modulated STDP (R-STDP). Using LIF neurons throughout the network, the model was evaluated on the MIT-BIH arrhythmia database under a patient-specific training protocol. The proposed system achieved classification performance of 97.9% accuracy, 80.2% sensitivity, 99.8% specificity, 97.3% PPR, and 88.0% F1, while consuming only 1.78 μ J per heartbeat [56].

Tian et al. also employed their NeuroCARE architecture for ECG classification, specifically targeting energy-efficient arrhythmia detection. They developed a CSNN that utilized Sparse Gaussian spike encoding and IF neurons. The hybrid system achieved 86.5% accuracy, 96.7% sensitivity, and an F1 of 98.2% on the MIT-BIH Arrhythmia Database, while significantly reducing computation complexity and energy consumption [49].

Buettner and George investigated the use of Intel's Loihi neuromorphic processor for energy-efficient ECG heartbeat classification through ANN-to-SNN conversion [61]. A one-dimensional CNN was first trained in the artificial domain and then converted into an architecturally identical SNN using the SNN-Toolbox framework, with IF neurons deployed on Loihi. Evaluated on the MIT-BIH Arrhythmia Database, the converted SNN achieved an accuracy of 97.8% and a macro-averaged F1 score of 87.9%, closely matching the original ANN's performance. While Loihi demonstrated the lowest dynamic power consumption among evaluated devices, its higher inference latency resulted in a larger energy-delay product compared to dedicated edge accelerators such as the Google Coral Edge TPU.

Loh and Gemmeke proposed a lossless sparse temporal coding method for converting a deep ANN into an SNN for continuous ECG classification. Their top-down conversion framework analytically derives a novel hybrid neuron model, positioned between IF neurons and conventional ANN neurons, ensuring numerical equivalence between the ANN and SNN outputs. Evaluated on the MIT-BIH Arrhythmia Dataset, the converted SNN method preserves the same classification performance as the original ANN, while reducing power consumption by 2.32 times and area by 7.22 times [67].

5.2.2. Fetal Arrhythmia Detection

Fetal arrhythmia detection, while a rather unexplored field, is a crucial application of SNN in biomedical signal processing. Shekhawat et al. proposed a binarized spiking neural network (BSNN) optimized using a Momentum Search Algorithm (MSA) for fetal arrhythmia detection and classification from ECG signals. The method targets the challenges posed by noise and artifacts in fetal ECG recordings collected from PhysioNet databases. Preprocessed ECG signals are first transformed using a Hexadecimal Local Adaptive Binary Pattern (HLABP) feature extraction scheme, after which classification is performed using a BSNN with binarized synaptic weights. The MSA is employed to optimize critical BSNN parameters, improving classification performance. Experimental results demonstrate that the proposed BSNN-MSA framework consistently outperforms existing approaches in terms of accuracy, sensitivity, F-measure, specificity, and AUROC [25].

5.2.3. Sleep Apnea Detection

Sleep apnea is a sleep-related disorder characterized by recurrent pauses in breathing, commonly referred to as “apneas,” throughout the sleep cycle. These episodes may arise from airway obstruction or from impaired neural signaling to the respiratory muscles.

The application of SNNs to ECG-based sleep apnea detection is an emerging area of research within physiological signal analysis. To date, only a limited number of studies have explored the automatic identification of sleep apnea using ECG signals processed through spiking neural networks.

Salam and Rafi explored the application of SNNs for sleep apnea detection by transforming single-lead ECG signals from the PhysioNet Apnea-ECG database into grayscale images. These images were used to train a fully connected SNN with LIF neurons, where unsupervised Spike-Timing-Dependent Plasticity (STDP) was employed for feature extraction. The study performed a comparative evaluation against a deep 2-D CNN using the same ECG image datasets. With a dataset size of 1300, experimental results show that the SNN achieved an accuracy of 89.2%, sensitivity of 87.27, and an F1 of 87.96%, slightly outperforming the CNN in accuracy, while exhibiting more stable training behavior and reduced computational complexity [63].

5.3. Problems and Recent Work with EMG

As noted previously, the use of SNNs for diagnostic EMG classification remains relatively underexplored. In both diagnostic and control-oriented applications, EMG classification aims to accurately differentiate among distinct muscular activation patterns. A central challenge in this domain is the sensitivity of EMG signals to electrode placement, as even minor positional shifts can significantly alter the recorded signal characteristics.

Furthermore, substantial user training requirements and limited algorithmic robustness under electrode displacement have restricted the broader clinical and commercial adoption of EMG-based technologies [20]. To mitigate these limitations, numerous studies have investigated SNN-based approaches to enhance robustness and adaptability under varying recording conditions.

Most existing work emphasizes rehabilitative applications for individuals with muscular impairments or physical disabilities. In particular, SNNs have been extensively applied to EMG pattern recognition tasks, especially gesture recognition [20,49,68–73]. Additionally, SNNs have been widely utilized in EMG-driven myoelectric control systems, with a primary focus on prosthetic control [74–78].

Xu et al. proposed a spiking convolutional neural network (SCNN) composed of cyclic convolutional modules and fully connected layers for electromyography pattern recognition, targeting robustness against electrode shifts and reduced training burden [20]. High-density surface EMG (HD-sEMG) signals collected from six gestures across ten subjects and multiple electrode positions were encoded using an event-driven differential coding scheme. The network used LIF neurons and was trained using STBP with surrogate gradients. Compared to CNN, CNN-LSTM, LDA, and spiking MLP baselines, the proposed SCNN achieved up to 50.69% higher accuracy in small-sample settings and demonstrated strong robustness to electrode shifts, while consuming approximately 1/93 of the power required by a CNN with the same structure [20].

Behrenbeck et al. implemented the NeuCube SNN architecture on SpiNNaker neuro-morphic hardware for low-power classification of spatio-temporal biosignals. Focusing on hand-gesture recognition from raw surface EMG (sEMG) data, the system used LIF neurons, temporal difference-based spike encoding, and STDP within a three-dimensional recurrent reservoir. The model achieved a mean test accuracy of 84.8% for sEMG gesture

classification, outperforming conventional machine-learning baselines when operating directly on raw signals [70].

Employing a feedforward spiking neural network with population coding and the SpikeProp supervised learning algorithm, Liu et al. designed a compact model for surface EMG-based hand gesture recognition in rehabilitation applications. Four time-domain sEMG features were encoded using population coding and processed by a three-layer fully connected SNN composed of LIF neurons. Using data collected from 15 subjects performing eight standard Fugl–Meyer hand gestures, the model achieved a maximum classification accuracy of 96.5% while using only 15 spiking neurons in the hidden layer. Under identical network sizes, the proposed SNN outperformed multilayer perceptron (MLP), radial basis function (RBF) networks, and support vector machines (SVMs) [77].

Du et al. proposed an SNN framework for continuous elbow joint motion decoding from surface EMG signals to support real-time prosthetic and exoskeleton control [76]. EMG data was collected using an eight-channel Myo armband during elbow flexion and extension tasks, and time-domain waveform-length features were encoded into spike trains through an input spiking layer. The model consisted of multiple spiking layers using LIF neurons and was trained using a supervised backpropagation-through-time approach implemented with SLAYER. Performance was evaluated using regression metrics, demonstrating that the proposed SNN achieved comparable coefficient-of-determination (R^2) values to LSTM-based models while maintaining lower computational complexity [76].

Tieck et al. proposed an SNN framework for classifying sEMG signals and triggering reflex-like finger motions on a robotic hand. Using non-invasive sEMG data collected from an eight-channel Myo armband, the system encodes muscle activity into spikes and employs a multi-population feedforward SNN with LIF neurons. Supervised training of the classification subnetwork is performed offline using the Prescribed Error Sensitivity (PES) learning rule. The classified finger activation subsequently drives motion generation through oscillatory motor primitives mapped to the robot's kinematics. Experimental results demonstrate reliable per-finger classification and successful real-time control of a five-finger robotic hand [74].

In a feasibility study on the application of SNNs in myoelectric control systems, Sun et al. proposed a directly trained SNN using LIF neurons and adaptive threshold temporal contrast encoding to improve robustness against electrode shifts and inter-subject variability. The model was evaluated on a custom high-density (128-channel) and low-density (8-channel) sEMG dataset comprising nine hand gestures recorded from eight participants. Experimental results demonstrated average classification accuracies of $72.59 \pm 23.04\%$ and $48.66 \pm 16.29\%$ for the HD-sEMG and LD-sEMG datasets, respectively, outperforming CNN and LDA baselines, and achieving comparable accuracies with LSTM, under comparable settings, and reducing training burden and power consumption by 1–2 orders of magnitude [78].

Utilizing the fully-custom, asynchronous, mixed-signal neuromorphic chip, Ma et al. implemented a spiking recurrent neural network (SRNN) based on a Liquid State Machine (LSM) architecture for EMG-based hand gesture classification. Surface EMG signals corresponding to the rock, paper, and scissors gestures were encoded into spike trains using a delta conversion algorithm and processed by a recurrent reservoir composed of spiking neurons implemented on-chip. Two hardware-friendly, spike-based readout methods were evaluated: a spiking-rate state-distance classifier and a trace-based STDP learning rule applied at the readout layer. The spiking-rate distance method achieved a classification accuracy of $77.0 \pm 0.5\%$, outperforming an SVM baseline, while the trace-based STDP approach achieved $60.0 \pm 1.4\%$ [73].

6. Discussion and Conclusions

6.1. General Trends

Based on the surveyed literature, several unifying trends and domain-specific distinctions can be observed in the application of SNNs to physiological signal analysis. Across EEG, ECG, and EMG modalities, SNNs have demonstrated competitive diagnostic performance, as well as consistently offer substantial reductions in computational cost and energy consumption when compared to conventional artificial neural networks. However, the mechanisms by which these advantages are realized, and the challenges that remain, vary significantly by task and signal type. A summary of the corresponding architectures, neuron models, encoding strategies, learning rules, and reported performance metrics for EEG, ECG, and EMG methods are provided in Tables 1, 2 and 3, respectively. The evaluation metrics and validation protocols used throughout this review, including those summarized in these tables, are discussed in Section 4.

A prominent pattern emerging from the literature is the widespread adoption of convolution-based architectures within the spiking domain. Convolutional SNNs, as well as ANN-to-SNN converted CNNs, dominate across all three physiological modalities reviewed. This architectural convergence suggests that SNNs are not replacing established spatial inductive biases, but rather extending them with spike-based temporal dynamics and event-driven computation. Even advanced architectures incorporating recurrence, attention mechanisms, or transformer-like structures retain convolution as the primary feature extraction mechanism, pointing towards its centrality for physiological signal modeling.

Encoding strategy emerges as a critical, and often underappreciated, determinant of SNN efficiency. Models employing event-driven temporal encodings, such as delta modulation, level-crossing sampling, sparse Gaussian encoding, and spike-native signal acquisition, consistently achieve the largest reductions in energy consumption. In contrast, rate-based Poisson encoding, while widely used in conversion-based pipelines, often requires longer simulation windows to achieve comparable accuracy, thus partially offsetting its computational benefits. These observations indicate that encoding choice may have a greater impact on energy efficiency than neuron model complexity or network depth, particularly in applications that utilize continuous monitoring.

Training methodology seems to exhibit a strong dependency on application maturity and task complexity. EEG-based diagnostic tasks, especially seizure detection and prediction, increasingly rely on surrogate-gradient and spatio-temporal backpropagation methods in order to capture subtle preictal dynamics. ECG applications, by contrast, frequently leverage ANN-to-SNN conversion strategies, indicative of the relatively stable morphological structure of cardiac signals, as well as the maturity of CNN baselines. EMG-based systems often implement task-specific, supervised SNNs, or local plasticity rules, prioritizing robustness, low latency, and real-time control over global optimization. This suggests that training difficulty is not necessarily an inherent limitation of SNNs, but rather a function of signal complexity and application constraints.

Finally, neuromorphic hardware platforms play a nuanced role in the SNN ecosystem. While devices such as Intel's Loihi and SpiNNaker enable native event-driven computation and ultra-low-power operation, many energy gains reported in the literature arise from algorithmic sparsity and encoding efficiency rather than hardware alone. This suggests that SNNs have the potential to deliver meaningful benefits on conventional hardware under the right conditions, while neuromorphic accelerators simply help to amplify these advantages.

Table 3. Summary of SNN-Based Methods for movement and gesture classification using EMG signals. “PS” and “CP” represent Patient-Specific and Cross-Patient evaluations, respectively. “Acc.” represents Accuracy. Entries taking the form of “(#/#)” represents Hold-Out Train/Test.

Task	Author(s)	Dataset	Model Architecture	Neuron Model	Encoding/Feature Extraction	Learning Rules	Validation Method	Evaluation	Acc. (%)
Movement and Gesture Classification	F. Tian et al. 2023 [49]	Nina Pro	Spiking-CNN	LIF	Sparse Gaussian Spike Encoder	Backpropagation-Based Weight Mapping	Random Hold-Out (80/20)	CP	92.5
	J. Behrenbeck et al. [70]	Custom sEMG Dataset	SNN	LIF	Temporal Difference (TD) Encoding (for sEMG and EEG), Ben’s Spiker Algorithm (for force regression)	STDP, Rank-Order (RO) learning + deSNN, K-Nearest Neighbors (KNN)	Hold-Out (70/30), 5-Fold CV (training)	PS	84.8
	Y. Liu and L. Cheng [77]	Custom sEMG Dataset	SNN	LIF	Population coding using Gaussian receptive fields	SpikeProp, Gradient-Decent-Based Spike-Timing Backpropagation	10-Fold CV, Hold-Out (80/20)	PS	96.5
	A. Sun et al. [78]	Custom sEMG Dataset	SNN	LIF	Adaptive Threshold Temporal Contract Encoding	Surrogate Gradient Backpropagation	LOOCV	PS	72.59
	Y. Ma et al. [73]	Custom sEMG Dataset	Spiking-RNN	AEIF	Delta Encoding Algorithm	STDP	Hold-Out (2/1)	CP	77

6.2. Current Challenges of Using SNNs for Physiological Signal Analysis

6.2.1. Encoding Dependence

A fundamental challenge in SNN-based physiological signal analysis is the strong dependence on input encoding strategies. As discussed in Section 3.3, physiological signals such as EEG, ECG, and EMG are inherently continuous and must be transformed into discrete spike trains prior to processing. However, the choice of encoding scheme, whether rate-based, temporal, or hybrid, can significantly influence both model performance and computational efficiency [79,80]. This dependence introduces variability across studies, as identical architectures may yield substantially different results under alternative encoding methods. Furthermore, encoding schemes often introduce implicit biases in how temporal information is represented, potentially amplifying or suppressing diagnostically relevant features. Despite its critical role, encoding selection is frequently treated as a simple preprocessing step, rather than an integral component of model design, leading to inconsistencies in evaluation and limited reproducibility across datasets and tasks.

6.2.2. Evaluation Standardization and Benchmarking

Despite the strong reported performance of many SNN-based models, there remains a significant lack of standardization in evaluation protocols [81]. Variations in dataset partitioning strategies, including patient-specific versus cross-patient validation, as well as inconsistencies in metric definitions and reporting practices, hinder direct comparison across studies [51]. This issue is particularly pronounced in EEG-based applications, where inter-patient variability can substantially influence reported performance. As a result, models evaluated under patient-specific settings may exhibit inflated performance relative to more clinically realistic cross-patient scenarios. Without standardized benchmarks, evaluation pipelines, and reporting guidelines, it remains difficult to accurately assess the generalization capability and real-world applicability of SNN-based diagnostic systems.

6.2.3. Limited Clinical Validation and Translation

Despite promising performance across benchmark datasets, the clinical translation of SNN-based methods remains limited [81,82]. As highlighted throughout the literature, most studies rely on retrospective evaluations using publicly available datasets, with minimal validation in real-world clinical environments. This gap introduces several challenges, including dataset bias, lack of demographic diversity, and limited robustness to real-world noise and variability. In addition, regulatory approval pathways for medical devices require rigorous prospective validation, interpretability, and reliability guarantees, which are not yet fully addressed by current SNN frameworks. As a result, while SNNs demonstrate strong potential for low-power diagnostic systems, their adoption in clinical workflows remains constrained by validation, regulatory, and trust-related barriers.

6.2.4. Real-Time Constraints and Deployment Limitations

Although SNNs are often promoted for their event-driven efficiency, achieving true real-time performance in practical deployments remains a non-trivial challenge. Many SNN models require multiple simulation time steps to generate stable outputs, introducing latency that may be incompatible with time-sensitive clinical applications such as seizure prediction or cardiac monitoring. Additionally, the computational overhead associated with spike encoding, temporal simulation, and membrane state updates can offset the theoretical efficiency gains, particularly when implemented on conventional hardware [51,79]. While neuromorphic platforms offer a pathway toward low-latency inference, their limited availability and programming complexity further restrict widespread adoption [81]. Consequently, there exists a

trade-off between temporal resolution, computational cost, and inference latency, which must be carefully balanced for real-time physiological signal processing.

6.2.5. Data Availability and Modality-Specific Fragmentation

The EMG domain highlights both the promise and limitations of current SNN research, while also reflecting broader challenges in data availability and modality-specific fragmentation. Although EMG-based SNN approaches demonstrate strong energy efficiency and robustness to electrode displacement, the field remains constrained by limited access to large-scale, standardized datasets and a lack of consistent evaluation frameworks [83,84]. Thus, research in this domain is often conducted on custom or proprietary datasets, which restricts reproducibility and cross-study comparison. This fragmentation has led to a disparity between engineering advancements and clinically validated diagnostic applications, with many proposed methods demonstrating technical feasibility, but with limited translation to real-world clinical settings.

6.2.6. Patient Privacy, Data Security, and Regulatory Considerations

The deployment of SNN-based systems in healthcare environments introduces important challenges related to patient privacy, data security, and regulatory compliance. Physiological signals such as EEG and ECG contain sensitive biometric information that must be handled in accordance with strict data protection standards [85]. The integration of SNN models into wearable or edge-based systems raises additional concerns regarding secure data transmission, on-device storage, and vulnerability to adversarial attacks. Furthermore, regulatory approval for medical AI systems requires not only high performance, but also transparency, robustness, and reproducibility [86]. The stochastic and event-driven nature of SNNs, combined with variability introduced by encoding and training strategies, can complicate efforts to standardize and certify these systems. Addressing these concerns is essential for ensuring safe and ethical deployment in clinical settings.

6.3. Recommendations and Future Directions

In light of the challenges identified above, several actionable research directions emerge that can help to advance the development, evaluation, and deployment of SNN-based systems for physiological signal analysis.

6.3.1. Encoding-Aware Model Design and Evaluation

Given the strong dependence of SNN performance on input encoding strategies, future work should treat encoding as an integral component of model design rather than a fixed preprocessing step. Standardized evaluation protocols should include comparative analysis across multiple encoding schemes, such as rate-based, temporal, and hybrid approaches, applied to identical architectures and datasets. Additionally, encoding-aware training strategies, in which encoding parameters are jointly optimized with network weights, should be further explored. Performance reporting should include not only classification metrics, but also spike efficiency measures, such as spike rate and synaptic operations per inference, in order to better quantify the trade-offs between accuracy and energy efficiency.

6.3.2. Standardized Evaluation Frameworks and Benchmarking

To address the lack of comparability across studies, the development of standardized evaluation frameworks is essential. Future research should adopt consistent dataset partitioning strategies, prioritizing patient-wise and cross-patient validation over patient-specific splits, in order to better reflect real-world deployment scenarios. Benchmark suites should be established for EEG, ECG, and EMG modalities, incorporating standardized preprocessing pipelines, evaluation metrics, and reporting guidelines. Furthermore, stud-

ies should explicitly report generalization gaps between training and external datasets, enabling more transparent assessment of model robustness and clinical applicability.

6.3.3. Clinical Validation and Translational Pathways

Bridging the gap between experimental performance and clinical deployment requires a shift toward prospective, real-world validation. Future studies should incorporate cross-institutional datasets, longitudinal patient data, and real-world noise conditions to better approximate clinical environments. In addition, the development of interpretable SNN frameworks, such as spike-based saliency analysis or temporal attribution methods, is necessary to support clinical decision-making. Collaboration with clinical stakeholders and adherence to regulatory evaluation standards will be critical for translating SNN-based systems from research prototypes to deployable medical technologies.

6.3.4. Real-Time Optimization and Hardware-Aware Design

To meet real-time constraints, SNN models should be explicitly optimized for latency, computational efficiency, and deployment conditions. Future work should report end-to-end inference latency, measured in milliseconds per sample or time window, alongside traditional performance metrics. Optimization strategies may include reducing the number of simulation time steps, enforcing spike sparsity, and leveraging event-driven processing mechanisms. Additionally, evaluation on edge and neuromorphic hardware platforms should be incorporated to assess practical deployment feasibility, with metrics such as energy per inference and synaptic operation counts, thus providing standardized measures of efficiency.

6.3.5. Data Availability and Cross-Domain Generalization

Addressing data fragmentation requires the development of larger, standardized, and publicly available datasets, particularly for underrepresented modalities such as EMG. Future research should prioritize the creation of multi-subject, multi-session datasets with standardized acquisition protocols, enabling more robust cross-study comparisons. In parallel, domain generalization techniques, such as transfer learning and adaptive encoding strategies, should be explored in order to improve model robustness across varying signal conditions, electrode placements, and patient populations.

6.3.6. Privacy, Security, and Regulatory Compliance

To ensure safe and ethical deployment, future SNN-based systems should incorporate privacy-preserving, security-aware design principles. On-device inference using edge-based SNN implementations can reduce the need for transmitting sensitive physiological data, thereby enhancing data security. In addition, federated learning frameworks and privacy-preserving training methods should be explored to enable collaborative model development without centralized data sharing. Robustness to adversarial perturbations in spike-based representations should also be evaluated. Finally, adherence to regulatory standards will require reproducible pipelines, transparent reporting, and rigorous validation procedures, aligning SNN-based systems with established medical device certification requirements.

6.4. Summary

This review examined the current landscape of Spiking Neural Networks (SNNs) for physiological signal analysis across EEG, ECG, and EMG modalities, encompassing both diagnostic and rehabilitative applications. The surveyed literature demonstrates that SNNs have progressed beyond early proof-of-concept systems, now achieving performance comparable to conventional artificial neural networks, while still offering distinct advantages

in energy efficiency, temporal modeling, and suitability for edge-based and continuous monitoring applications.

Several unifying trends emerge across domains. Convolution-based architectures, including both native SNN designs and ANN-to-SNN conversion pipelines, dominate current implementations, indicating that SNNs extend rather than replace established deep learning paradigms. Encoding strategies play a central role in determining system efficiency, with event-driven temporal encodings consistently enabling the most significant reductions in computational cost. Training methodologies exhibit strong task dependence, reflecting the varying complexity of physiological signals and the maturity of corresponding application domains. Additionally, while neuromorphic hardware platforms provide substantial benefits, many observed efficiency gains arise from algorithmic design choices, suggesting that meaningful improvements can also be achieved on conventional computing platforms.

Despite these advances, several critical challenges remain. The strong dependence on encoding strategies, lack of standardized evaluation protocols, limited clinical validation, real-time deployment constraints, and fragmentation in available datasets collectively hinder reproducibility, comparability, and real-world adoption. Furthermore, concerns related to patient privacy, data security, and regulatory compliance introduce additional barriers to the deployment of SNN-based systems in clinical environments.

To address these limitations, this work outlined a set of actionable research directions aimed at improving the robustness, efficiency, and clinical applicability of SNN-based approaches. These include encoding-aware model design, the development of standardized benchmarking frameworks, increased emphasis on prospective and cross-institutional validation, hardware-aware optimization for real-time inference, expansion of publicly available datasets, and the integration of privacy-preserving, security-aware methodologies.

Overall, SNNs represent a promising computational paradigm for next-generation physiological signal analysis, especially in applications requiring low-power, real-time, and continuous monitoring capabilities. Continued progress in standardization, validation, and deployment will be essential to fully realize their potential in clinical and real-world healthcare settings.

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