Fractional-Order Spiking Neural Networks

Venue: ICLR 2026 (Poster)

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Spiking Neural Networks

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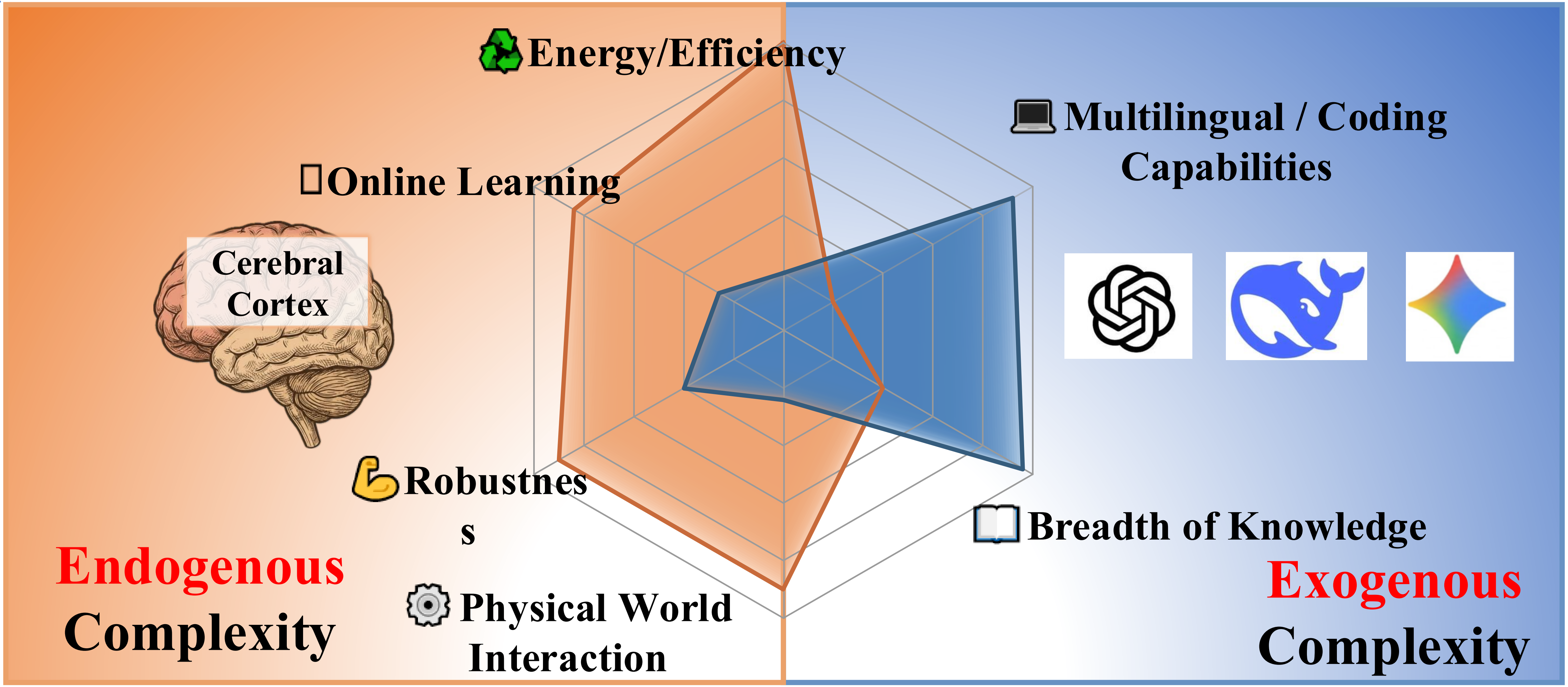
Background | **Brain vs. Mainstream LLMs**



Fractional-Order Continuous SNNs

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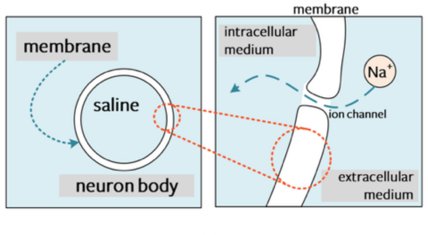
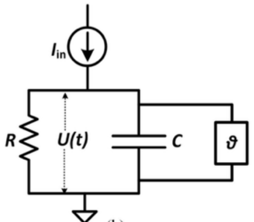
Motivation

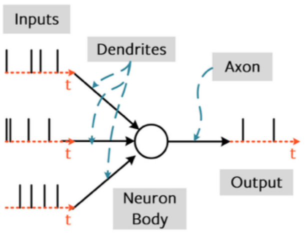
Current Mainstream SNN Paradigm：Discretization of recurrent neural networks (RNNs) based on integer-order differential equations.



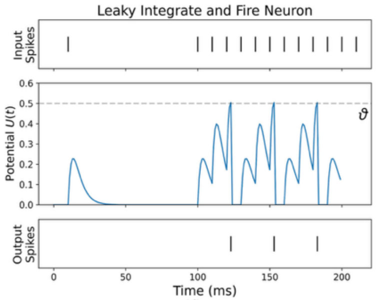
(a)



(b)



(c)



(d)

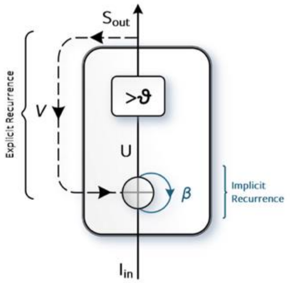
Current principles of SNNs

Dynamic： $\tau \frac{dU(t)}{dt} = -U(t) + I_{\text{in}}(t)R$

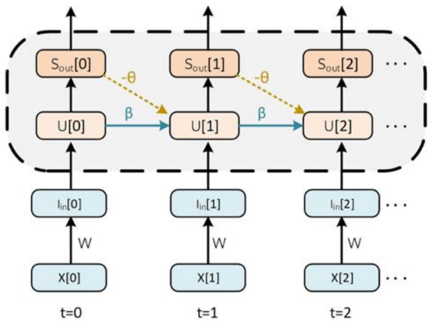
Euler Discretization：

$$\tau \frac{U(t+\Delta t) - U(t)}{\Delta t} = -U(t) + I_{\text{in}}(t)R$$

$$U(t+\Delta t) = \left(1 - \frac{\Delta t}{\tau}\right) U(t) + \frac{\Delta t}{\tau} I_{\text{in}}(t)R$$



(a)



(b)

RNN Form：

$$U[t+1] = \beta U[t] + (1-\beta) I_{\text{in}}[t+1]$$

$$U[t] = \underbrace{\beta U[t-1]}_{\text{decay}} + \underbrace{WX[t]}_{\text{input}} - \underbrace{S_{\text{out}}[t-1]\theta}_{\text{reset}}$$

Limitations

- **Lack of neurodynamical properties:** Constrained by simplistic exponential decay dynamics, current models exhibit **rapid forgetting** and **lack long-range memory**, making it difficult to capture complex historical dependencies.
- **Weak Temporal Robustness:** Algorithms heavily rely on **regular time grids**; their performance degrades significantly when confronted with irregular sampling or data loss in real-world scenarios.
- **High memory overhead:** Backpropagation through the entire time horizon leads to **linear growth of GPU memory usage with sequence length**, severely limiting the model's capacity to handle **long temporal sequences**.

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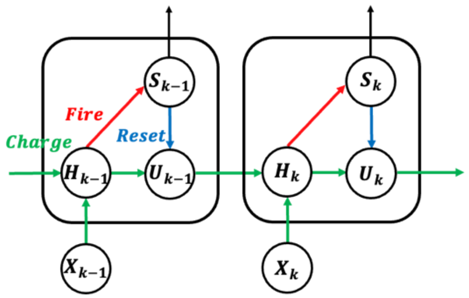
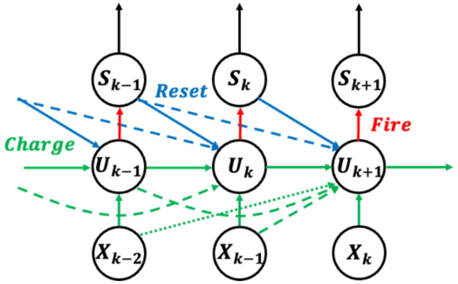
Method

f-SNN: SNN framework **driven by fractional-order differential equations**

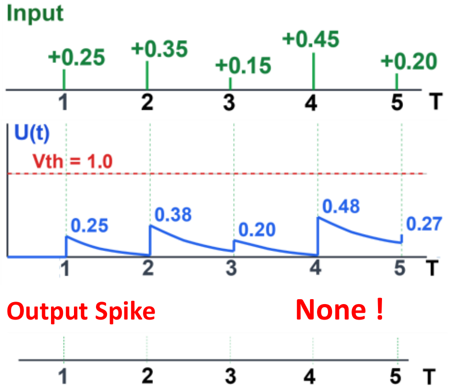
	Integer-order SNN (LIF)	Fractional-order SNN (*f*-LIF)
Dynamical equation	$\tau \frac{dU(t)}{dt} = -U(t) + I_{\text{in}}(t)R$	${}_{\text{left}}D_C^{\beta} U(t) = -U(t) + WX(t) - S_{\text{out}}(t)\theta$

Computational graph model

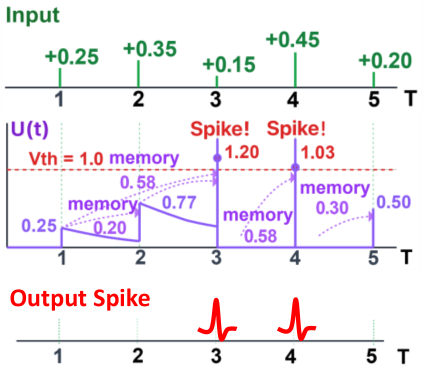




Membrane potential dynamics



LIF



f-LIF

Strengths

- **Rich neurodynamical properties**: Leveraging power-law decay dynamics, the model effectively captures complex **historical dependencies** and faithfully reproduces the **frequency adaptation** mechanisms observed in biological neurons.
- **Strong temporal robustness**: It eliminates reliance on regular time grids, maintaining exceptional inference stability under **irregular sampling** or **data loss**.
- **Efficient memory usage**: Network updates are performed by backward solving of ODEs or FDEs, obviating the need to store gradients at all time steps and thereby **substantially reducing memory consumption during training**.

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Experiments

Results： *f*-SNN vs. SNN

Datasets/Configs	Architecture	Timesteps	LIF (SpikingJelly)	LIF (snnTorch)	*f*-LIF (*f*-SNN)
N-MNIST	CNN-based	16	0.9927	0.9908	**0.9948**
DVS-Lip	CNN-based	16	0.4241	0.3271	**0.4342**
DVS128Gesture	CNN-based	16	0.9340	0.8899	**0.9480**
	Transformer-based	16	0.9514	0.8715	**0.9583**
N-Caltech101	CNN-based	16	0.6682	0.6521	**0.7026**
	Transformer-based	16	0.7263	0.6567	**0.7627**
HarDVS	CNN-based	8	0.4610	0.4626	**0.4766**
	Transformer-based	8	0.4520	0.4614	**0.4723**

Performance Comparison on Visual Tasks (Neuromorphic Datasets: *f*-LIF vs. LIF)

Datasets	Architecture	Timesteps	LIF (SJ)	LIF (snnTorch)	*f*-LIF (*f*-SNN)
CIFAR-10	Spiking-ResNet-18	4	0.9134	0.9026	**0.9215**
CIFAR-100	Spiking-ResNet-18	4	0.6813	0.6445	**0.6874**
ImageNet	SpikFormer	4	0.6637	0.6584	**0.6791**
ImageNet (spike encoder)	SpikFormer	4	0.5549	0.5432	**0.5738**

Performance Comparison on Visual Tasks (Static Datasets: *f*-LIF vs. LIF)

Results

Core Conclusion: f-LIF consistently demonstrates superior performance over the integer-order LIF across multimodal and multi-architecture tasks.

- **Visual Tasks**: On various neuromorphic and static visual datasets, f-LIF consistently achieves higher classification accuracy than the integer-order LIF, showing consistent performance across both CNN and Transformer architectures.

- **Graph Neural Network Tasks:** In graph neural network tasks, *f*-LIF significantly outperforms the integer-order LIF in both node classification and link prediction performance.

Experiments

Results： *f*-SNN vs. SNN

Methods	Cora	Citeseer	Pubmed	Photo	Computers	ogbn-arxiv
SGCN (SJ)	$81.81_{\pm 0.69}$	$71.83_{\pm 0.23}$	$86.79_{\pm 0.32}$	$87.72_{\pm 0.25}$	$70.86_{\pm 0.24}$	$50.26_{\pm 0.11}$
SGCN (snnTorch)	$83.12_{\pm 1.41}$	$71.68_{\pm 0.95}$	$59.82_{\pm 1.07}$	$83.34_{\pm 0.89}$	$74.88_{\pm 0.87}$	$21.55_{\pm 0.13}$
SGCN (*f*-SNN)	$\mathbf{88.08}_{\pm 0.58}$	$\mathbf{73.80}_{\pm 0.51}$	$\mathbf{87.17}_{\pm 0.28}$	$\mathbf{92.49}_{\pm 0.32}$	$\mathbf{89.12}_{\pm 0.21}$	$\mathbf{51.10}_{\pm 0.14}$
DRSGNN (SJ)	$83.30_{\pm 0.64}$	$72.72_{\pm 0.24}$	$87.13_{\pm 0.34}$	$88.31_{\pm 0.15}$	$76.55_{\pm 0.17}$	$50.13_{\pm 0.14}$
DRSGNN (snnTorch)	$80.98_{\pm 1.71}$	$68.00_{\pm 0.69}$	$59.56_{\pm 1.05}$	$82.28_{\pm 0.93}$	$76.78_{\pm 0.81}$	$28.46_{\pm 0.25}$
DRSGNN (*f*-SNN)	$\mathbf{88.51}_{\pm 0.62}$	$\mathbf{75.11}_{\pm 0.45}$	$\mathbf{87.29}_{\pm 0.32}$	$\mathbf{91.93}_{\pm 0.20}$	$\mathbf{88.77}_{\pm 0.20}$	$\mathbf{53.13}_{\pm 0.13}$

Performance Comparison on Graph Neural Network Tasks (Node Classification: *f*-LIF vs. LIF)

Methods	Computers	Photos	CS	Physics
MSG (SJ)	$94.65_{\pm 0.73}$	$96.75_{\pm 0.18}$	$95.19_{\pm 0.15}$	$93.43_{\pm 0.16}$
MSG (*f*-SNN)	$\mathbf{94.91}_{\pm 0.12}$	$\mathbf{96.80}_{\pm 0.16}$	$\mathbf{96.53}_{\pm 0.15}$	$\mathbf{96.57}_{\pm 0.08}$

Performance Comparison on Graph Neural Network Tasks (Link Prediction: *f*-LIF vs. LIF)

Results

Core Conclusion: f-LIF consistently demonstrates superior performance over the integer-order LIF across multimodal and multi-architecture tasks.

- **Visual Tasks**: On various neuromorphic and static visual datasets, f-LIF consistently achieves higher classification accuracy than the integer-order LIF, showing consistent performance across both CNN and Transformer architectures.

- **Graph Neural Network Tasks:** In graph neural network tasks, *f*-LIF significantly outperforms the integer-order LIF in both node classification and link prediction performance.

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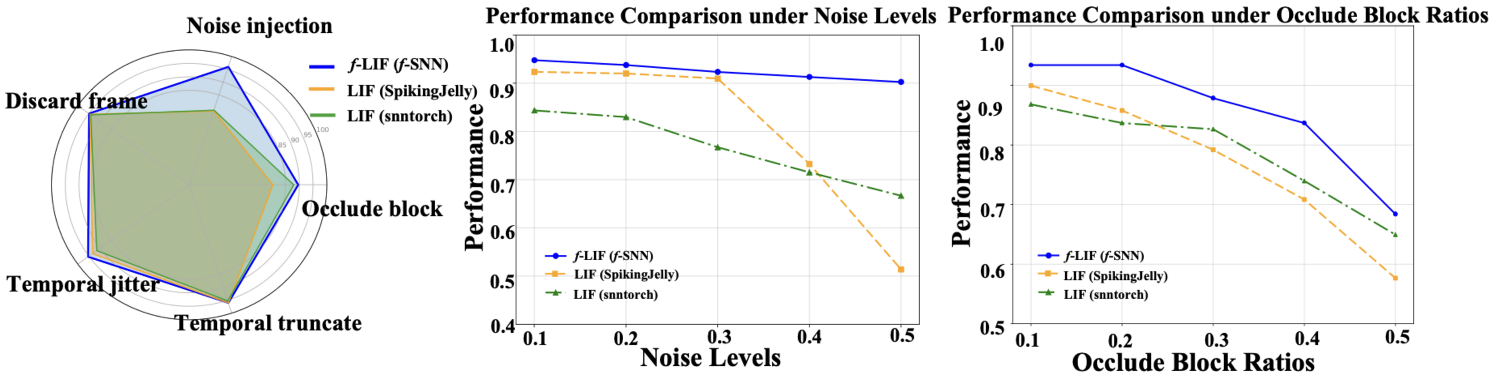
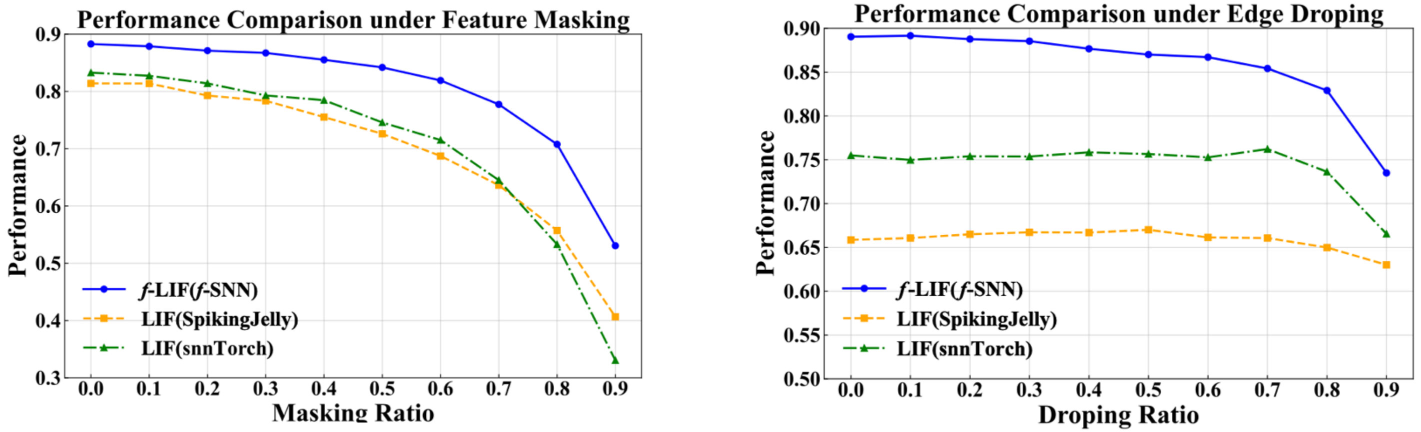
Experiments

Results: *f*-SNN vs. SNN



Robustness Comparison on Vision Tasks (*f*-LIF vs. LIF)



Robustness Comparison on Graph Neural Network Tasks (*f*-LIF vs. LIF)

Results

Core Conclusion: *f*-LIF consistently demonstrates superior robustness over the integer-order LIF across **multimodal and multi-architecture tasks**.

- **Visual Tasks**: *f*-LIF exhibits enhanced robustness against scenarios such as **noise injection**, **occlusion**, and **data loss** compared to the integer-order LIF.
- **Graph Neural Network Tasks:** *f*-LIF exhibits enhanced robustness against scenarios such as **noise injection**, **feature masking**, and **link perturbation** compared to the integer-order LIF.

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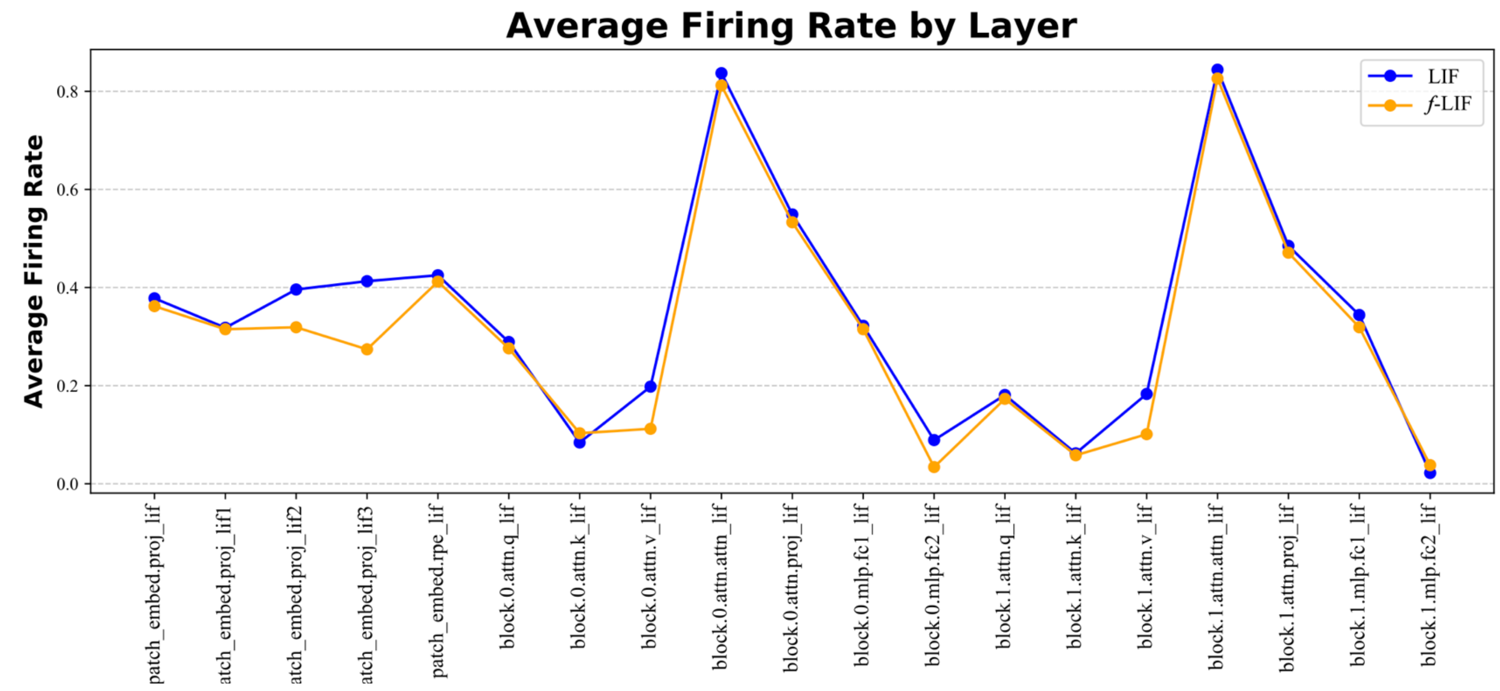
Experiments

Results: *f*-SNN vs. SNN



Layer-wise Firing Rates within the Transformer Framework

LIF

$E_{\text{synaptic total}} = \mathbf{2.69mJ}$

$E_{\text{neuron total}} = 0.235\text{mJ}$

$E_{\text{total}} = \mathbf{2.93mJ}$

***f*-LIF**

$E_{\text{synaptic total}} = 2.49\text{mJ}$

$E_{\text{neuron total}} = \mathbf{0.421mJ}$

$E_{\text{total}} = 2.91\text{mJ}$

Results

Core Conclusion: While *f*-LIF introduces **intrinsic complexity**, the overall network energy consumption remains comparable to that of LIF networks.

- **Neuronal Energy Consumption**: *f*-LIF incorporates **whole historical state variables** for computation, resulting in higher energy consumption at the neuronal layer level.
- **Network Layer Energy Consumption**: *f*-LIF exhibits **lower spike firing rates across network layers**, leading to lower overall network energy consumption compared to LIF.

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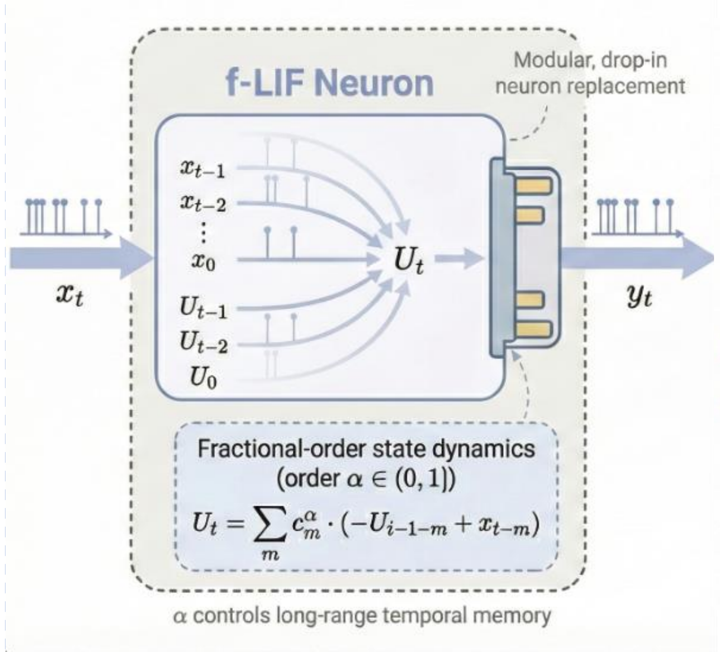
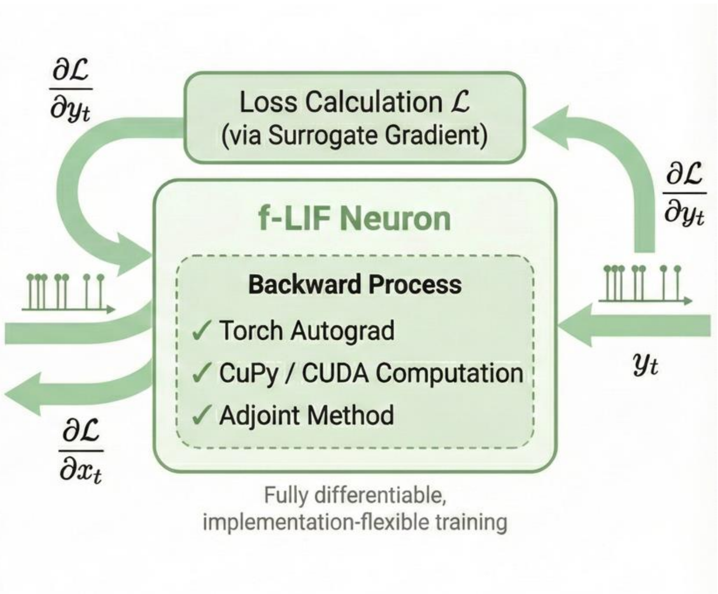
Community

Fractional-order Spiking Neural Network Open-source Platform spikeDE

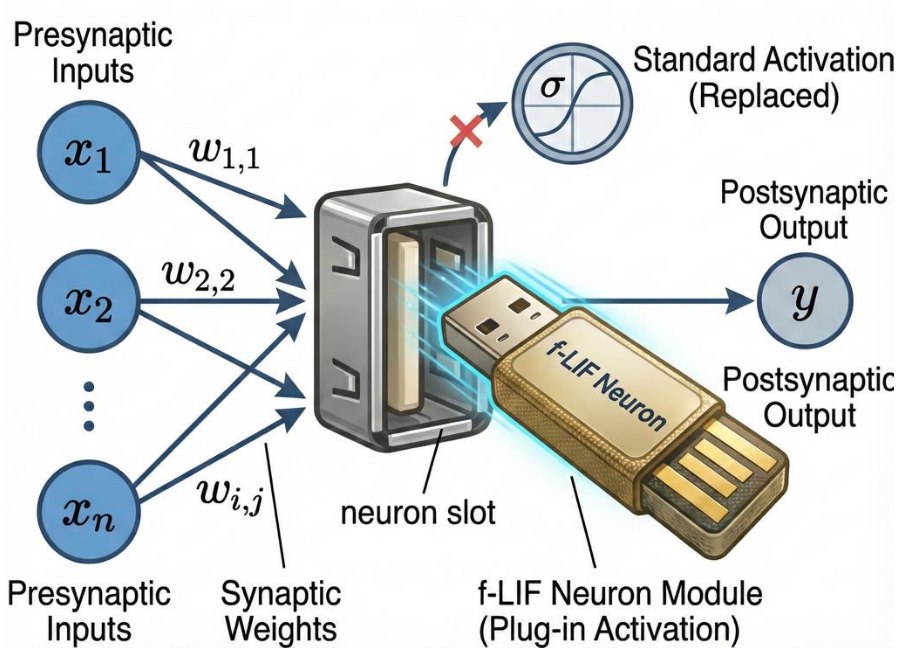
Forward



Backward



Plug-and-Play



Forward: Supports various fractional-order neural dynamical equations.

Backward: Supports PyTorch automatic differentiation, CuPy acceleration, and the adjoint method for solving.

The *f*-LIF neuron supports a **plug-and-play** design, facilitating its integration into mainstream neural networks to replace conventional activation functions.

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