BIOFLEXNET: LEARNABLE PATH SWITCHING BETWEEN SELECTIVITY AND INVARIANCE INSPIRED BY SYNAPTIC PLASTICITY

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1. ABSTRACT

The brain balances detail and abstraction through dynamic routing. Inspired by this, we propose BioFlexNet, a spiking neural network (SNN) with spike-driven path switching between selectivity and invariance, which operates under discrete, event-driven dynamics, enhancing adversarial robustness and preserving biological plausibility.

Our results highlight the potential of dynamic routing in spike-based systems for building resilient, energy-efficient neuromorphic architectures.

2. MOTIVATION

Biological perception is inherently adaptive, balancing selectivity and invariance through dynamic routing—a process shaped by synaptic plasticity and temporal dynamics.

In contrast, conventional ANNs and SNNs rely on fixed, static architectures, limiting adaptability, robustness, and biological plausibility.

Inspired by cortical computation, we propose PlasticFlexLayer, a trainable, spike-driven module that enables context-dependent routing between specialized pathways. Integrated into a spiking framework, our model captures essential principles of brain-like computation: temporal integration, event-driven efficiency, and resilience against perturbations.

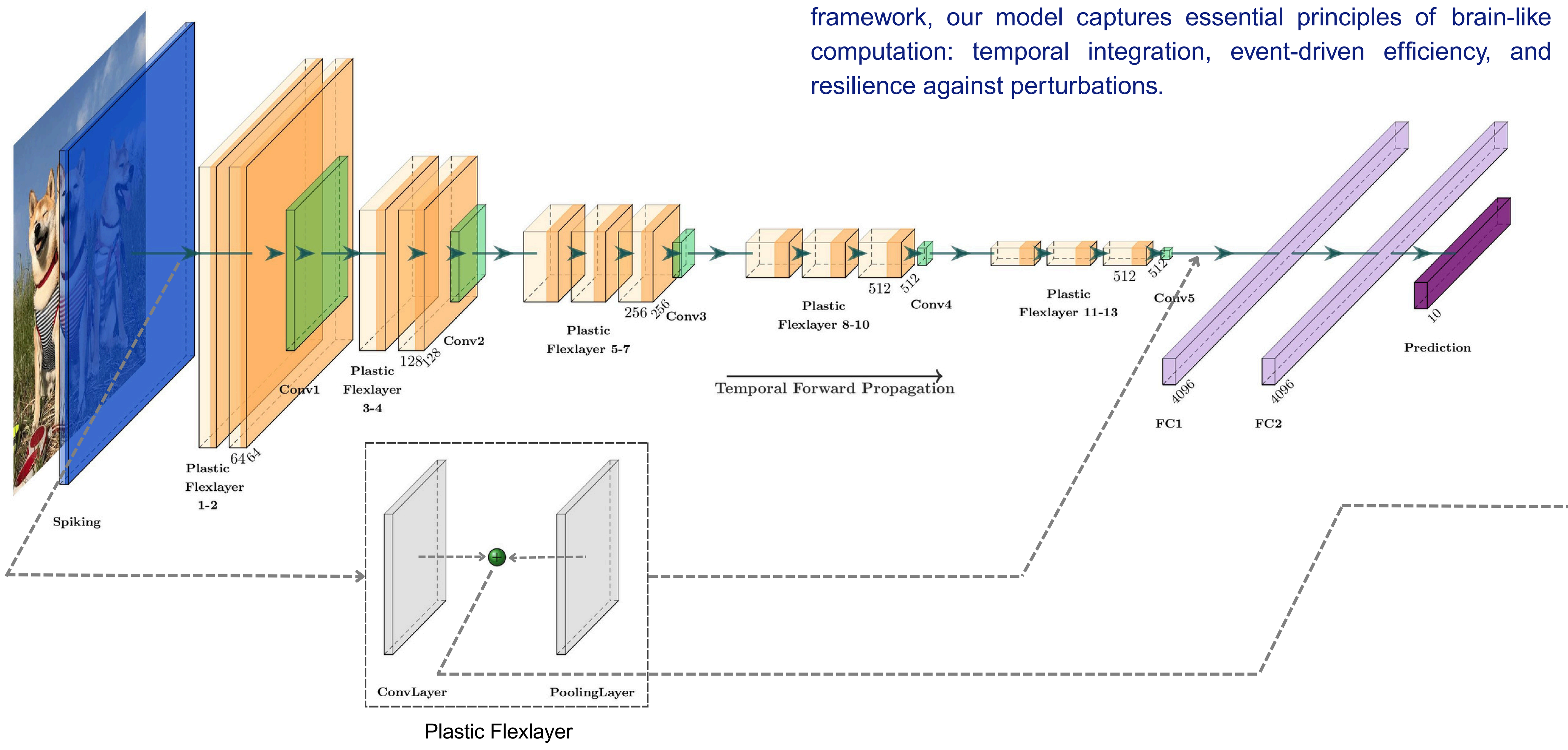

Figure 1: Overview of BioFlexNet architecture, integrating PlasticFlexLayers within a VGG-like backbone. Each PlasticFlexLayer adaptively routes features between selectivity and invariance pathways via a learned mask. The model supports both ANN and SNN modes, with temporal forward propagation and surrogate gradient (STBP) training for spiking dynamics.

3. METHODS

BioFlexNet integrates conventional feedforward structures with PlasticFlexLayers, biologically-inspired modules that enable dynamic routing between computational pathways. Each PlasticFlexLayer computes the output as:

$$u = m(x,t) \cdot Conv(x) + (1 - m(x,t)) \cdot Pool(x)$$

where the mask *m(x, t)* dynamically balances selectivity and invariance based on both feature and temporal context:

$$m(x,t) = \sigma(logits(x) + \eta(t)).$$

During training, we further encourage adaptive plasticity by updating masks according to the competition between pathways:

$$\Delta m = \lambda \cdot (r_{selectivity} - r_{invariance}).$$

In ANN mode, conventional activations are used; in SNN mode, the model performs temporal forward propagation and employs STBP for surrogate gradient training:

$$\frac{\partial u}{\partial y} \approx \frac{\partial}{\partial u} Spike(u).$$

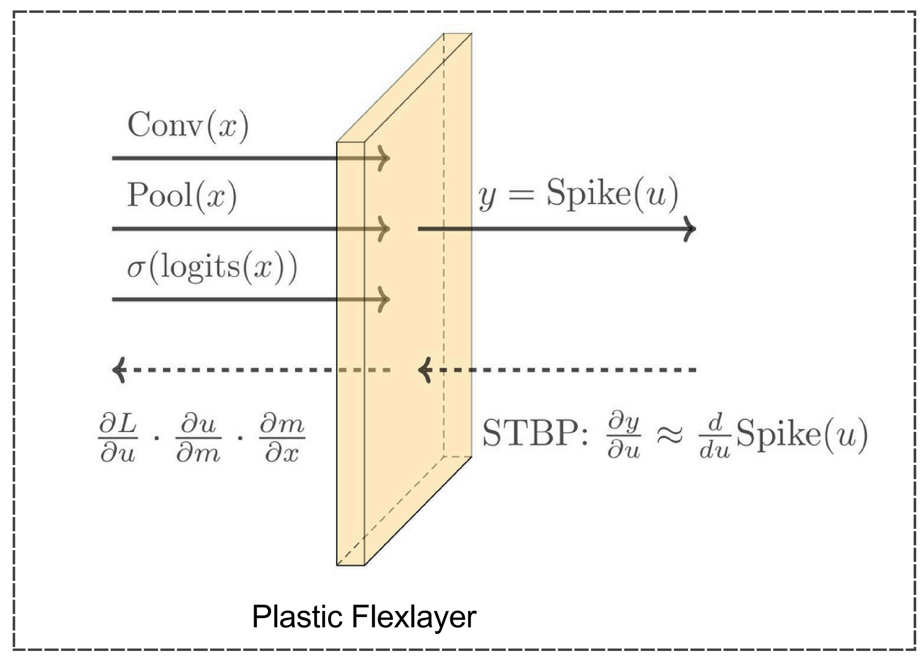

Figure 2: Diagram of the PlasticFlexLayer, which dynamically routes features between convolutional and pooling pathways via a learned mask and supports spiking activation with surrogate gradient training for end-to-end optimization.

4. ACCURACIES

We evaluated BioFlexNet and baseline VGG16 models under three configurations: ANN (ReLU activations), hybrid SNN (spike-based without gradient flow), and spiking SNN with surrogate gradient training (STBP). All models were trained on CIFAR-10 for 120 epochs, with SNN models using 10 timesteps for temporal forward propagation.

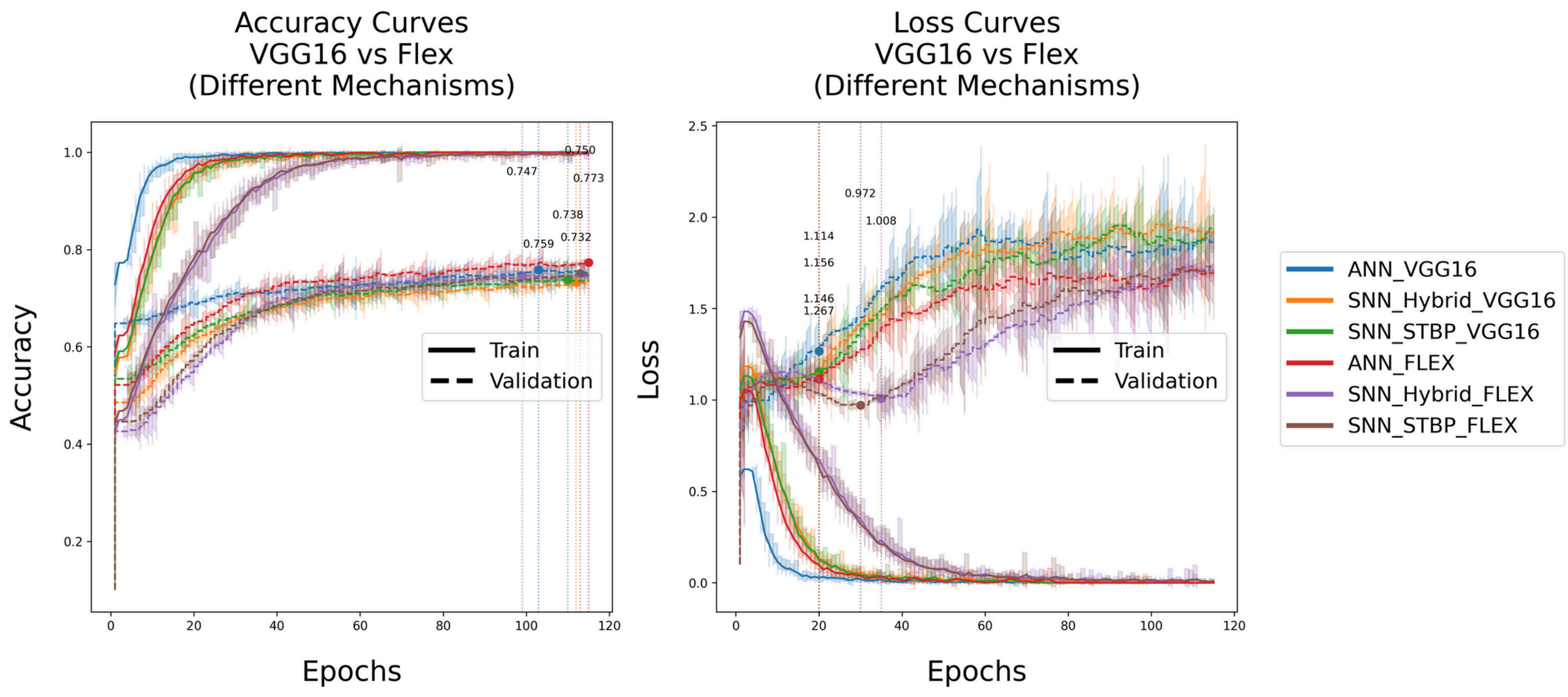

Figure 3: Accuracy (left) and loss (right) curves comparing VGG16 and FLEX architectures under ANN and SNN configurations. FLEX models exhibit more stable convergence patterns and reduced variance, particularly in spiking regimes with surrogate gradient training.

- FLEX architectures outperform VGG16 across modes.
- PlasticFlexLayer improves adaptability via dynamic routing.
- STBP improves spiking models but complements FLEX design.
- FLEX models remain stable across learning paradigms.

5. ADVERSARIAL ATTACK

SNNs are vulnerable to adversarial perturbations due to their discrete, spike-based dynamics. To address this, we investigate how integrating PlasticFlexLayer impacts SNN robustness. Under FGSM, PGD, and SPGD attacks, BioFlexNet consistently outperforms conventional SNNs and achieves robustness comparable to ANN models. These results demonstrate that combining dynamic routing with spike-based computation significantly enhances the resilience of spiking architectures against adversarial threats.

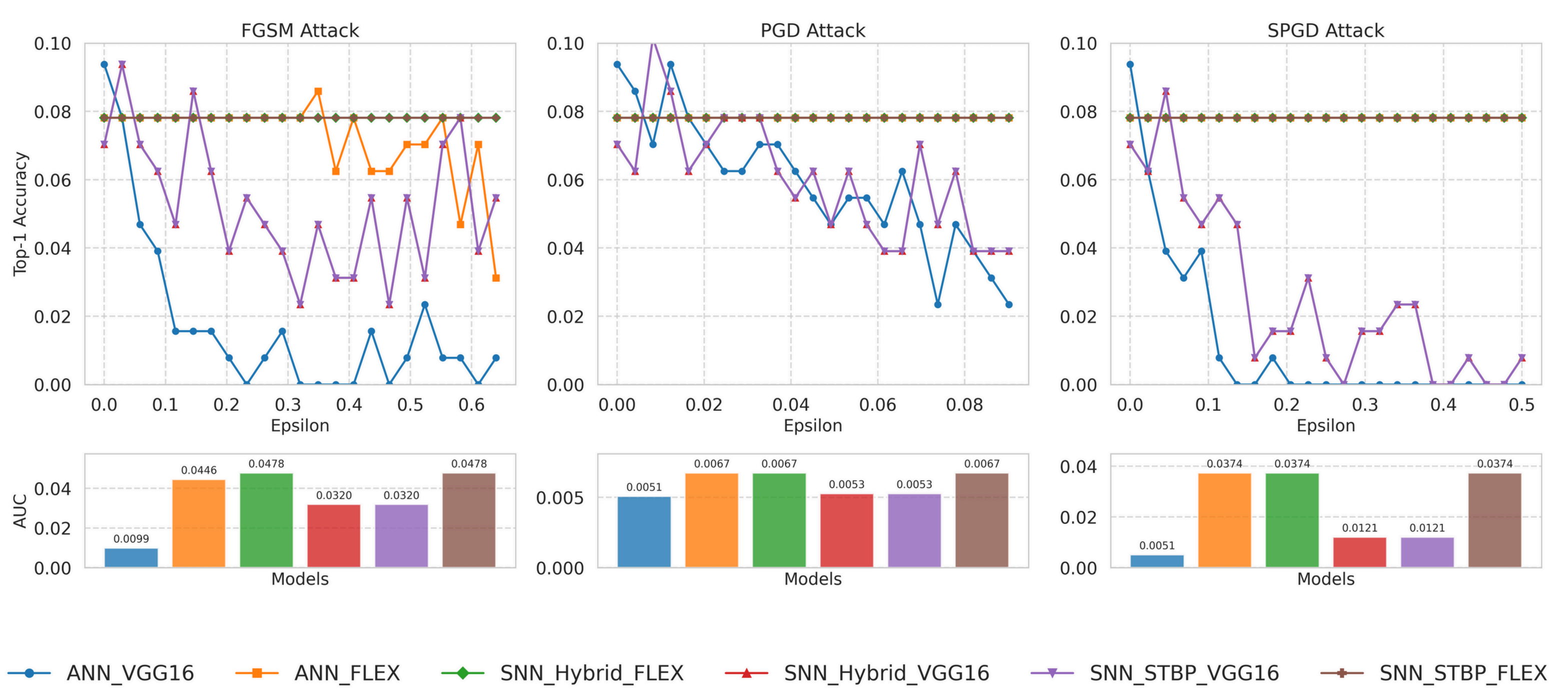

Figure: Top-1 accuracy under FGSM, PGD, and SPGD attacks for various models. Performance is evaluated across perturbation strengths (ϵ\epsilonϵ) with area under curve (AUC) summarizing overall robustness.

6. SPARSITY

Biological neural circuits rely on sparse, selective spiking to achieve energy-efficient computation. BioFlexNet, through its PlasticFlexLayer, learns to dynamically balance selectivity and invariance, leading to significantly sparser and more structured spiking patterns compared to traditional SNN architectures.

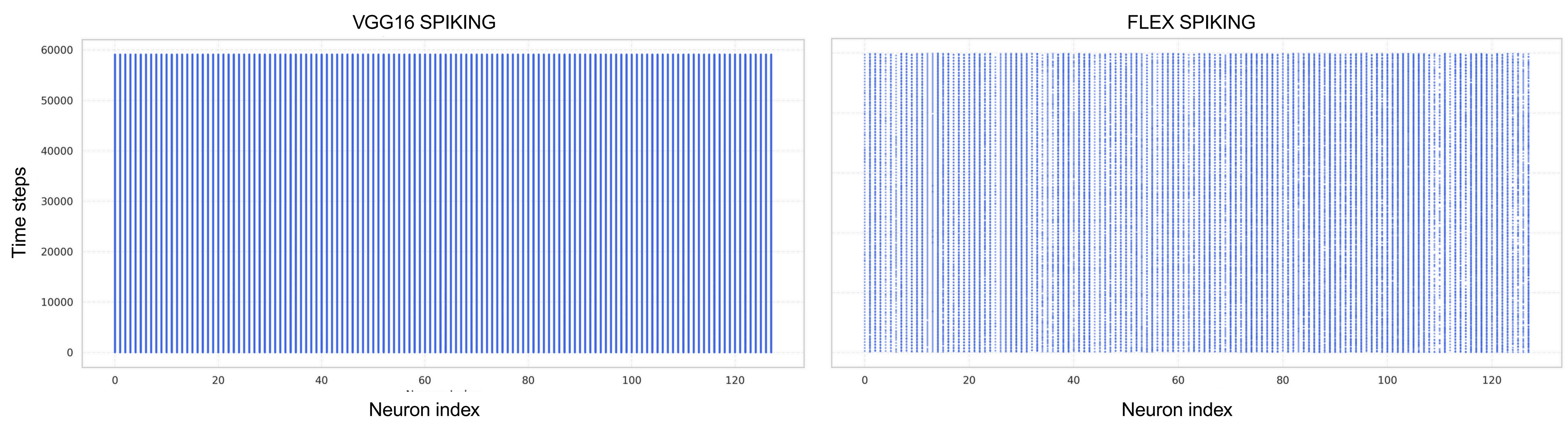

Figure 5: Spike raster plots for VGG16 (left) and BioFlexNet (right). BioFlexNet exhibits biologically-inspired sparse and structured spiking activity, reducing energy consumption while maintaining competitive performance.

7. LOSS LANDSCAPE EVOLUTION

Loss landscapes in SNNs are often chaotic and sharp, hindering optimization and generalization. Integrating PlasticFlexLayer introduces dynamic routing, smoothing the loss surface and broadening minima. Further applying surrogate gradient training with BioFlexNet leads to significantly flatter landscapes, indicating improved optimization stability and generalization.

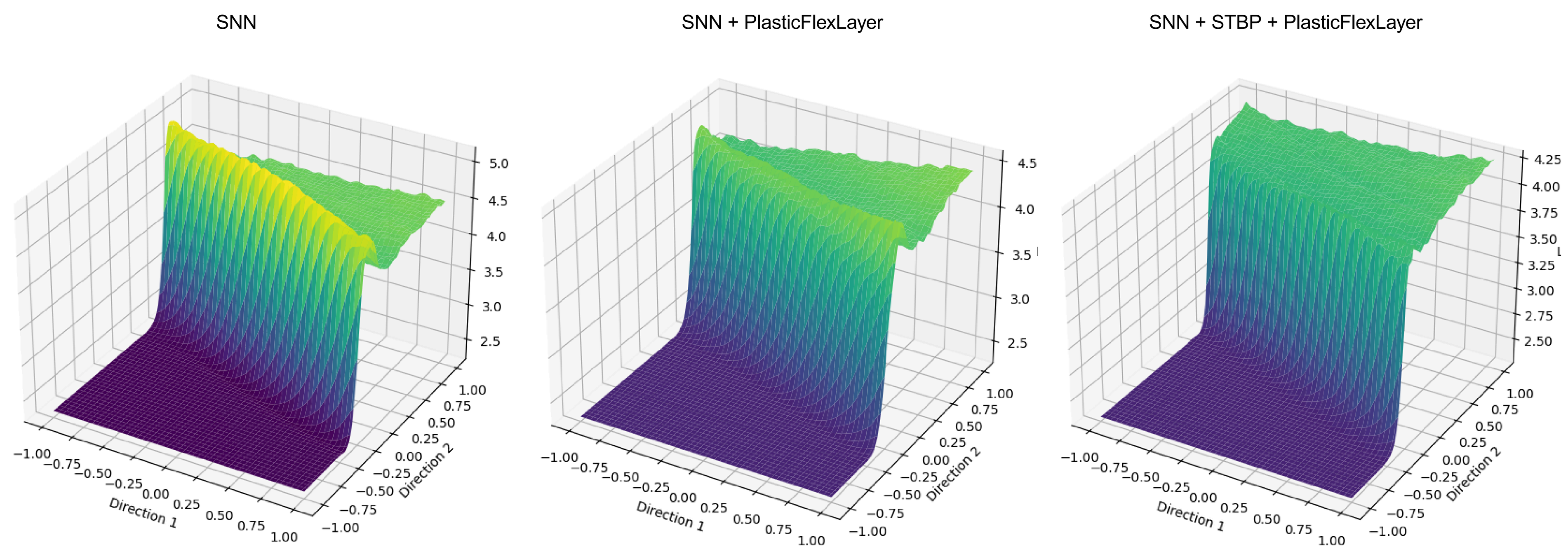

Figure 6: 3D loss surfaces for SNN variants. PlasticFlexLayer and STBP progressively smooth the loss landscape, improving optimization stability and generalization.

8. CONCLUSION

BioFlexNet integrates spike-driven dynamic routing via PlasticFlexLayer, capturing biological plausibility while improving optimization stability and adversarial robustness.

These results demonstrate that structural flexibility, combined with spike-based computation, offers a promising path toward resilient and energy-efficient neuromorphic systems.

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