A Survey of Spiking Neural Networks and Their Learning Strategies

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Survey Overview

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- Section 2: Foundations of SNNs
- Section 3: Neuron Models and Signal Encoding
- Section 4: Learning and Training Methods
- Section 5: Challenges and Future Directions
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Overview of Spiking Neural Networks (SNNs)

Artificial Neural Networks (ANNs)

- Efficient at processing large data and solving complex problems through parallel computation.
- Learn from experience, improving accuracy and performance with exposure to new data.
- High computational power and energy consumption, particularly in real-time and edge device applications.
- Limited in processing time-dependent information like biological brains.

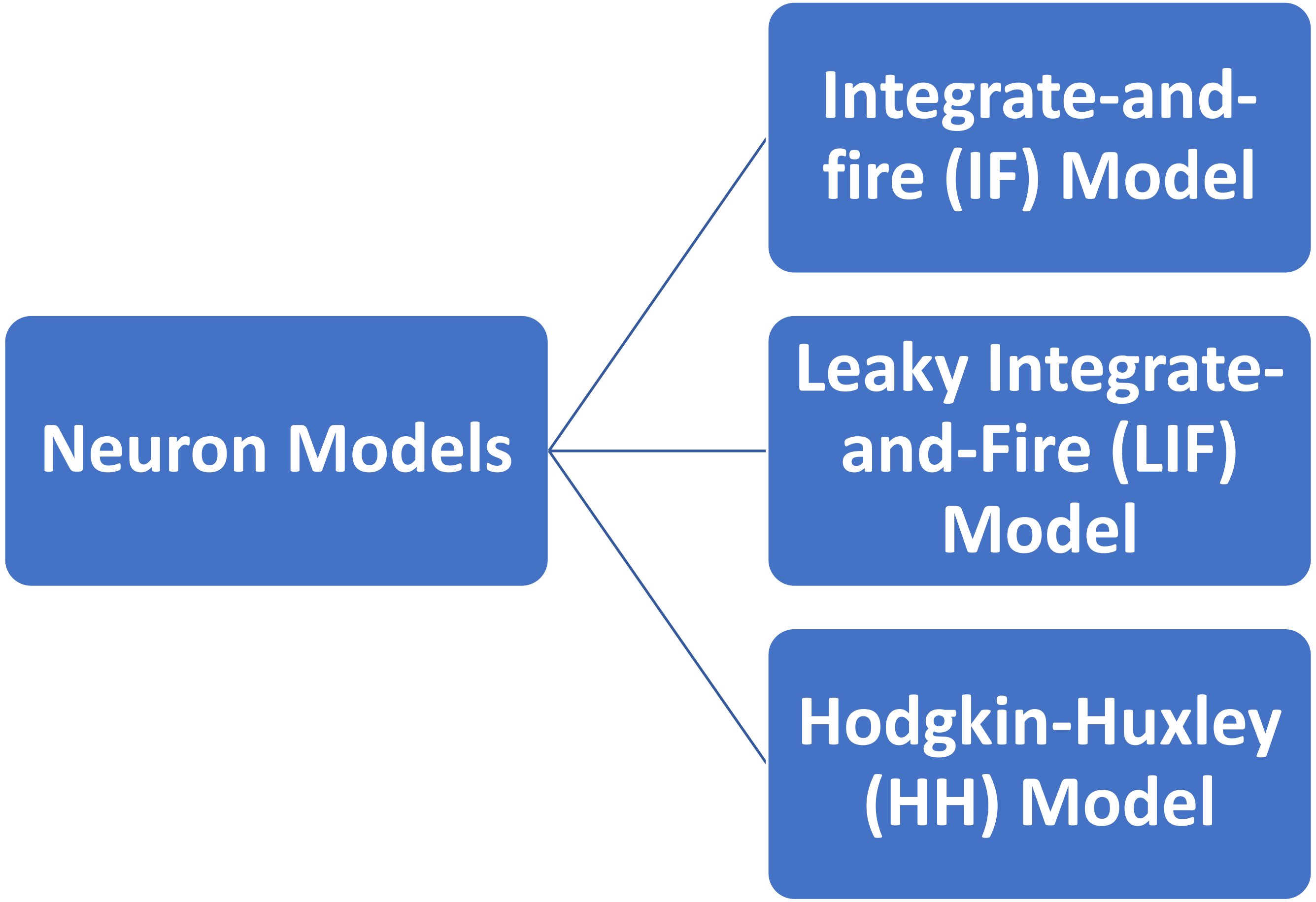
Spiking Neural Networks (SNNs)

- Overcome the limitations of ANNs with brain-inspired communication methods.
- Instead of continuous activation, SNNs send signals (spikes) only at specific times.
- Energy-efficient and better suited for processing time-based information

Terminologies

Term	Definition
Spike (Action Potential)	A brief electrical pulse emitted by a neuron to signal its activation to other neurons; It is a binary event - either a full spike occurs or nothing.
Membrane potential	The internal voltage level of a neuron that rises and falls in response to inputs.
Threshold	The voltage level that the membrane potential must reach for the neuron to emit a spike.
Firing	The act of a neuron emitting a spike once its threshold is reached.
Resting potential	The baseline voltage of a neuron when it is not receiving any input.
Refractory period	A short time after firing, during which the neuron cannot fire again
Leak	The gradual decay of a neuron's voltage back to its resting potential when it is not receiving input.
Time-step	A small moment in time when all neurons check inputs and update their voltages.
Event-driven	A mode where neurons update only when spikes occur, rather than at every time-step.
Asynchronous	Neurons update on their own timing instead of all updating together.

Neuron Models



Leaky Integrate-and-Fire (LIF) Model

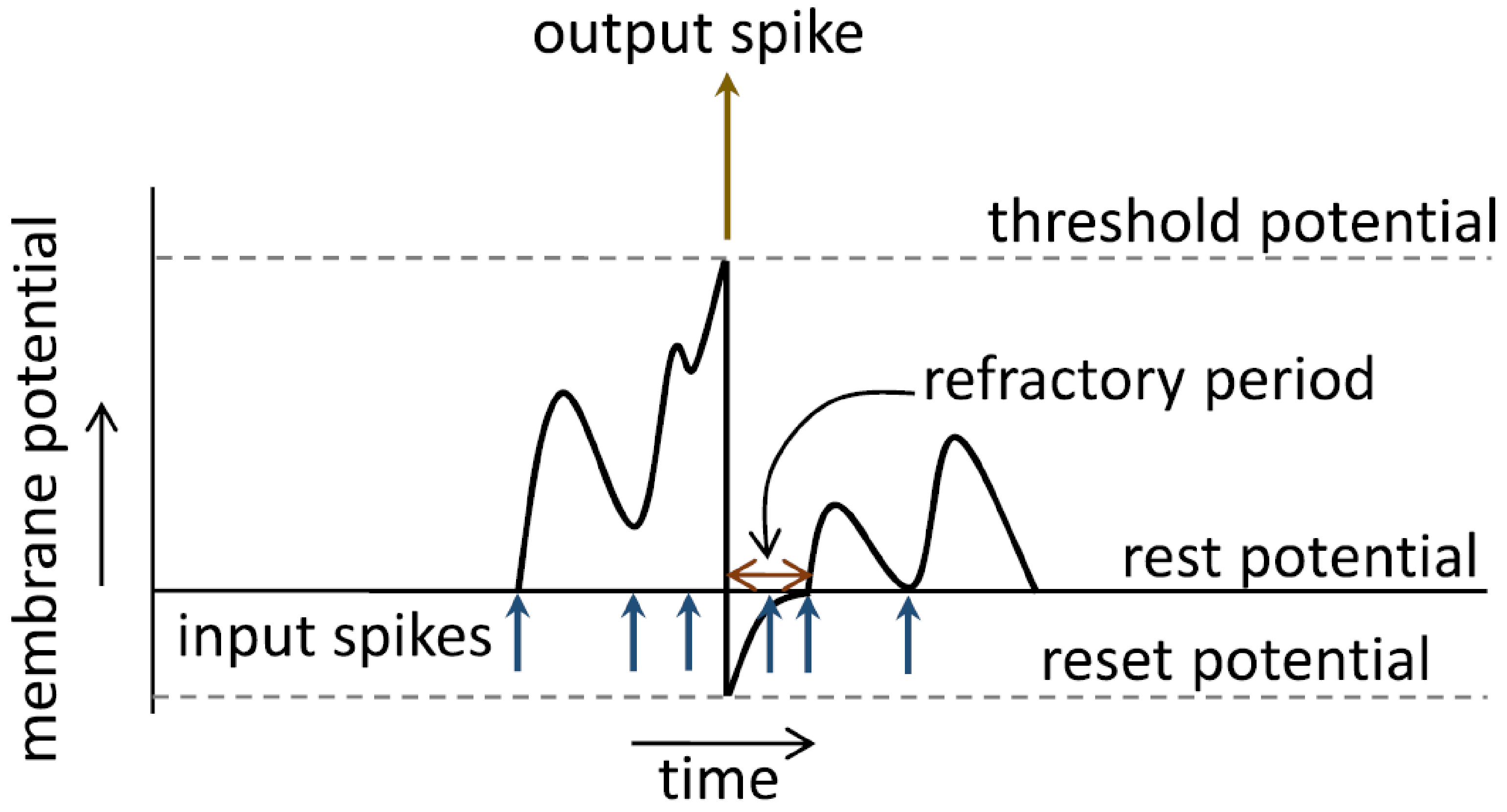
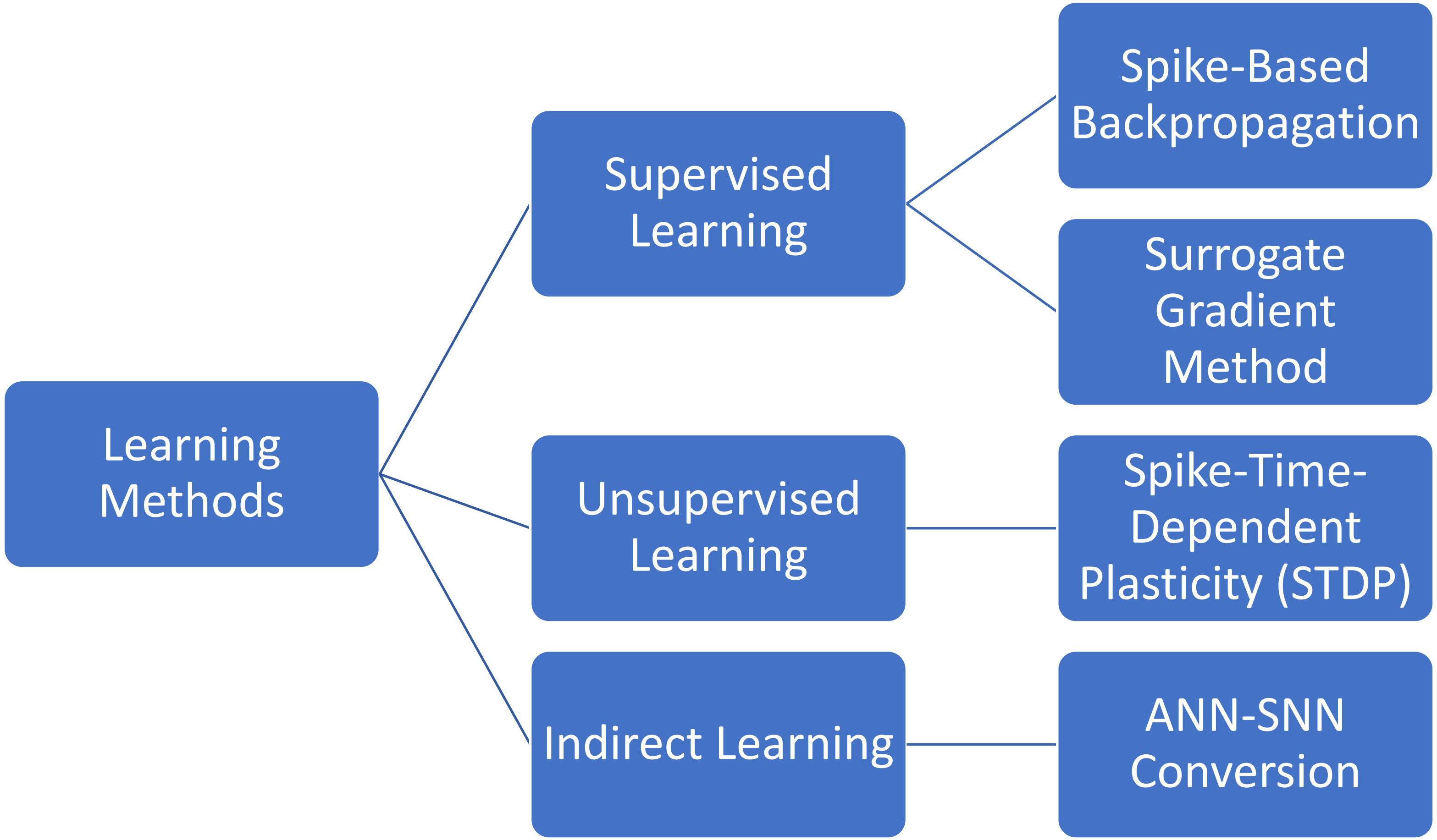


Figure-1: Dynamics of a leaky-integrate-and-fire (LIF) model in response to input spikes. (Rathi et al., 2023)

Learning Methods in SNNs



Spike-Time-Dependent Plasticity (STDP)

- A biologically feasible, unsupervised learning rule based on Hebbian principles (Legenstein et al., 2005; Markram et al., 2012; Ruf & Schmitt, 1997).
- Spike order matters:
  - First Case: If presynaptic spike occurs before postsynaptic spike, the synapse may be **strengthened or weakened**.
  - Second Case: If postsynaptic spike occurs before presynaptic spike, the synapse may also be **strengthened or weakened**.
- Hebbian STDP: First case leads to strengthening and the second case leads to weakening
- Anti-Hebbian STDP: First case leads to weakening and the second case leads to strengthening

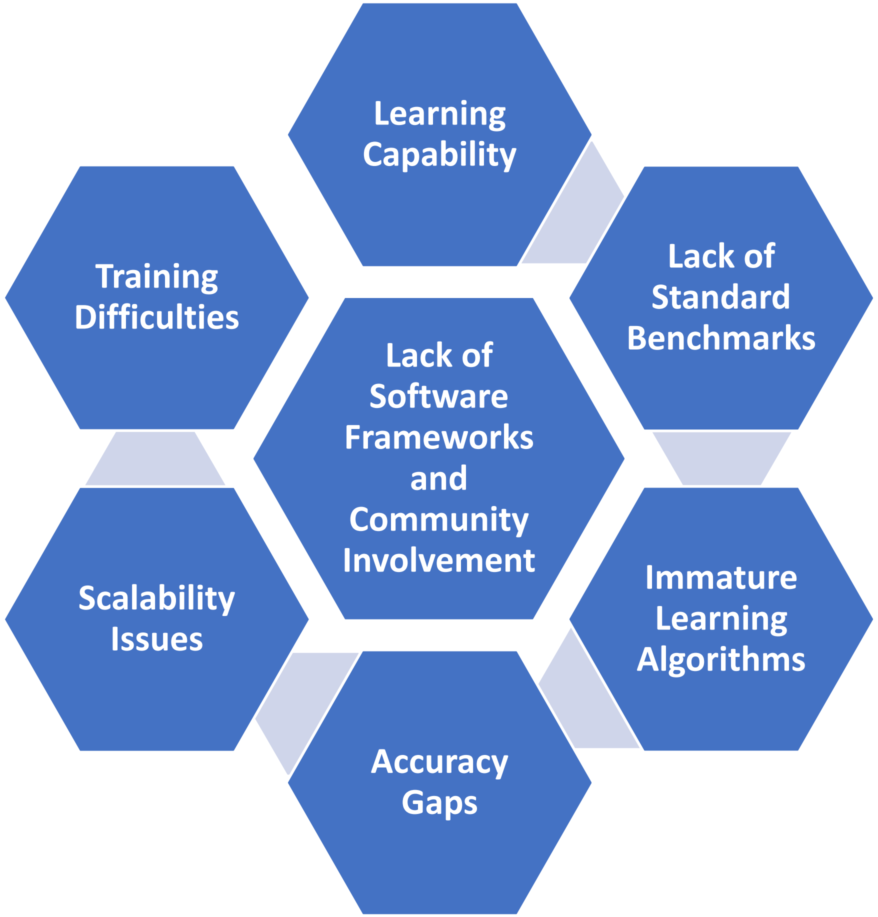
Unsupervised Learning of Digit Recognition using STDP
(Diehl & Cook, 2015)

- Biologically Plausible Design:
  - Leaky Integrate-and-Fire (LIF) Neurons
  - Conductance-based Synapses
  - Lateral Inhibition to ensure competition between neurons.
  - Adaptive Spiking Threshold for homoeostasis.
- Network Performance:
  - Accuracy: Achieved 95% accuracy on the MNIST dataset
  - Scalability: Performance scales well as the number of neurons increases.

ANN-to-SNN Conversion for Image Classification (Rueckauer et al., 2017)

- Converts analog deep networks (CNNs) into SNNs for image classification.
- Key Innovations:
  - Converts ANN activations to equivalent SNN spike rates.
  - Replaces ANN components with spike-based equivalents (e.g., softmax, batch normalization, max-pooling).
  - Percentile-based normalization improves firing rate estimates and reduces error.
- Results:
  - LeNet on MNIST: 2x reduction in operations with minimal error increase.
  - Lower computing costs in SNNs compared to traditional ANNs.

Challenges and Limitations



Future Research Directions

Neuron Models & Learning Capacity	Expanding Applications	Edge Device Adoption	Training Efficiency
Scalability	Distributed & Asynchronous Models	Standardized Benchmarks	Spike Encoding Schemes

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