Rayyan_key	My_Key	Year	Title	Author	Publication Title	DOI	Url	RQ1a_Encoding_Type	RQ1b_Learnable_encoding_parameter	RQ1c_Training_mechanism	RQ1d_Hybrid_Integration_Type	RQ2a_spike_wise_efficiency	RQ2b_Resource_efficiency	RQ2c_Training_Behavior	RQ2d_Model_Behavio	RQ3a_Dataset_modality	RQ3b_Input_Representation	RQ3c_Datasets_Used	RQ3d_Task_or_Domain	RQ3e_Evaluation_Metrics	RQ4a_Limitation_Category	RQ4b_Reported_Limitations	RQ4c_Research_Gaps	hardware_or_simulator	paper_type	Architecture_Type	code_availability	training_config_short
rayyan-388589274	P01	2024	Accurate and {Efficien	Zhang, Ru	Optics Express	10.48550	http://ar›	learnable and adaptive encoding	Synaptic weights Temporal decay parameters	Surrogate gradient	Pure SNN architecture	Sparse spike activity Reduced firing rate Stable spike behavior Efficient Timesteps	Reduced computational operations Multiplication-free inference (MFI) Energy efficiency computation Memory-efficient	Stable Smoothness	Robustness Generalization Performance	Vision	Event streams Grayscale images RGB images	DDD17 DSEC-Semantic	Semantic Segmentation task	# Timesteps # Params MIoU # Add # Mult Energy	Architectural Limitations Theoretical Limitations Hardware Limitations Energy Estimation Limitations Optimization Limitations	Suboptimal Sparsity/Architecture Lacks Deep Theoretical Justification Theoretical Energy Estimates Only No Neuromorphic Hardware Deployment No Real-World/Practical Deployment Early-Stage Architecture Search Sensitivity	Neuromorphic Hardware Deployment Real-World Application AiLIF Theoretical Justification SNN Sparsity Optimization	GPU \CPU CMOS energy model	Architecture proposal	Spiking Encoder-Decoder Network	Promised.	Neuron: LIF Method: Direct SNN Training (Spatio-Temporal BP + Dspike) Optimizer: Adam (Poly LR Decay) Loss: Per-pixel Cross-Entropy Epochs: Search: 20, Retraining: 50–100 Inference: Single Time-Step Input: SBT (Δt = 50ms, n = 5)
rayyan-388589102	P02	2024	Brain-Inspired Archite	Tang, Fen	IEEE Access	10.3390/l	https://w	learnable and adaptive encoding	Synaptic weights	Surrogate gradient	Pure SNN architecture	Efficient Timesteps Reduced firing rate	Reduced computational operations Energy efficiency computation Memory-efficient	Stable Convergence Randomness reduced	Robustness Generalization Performance	Vision	Grayscale images RGB images	MNIST Fashion-MNIST CIFAR-10	Classification task	Accuracy # Timesteps	Biological Limitations Generalizability Limitations Hardware Limitations	Limited exploitation of biological mechanisms Absence of lateral interactions and recurrent connectivity Evaluated only on image classification tasks No Neuromorphic Hardware Deployment	Extension to more biologically realistic learning rules Inclusion of lateral/recurrent connections Application to speech and time-series tasks	GPU \CPU	Architecture proposal	Convolutional Spiking Neural Network (Conv-SNN)	Not Available	Neuron: IF, LIF Random weight initialization Dropout = 40% in fully connected layers Batch normalization (BN) Loss: Loss function = L2 norm (MSE) Method: Surrogate gradient comparison Optimizer: Adam (sigmoid vs arctan) Recommended α = 4.0 30 epochs MNIST: LR = 0.0002, Batch size = 128, Epochs = 60, Surrogate gradient = Atan Fashion-MNIST: LR = 0.0005, Batch size = 128, Epochs = 120, Surrogate gradient = Atan CIFAR10: LR = 0.0001, Batch size = 32, Epochs = 140, Surrogate gradient = Sigmoid
rayyan-378478369	P03	2024	Brain-Inspired Spiking	Tandale, :	Neurocomputing	10.1007/s00366-024		learnable and adaptive encoding	Synaptic weights Temporal decay parameters Membrane thresholds	Surrogate gradient	Hybrid ANN–SNN architecture	Sparse spike activity Reduced firing rate	Energy efficiency computation Memory-efficient Faster infrence	Convergence Higher simulation speed Smoothness	Robustness Generalization Performance	Real Numbers	Real Numbers	Custom	Regression task	Root Mean Squared Error (RMSE) Energy Simulation speed	Accuracy Limitations Energy Estimation Limitations Generalizability Limitations Hardware Limitations Methodological Limitations	No on-chip training for Xylo-Av2 Energy estimates from KerasSpiking are conjectural and based on simplifying assumptions Low number of online training steps can introduce errors Model evaluated on specific material models	Extension to broader material laws Large-scale 3D problems Full neuromorphic FEM solvers Real experimental validation. Brain-inspired neural network-enhanced FEM for mechanical BVPs was previously unavailable in literature Limited application of SNNs in FEM solvers	Xylo-Av2 KerasSpiking GPU \CPU	Architecture proposal	Hybrid Recurrent Spiking Neural Network (SNN)	Not Available	Neuron: LIF Optimizer: Adam Batch Size: 32 Initial Learning Rate: 1e-4 Maximum Learning Rate: 1e-3 Epochs (Pre-training): <=4000 Learning Rate Schedule: Cyclical, Triangular Mode Activation Function (Output Layer): Soft Plus Pre-training Phase: Combination of data-driven Ld and physics-based Lp loss functions. Online Training: Physics-based Lp only
rayyan-388589111	P04	2024	Diagnostic Biomarker	Saeedinia, Samaneh Alsadat; Ja		10.1038/:	https://w	Adaptive encoding	Adaptive (data-driven) parameters	Local learning rule	Pure SNN architecture	Sparse spike activity Efficient Timesteps	Reduced computational operations Energy efficiency computation Memory-efficient Faster infrence	Convergence	Robustness Performance	Biosignals	Electroencephalogram (EEG)	Custom	Classification task Biomarker discovery	Accuracy Neuron firing patterns Execution time	Accuracy Limitations Computational Constraints Generalizability Limitations Hardware Limitations	Small and imbalanced dataset Overfitting with large reservoirs Lack of large-scale validation No neuromorphic hardware deployment	Validation on larger Multi-center datasets Early prediction of disease onset; Deployment on neuromorphic hardware Longitudinal EEG analysis	MATLAB simulation GPU \CPU	Architecture proposal Novel Encoding Mechanism	Reservoir-based SNN	Available	Neuron: Izhikevich spiking neurons (70% excitatory / 30% inhibitory) Pipeline: raw EEG → adaptive Online Spike Encoding → partially observed reservoir SNN → firing-rate classifier Learning: hybrid local learning (supervised ReSuMe for observed neurons + unsupervised STDP for hidden neurons) Classifier calibration: firing-rate threshold trained on 70% of data Evaluation: leave-one-out cross-validation

rayyan-378477363	P05	2022	DTS-SNN: Spiking Neu	Yoo, Donghyung; Jeong, Doo S		10.1109/ACCESS.20		learnable and adaptive encoding	Trainable DTS aggregation weights ai	Surrogate gradient	Pure SNN architecture	Activity-driven suppression Activity-driven responsiveness Efficient Timesteps	Reduced computational operations Energy efficiency computation Memory-efficient	Stable	Performance Robustness	Vision Audio	Event streams	DVS128 Gesture Spiking Heidelberg Dataset (SHD) N-Cars	Classification task Action/Gesture Recognition	Accuracy # Params # Ops # Timesteps	Generalizability Limitations Hardware Limitations Accuracy Limitations	Kernel time constants selected manually Evaluation limited to simple FC SNN No systematic study of kernel behavior across tasks No deployment on real neuromorphic hardware Slight accuracy drop compared to top convolution-based SNNs despite major efficiency gains.	Fixed (non-learnable) temporal kernels, motivating learnable or adaptive kernel designs. Extension to deeper SNN architectures and neuromorphic tasks beyond classification. Lack of hardware-level neuromorphic validation.	GPU \CPU	Novel Encoding Mechanism	DTS-SNN (Dynamic Time-Surfaces Spiking Neural Network)	Available	Neuron: LIF Optimizer: Adam (no weight decay or LR scheduling) Timesteps: 300 (Gesture), 500 (SHD), 100 (N-Cars) Batch sizes: 16, 64, or 256 depending on dataset
rayyan-388589278	P06	2025	Efficient {ANN}-{SNN}	Liu, Chang; Shen, Jiangrong; Ra		10.48550	http://ar	learnable encoding	Learnable clipping threshold Dual-threshold neuron parameters Membrane potential initialization value	ANN-to-SNN Conversion Method	ANN-to-SNN conversion	Reduced firing rate Efficient Timesteps	Energy efficiency computation Reduced computational operations	Stable	Performance Inference Robustness	Vision	Grayscale images RGB images	CIFAR-10 CIFAR-100 ImageNet	Classification task	Accuracy # Timesteps Energy	Energy Estimation Limitations Generalizability Limitations	No real neuromorphic hardware deployment (simulation-based) Energy evaluated via analytical SOP/FLOP estimates Method validated only on image classification	Extension to non-vision modalities On-chip neuromorphic validation Exploration beyond rate-based conversion	GPU \CPU	Conversion framework	Converted deep CNN-based SNN	Not Available	Neuron: IF ANN trained with quantized clip-floor-shift activation (learnable λ, L=4–8 recommended) Inference at T = 2–16 time steps
rayyan-378478131	P07	2022	Encoding Event-Based	Stewart, I	Nature Communicat	10.1145/:	https://d	learnable encoding	Synaptic weights Latent parameters	Surrogate gradient	Hybrid ANN–SNN architecture	Sparse spike activity Activity-driven suppression	Energy efficiency computation	Hardware-induced performance degradation	Performance Robustness	Vision	Event streams	NMNIST IBM DVSGesture Custom	Classification task	Accuracy Qualitative latent-space evaluation (T-SNE)	Hardware Limitations Accuracy Limitations Generalizability Limitations	Hardware performance degradation Precision-sensitive latent disentanglement Partial hardware deployment Class confusion	Evaluation on higher-precision neuromorphic hardware Extension to more complex tasks and larger class counts Missing adaptive-encoding comparisons Limited scalability analysis No quantitative energy benchmarks Improved on-chip learning algorithms	GPU \CPU Loihi	Novel Algorithmic Framework	Hybrid Guided Variational Autoencoder with SNN encoder	Not Available	Neuron: LIF (Δt = 1 ms) Surrogate gradients (fast sigmoid) Truncated BPTT (100 ms) VAE loss + excitation/inhibition losses GPU training with PyTorch Loihi deployment using SLAYER with quantized spiking μ, Σ
rayyan-378476879	P08	2022	Enhancing spiking neu	Liu, Faqia	Nature Communicat	10.3389/	https://w	learnable and adaptive encoding	Synaptic weights Membrane thresholds Temporal decay parameters	Surrogate gradient	Hybrid ANN–SNN architecture	Activity-driven suppression Reduced firing rate Sparse spike activity	Reduced computational operations Energy efficiency computation MAC operations reduction	Stable Efficiency	Performance Robustness Inference Generalization	Vision	Grayscale images RGB images Event streams	CIFAR-10 CIFAR-100 MNIST N-MNIST	Classification task	Accuracy Adversarial robustness (PGD under L∞ constraint) Firing rate # MAC # Params # Timesteps	Hardware Limitations Architectural Limitations Methodological Limitations	Additional ANN introduces extra parameters and computation Attention applied mainly to encoder layer (limited exploration of deeper feedback) No direct deployment or benchmarking on neuromorphic hardware	End-to-end deployment on neuromorphic chips Extension to non-vision modalities More complex or multi-level attention mechanisms	GPU \CPU	Architecture proposal	Hybrid ANN–SNN (Convolutional SNN with ANN-based top-down attention)	Available	Neuron: LIF SGD with momentum 0.9 Batch size 200 Initial LR 0.1 with warm-up Time step Td = 1 ms K = 6 (static) / 10 (neuromorphic) Attention period Tf = 2Td Temperature-scheduled sigmoid (max Te = 6) Loss weight α ∈ {0.01, 0.1} Sparsity coefficients β = 0.40, γ = 0.51.
rayyan-388589281	P09	2023	Event-{Enhanced} {Mu	Wang, Ya	npj Unconventional	10.1145/:	http://ar	learnable and adaptive encoding	Synaptic weights Latent parameters Membrane thresholds	Surrogate gradient	Hybrid ANN–SNN architecture	Sparse spike activity	Reduced computational operations Energy efficiency computation Memory-efficient	Stable Convergence Faster training	Performance Robustness Inference Generalization	Multimodal	Event streams Laser scans	Custom	Reinforcement learning task	Success rate # Add # Mult	Hardware Limitations Generalizability Limitations	Evaluated only in simulation No real-robot deployment Need more real challenging scenes	Lack of real-world neuromorphic deployment No UAV or subterranean robot validation Absence of energy benchmarks on hardware	Gazebo simulator+AA19 GPU \CPU	Architecture proposal	Spiking Actor–Critic Architecture	Not Available	Neuron: LIF DDPG (Deep Deterministic Policy Gradient (DDPG)) Batch size 256 Learning rate 1e-4 MFDM-LT timestep = 5 Laser 20 Hz, DVS 100 Hz Current decay 0.5, voltage decay 0.75 Population size = 10
rayyan-388589103	P10	2023	Feasibility study on th	Sun, Anto	Nature Communicat	10.3389/	https://w	Adaptive encoding	Adaptive (data-driven) parameters	Surrogate gradient	Pure SNN architecture	Sparse spike activity Activity-driven suppression	Reduced computational operations Low latency AC-dominant computation Energy efficiency computation	Stable Faster training	Inference Robustness	Biosignals	Event streams	Custom	Classification task Action/Gesture Recognition	Accuracy Energy # Add # Mult Inference latency Spike release rate (SRR) Statistical significance (ANOVA)	Methodological Limitations Generalizability Limitations Hardware Limitations Architectural Limitations Accuracy Limitations	Single encoding method and neuron model Only steady-state EMG used Evaluated on limited datasets Lower accuracy than some advanced DNN approaches ower/latency are algorithmic estimates only No real neuromorphic hardware deployment	Exploration of alternative encoding schemes Evaluation on public datasets Inclusion of transition-phase EMG Integration of advanced training strategies On-chip neuromorphic deployment	GPU \CPU	Feasibility study	SNN	Not Available	Neuron: LIF Optimizer: Adam Learning rate: 0.1, 0.01 Batch size: 1/8 of training set Loss: cross-entropy Integration window: T=100 θ=0.6 Vthr2=10.

rayyan-378476870	P11	2023	Hybrid photonic deep	Zhang, Ya	Neuromorphic Com	10.1364/	https://w	learnable encoding	Synaptic weights	Surrogate gradient ANN-to-SNN Conversion Method	Hybrid ANN–SNN architecture ANN-to-SNN conversion	Efficient Timesteps	Energy efficiency computation	Convergence Performance sensitive to time-step	Inference	Texts	Word embeddings	MR AG News IMDB Yelp review polarity	Classification task	Accuracy # Timesteps	Generalizability Limitations Hardware Limitations Energy Estimation Limitations	Energy efficiency discussed conceptually without measured neuromorphic power metrics Photonic SNN limited to classifier stage Evaluation limited to text classification benchmarks No direct deployment or benchmarking on neuromorphic hardware	End-to-end photonic SNN training Deeper photonic integration beyond classifier Broader NLP tasks and multilingual datasets	GPU \CPU	Architecture proposal	Deep convolutional residual spiking neural network (DCRSNN)	Not Available	Neuron: LIF surrogate gradient (arctan/softsign/sigmoid) Adam optimizer (lr = 0.001) Batch size 256 Time window T = 1–16 ms 50 epochs
rayyan-378476869	P12	2023	Hybrid Spiking Fully Cc	Zhang, Ta	Frontiers in Neurosc	10.3390/	https://w	learnable encoding	Synaptic weights	Surrogate gradient	Hybrid ANN–SNN architecture		AC-dominant computation Energy efficiency computation	Stable Performance sensitive to time-step	Performance	Vision	RGB images	VOC2012 COCO2017 DRIVE Cityscapes	Semantic Segmentation task	MIoU Pixel Acc # Params Precision Recall F1 Energy	Training scalability Limitations Accuracy Limitations Hardware Limitations Energy Estimation Limitations	Performance inferior to CNNs Sensitive to time-step selection Long training time Lack of pretrained SNN models Energy based on theoretical estimation No direct deployment or benchmarking on neuromorphic hardware	Lack of pretrained SNN backbones Limited exploration of deeper adaptive encoding No real neuromorphic hardware deployment	GPU \CPU CMOS energy model	Architecture proposal	Hybrid spiking fully convolutional neural network (SFCNN)	Not Available	Neuron: IF Time window=6 Simulation time step=1 ms Adam optimizer LR=0.0005 Batch size=8 Cosine LR scheduler Softsign surrogate Cross-entropy loss
rayyan-378478374	P13	2025	NeuBridge: bridging qu	Yang, Yuchen; Liu, Jingcheng; Y		10.1088/	https://w	learnable and adaptive encoding	Synaptic weights Temporal decay parameters	ANN-to-SNN Conversion Method	ANN-to-SNN conversion	Reduced spike count	Low latency AC-dominant computation Energy efficiency computation	Stable	Inference Performance	Vision	Grayscale images RGB images	CIFAR-10 ImageNet	Classification task	Accuracy # Add # Mult # Timesteps Energy	Hardware Limitations Energy Estimation Limitations Generalizability Limitations Methodological Limitations	No physical neuromorphic chip deployment Energy estimated analytically Evaluation limited to vision benchmarks Comparison with adaptive-at-runtime encoding mechanisms2	Lack of real neuromorphic hardware validation No evaluation on non-vision modalities Absence of on-chip learning	GPU \CPU	Novel Algorithmic Framework	Converted spiking neural network (LIF-based)	Available	Neuron: LIF Quantization-aware ANN training SGD (momentum 0.9) Cross-entropy loss Quantization-aware training Trainable τ ∈ [1, 4] ANN trained first SNN obtained via direct conversion
rayyan-378478161	P14	2023	Single {{Channel Spee	Riahi, Abi	Complexity	10.48550/arXiv.230		learnable encoding	Synaptic weights Temporal decay parameters Membrane thresholds	Surrogate gradient	Hybrid ANN–SNN architecture	Sparse spike activity Activity-driven suppression	Energy efficiency computation MAC operations reduction	Stable	Inference Performance Robustness	Audio	Time-frequency representation	Voice Bank Corpus (VCTK) + DEMAND noise dataset	Regression task Speech enhancement	Perceptual Evaluation of Speech Quality (PESQ) Short-Time Objective Intelligibility (STOI) Deep Noise Suppression Mean Opinion Score (DNSMOS: SIG, BAK, OVRL)	Generalizability Limitations Hardware Limitations Architectural Limitations Methodological Limitations	No physical neuromorphic chip deployment Performance is evaluated using a fixed encoding strategy (direct input encoding). Only a single neuron model (LIF) is considered. A single loss function (log-spectral distance, LSD) is used. The approach relies exclusively on a direct-mapping strategy (no masking-based formulation). No masking-based SNN variant is explored or compared. No neuron model diversity (e.g., IF, adaptive LIF, SRM) is investigated.	Extension to alternative encoding strategies (e.g., masking, adaptive encoders) Other neuron models Different loss functions Broader speech enhancement scenarios.	GPU \CPU	Architecture proposal	U-Net-based Spiking Neural Network	Not Available	Neuron: LIF Adam (lr=0.002, β1=0.5, β2=0.9) Batch size 32 60 epochs Surrogate gradient (ArcTan) Convolution weights ~ (0,0.2) Decay strengths & thresholds initialized from normal $\mathcal{N}$ distributions.
rayyan-378478320	P15	2022	SIT: {{A Bionic}} and {{	Jin, Chen	Biomimetics	10.48550/arXiv.220		learnable encoding	Synaptic weights	Surrogate gradient	Hybrid ANN–SNN architecture			Faster training		Vision	Grayscale images RGB images Event streams	MNIST Fashion-MNIST CIFAR-10 N-MNIS CIFAR10-DVS DVS128 Gesture	Classification task Action/Gesture Recognition	Accuracy	Methodological Limitations Interpretability Limitations Energy Estimation Limitations Hardware Limitations	PPA-based standardization quantitatively resolves only parameter b Other Izhikevich parameters rely on empirical or neuroscience heuristics No neuromorphic hardware deployment or energy evaluation.	Fully learnable or adaptive neuron parameterization beyond b Hardware-level neuromorphic validation (e.g., Loihi) Explicit energy/spike-efficiency benchmarking Extension beyond vision-classification tasks	GPU \CPU	Architecture proposal	Hybrid CNN-SNN	Not Available	Neuron: Izhikevich Surrogate-gradient training Adam (lr = 0.01) with cosine annealing Batch = 16 τ = 2 simulation steps T = 8–20 depending on dataset SIT neurons inserted into selected convolutional layers.

rayyan-388589280	P16	2025	Spike {Encoding} for {I	Larroza, A	IEEE Access	10.48550	http://arx	Adaptive encoding	Adaptive (data-driven) parameters	Surrogate gradient	Pure SNN architecture	Reduced firing rate Reduced spike count	Energy efficiency computation	Stable		Audio	128-band Mel-spectrograms (20–20 kHz)	ESC-10 UrbanSound8K TAU Urban Acoustic Scenes (TAU-3Class)	Classification task Regression task Signal reconstruction	Error in decibels (ERRdB) Signal-to-noise ratio (SNR) Accuracy Firing rate Encoding time Memory usage	Methodological Limitations Architectural Limitations Accuracy Limitations Hardware Limitations	All SNN results remain below ANN baselines No encoder–architecture co-design Fixed SNN architecture not optimized for audio No neuromorphic hardware deployment	Lack of learnable or gradient-trained spike encoders for environmental audio Need for encoder–architecture co-design Evaluation on neuromorphic hardware Exploration of attention-based SNNs paired with efficient encoders	GPU \CPU	Comparative Benchmark Study	Pure SNN classifier with external spike encoder	Not Available	Neuron: LIF Mel-spectrogram => spike encoding (MW / SF / TAE) => FC-SNN (LIF) Batch = 32 Lr = 0.01, 100 epochs Macro-accuracy evaluation
rayyan-378478367	P17	2024	Spiking Neural Networ	Stoffel, Marcus; Tandale, Saura		10.1038/s44335-024		learnable and adaptive encoding	Synaptic weights Temporal decay parameters Membrane thresholds	Surrogate gradient	Hybrid ANN–SNN architecture	Sparse spike activity	Energy efficiency computation	Slower Stable	Robustness	Real Numbers	Real Numbers	Custom	Regression task	Root Mean Squared Error (RMSE) Energy	Training scalability Limitations Hardware Limitations Energy Estimation Limitations	Energy values are estimated using KerasSpiking (not direct hardware measurements) Training time of SNNs is longer than ANN counterparts Full deployment on neuromorphic hardware is constrained by dense layers	Limited prior work on nonlinear regression with SNNs Need for broader application domains and deeper fully spiking architectures Further validation on real neuromorphic hardware beyond partial deployment	Loihi GPU \CPU	Novel Algorithmic Framework	Recurrent Spiking Neural Network (RSNN)	Not Available	Neuron: LIF Adam optimizer (lr = 0.001, β_1 = 0.9, β_2 = 0.999) Surrogate-gradient learning Hyperband architecture search RMSE loss
rayyan-388589275	P18	2024	STAL: Spike Threshold	Hens, Freek; Dehshibi, Moham		10.48550	http://arx	learnable and adaptive encoding	Synaptic weights Membrane thresholds	Surrogate gradient	Hybrid ANN–SNN architecture	Sparse spike activity	Energy efficiency computation	Stable	Robustness Performance	Multimodal	Electromyography (EMG) Inertial measurement unit (IMU)	EmoPain dataset	Classification task	Accuracy F1 AUC Matthews Correlation Coefficient (MCC) Spike density	Hardware Limitations Energy Estimation Limitations Generalizability Limitations	Small dataset size and class imbalance Higher spike density for best-performing STAL–Stacked variant No deployment on neuromorphic hardware Performance lower than deep learning models in AUC	Neuromorphic hardware implementation and benchmarking Extension to multi-level pain intensity and behavior classification Broader biosignal domains Real-world wearable deployment	GPU \CPU	Architecture proposal	Ensemble of Spiking Recurrent Neural Network (SRNN)	Available	Neuron: LIF AdamW optimizer LR = 5e-3 (encoder), 7.5e-4 (SRNN) batch sizes {sEMG:32, Energy:8, Angle:16} ψ = 5 spikes/step dropout = 0.5 30 encoder epochs 25 SRNN epochs early stopping LOSO (Leave-One-Subject-Out) cross-validation
rayyan-388589277	P19	2024	Ternary {Spike}-based	Wang, Shuai; Zhang, Dehao; Be		10.48550	http://arx	Adaptive encoding	Adaptive (data-driven) parameters	Surrogate gradient	Pure SNN architecture	Sparse spike activity Reduced firing rate	Energy efficiency computation Memory-efficient Multiplication-free inference (MFI)	Stable	Robustness Performance	Biosignals Audio	Electroencephalogram (EEG) Raw audio waveform (time-domain signal)	Google Speech Commands(GSC) KUL EEG dataset DTU EEG dataset	Classification task Speech recognition	Accuracy Memory usage Precision(weights / membrane potentials) # Timesteps # Add # Mult Energy	Hardware Limitations Energy Estimation Limitations Generalizability Limitations	Energy evaluation based on theoretical analysis only No real neuromorphic hardware deployment Evaluation limited to speech and EEG tasks	Deployment on real neuromorphic chips Extension to additional signal modalities On-chip learning validation	GPU \CPU	Architecture proposal	Quantized Ternary Spiking Neural Network (QT-SNN)	Not Available	Neuron: LIF STBP; τ = 0.5 Learnable Vth/α_1 => inside the QT-SNN neuron model (not in the encoding stage) α_3/α_1 constrained to powers of two 4 inference timesteps Raw signal → TAE → ternary spikes → QT-SNN; STBP training; learnable threshold scaling & spike amplitude; quantized inference with bit-shift operations