

Ferroelectric-based leaky integrate-and-fire neurons: A review on device design and performance optimization

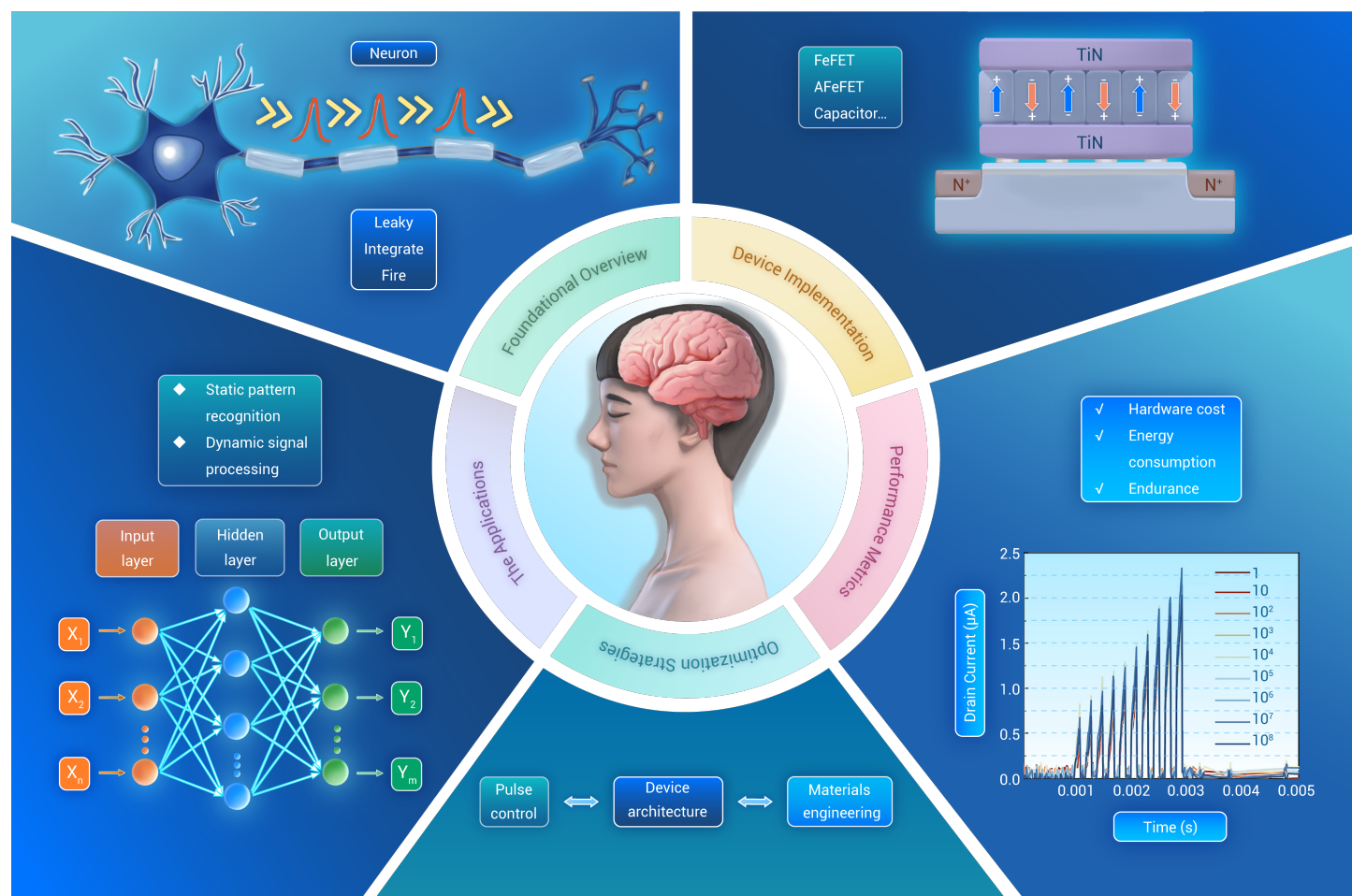
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Ferroelectric devices are promising candidates for implementing leaky integrate-and-fire (LIF) neurons.
- Foundational overview and device designs of ferroelectric/antiferroelectric neurons are introduced.
- Key performance metrics and optimization strategies are discussed.
- Applications of ferroelectric-based neurons for high-performance neuromorphic computing are presented.

Ferroelectric-based leaky integrate-and-fire neurons: A review on device design and performance optimization

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The leaky integrate-and-fire (LIF) neurons implemented in hardware have been proposed as a key approach for neuromorphic computing, offering a promising pathway to overcome the limitations of traditional von Neumann architectures. Among various candidates, ferroelectric-based neuromorphic devices (including antiferroelectric devices) offer a compact, energy-efficient, and highly scalable neuromorphic hardware, making them promising candidates for LIF neurons. This review systematically explains ferroelectric-based LIF neurons, covering the fundamental principles of neuronal operation, the implementation of neuronal functionalities, the key performance metrics, and strategies for performance optimization. Specifically, the implementation of neuronal functionalities is discussed focusing on the realization of leaky behavior by introducing depolarizing or inducing antiferroelectric phase to achieve volatility, since the neuronal integration and firing behaviors can be easily mimicked through the inherent cumulative polarization switching. Moreover, the key performance metrics, including hardware cost, energy consumption, and endurance of devices are identified to demonstrate the comprehensive advantages of ferroelectric LIF neurons. Additionally, the review also covers the applications of ferroelectric LIF neurons. Finally, this review summarizes challenges and prospects of ferroelectric-based artificial neurons for advanced neuromorphic computing systems. This review aims to provide theoretical guidance and practical insights to support further progress in neuromorphic computing systems based on ferroelectric materials.

INTRODUCTION

Conventional von Neumann computing architectures is severely limited by the “von Neumann bottleneck”, where intensive data transfer between memory and processing units leads to high energy consumption and severe time delay.¹ To address these limitations, neuromorphic computing systems, which are inspired by biological neural network have been proposed. The core of neuromorphic computing systems is artificial neurons, which serve as the fundamental computing units along with artificial synapses.² The model and implementation of artificial neurons are critical to the performance and efficiency of neuromorphic computing systems. The leaky integrate-and-fire (LIF) model is one of the most widely used artificial neuron models in neuromorphic systems. This model captures the essential characteristics of neuronal firing behavior by abstracting it as a leaky integration process followed by a threshold-triggered spike.³ The LIF neuron exhibits remarkable advantages of simplicity, high efficiency and scalability, making it particularly attractive for large-scale neuromorphic implementations. Importantly, the intrinsic properties of the LIF neuron determines its scalability for large-scale hardware integration. The LIF neuron model is highly similar to human brain information processing⁴ and exhibits high computational efficiency,⁵ allowing it to be scaled to tens of millions of neurons for constructing large-scale spiking neural networks (SNNs).⁶ Furthermore, biological neurons transmit information through asynchronous spikes, and the LIF neuron follows this event-driven sparse computing paradigm, which significantly reduces communication overhead and hardware complex.⁷ These characteristics inherently support the scalability of neuromorphic systems by enabling energy-efficient and massively parallel hardware architectures.

Early implementations of artificial neurons were predominantly based on conventional complementary metal-oxide semiconductor (CMOS) technology, as exemplified by systems such as IBM's True North,⁸ Intel's Loihi chip.⁹

However, CMOS-based neurons often suffer from large circuit complexity, high energy cost, and poor scalability.¹⁰ To simplify neuron designs, memristor-based neurons, which can implement neuron functions within single electric device, have been developed. Many types of memristor-based neurons have been extensively studied, such as Mott memristors,^{11–15} phase change memristors (PCMs),^{16–18} etc. Nevertheless, these types of neuron memristors usually limited by the shortcomings such as high electroforming voltages, limited reproducibility, and the requirement of bulky capacitors or additional reset circuits, hindering their large-scale application.¹⁹ Recently, ferroelectric type neuron devices (here the ferroelectric material/device is a generalized definition that includes the antiferroelectric subset) have attracted increasing attention as a potential solution for implementing LIF neurons. Ferroelectric devices can mimic neuronal integration and firing behaviors through cumulative polarization switching without the requirement of complex external circuits or large capacitors, offering a compact, energy-efficient, and highly scalable solution for neuromorphic hardware.²⁰

This review systematically explains the fundamental principles, device implementations, characteristics, optimization strategies and applications of ferroelectric LIF neurons, and finally discussions of future challenges and prospects in this kind of neuromorphic devices are presented. The structure of this review article is organized as follows: Section 2 provides a foundational overview and comparison between biological neurons and LIF models, elaborating on the structures, operational mechanisms, and critical functions. Section 3 focuses on the implementation of neuron functionalities of ferroelectric-based LIF neurons through material manipulation and device design. Section 4 summarizes the key performance metrics and comparison of ferroelectric LIF neurons with other device types. Section 5 and 6 discuss the optimization strategies and applications based on recent research progress, respectively. Then, the current challenges and prospects of ferroelectric-based neurons for advanced neuromorphic computing systems are concluded in Section 7.

BIOLOGICAL NEURON AND LIF MODELS

In biological neural networks, neurons and synapses function as the fundamental computing units. The human brain comprises approximately 10^{11} neurons and 10^{15} synapses,²¹ with each neuron forming connections with around 10^4 others through synapses. Neurons carry out information processing by integrating synaptic inputs, generating action potentials, and transmitting signals across these synaptic connections.²² The efficiency of synaptic transmission is not fixed but can change with the activity of presynaptic and postsynaptic neurons, a phenomenon known as synaptic plasticity. Synaptic plasticity primarily includes long-term plasticity and short-term plasticity. Long-term synaptic plasticity is traditionally considered as the primary mechanism underlying learning and memory, whereas short-term synaptic plasticity plays a vital role in temporal information processing and adaptive behavior.²³ Long-term synaptic plasticity mainly includes long-term potentiation (LTP) and long-term depression (LTD), which respectively refer to the persistent enhancement and weakening of synaptic efficacy. These processes are commonly described by the spike-timing-dependent plasticity (STDP) learning rule, in which LTP is induced when the presynaptic spike precedes the postsynaptic spike, whereas LTD is induced conversely. Short-term synaptic plasticity occurs over milliseconds to minutes,²⁴ mainly including short-term potentiation (STP), short-term depression (STD), paired-pulse facilitation (PPF), paired-pulse depression (PPD), and post-tetanic potentia-

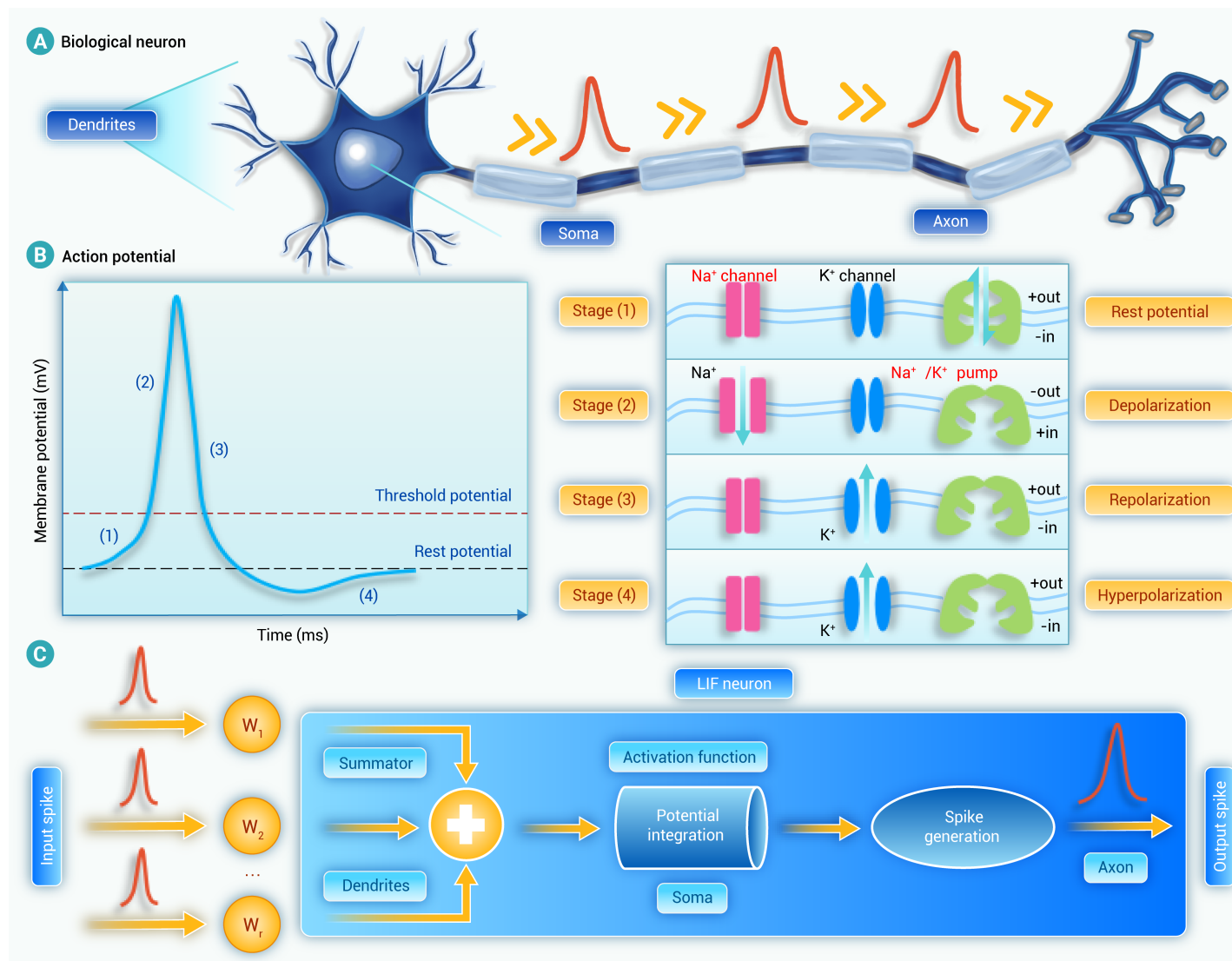


Figure 1. Comparison of biological neuron and the LIF neuron (A) The structure of biological neurons. (B) The generation of an action potential. (C) The operational process of LIF neurons.

tion (PTP). Among them, PPF and PPD respectively refer to the enhancement and inhibition of synaptic efficacy caused by the second pulse relative to the first pulse, while PTP is the gradual increase in synaptic efficacy caused by continuous presynaptic pulses. Additionally, to keep neuronal activity away from extremes of silence or runaway excitation, homeostatic plasticity is needed to provide negative feedback to boost neurons deprived of activity or depress those undergoing hyperactivity.²⁵ By regulating the integration of synaptic inputs and the generation of output spikes, these forms of plasticity enable neurons to act as the central computational entities through which learning, memory and adaptive behaviors are implemented. This section introduces and compares the structure, operational mechanisms, and representative functions of biological and artificial neurons, providing a foundation for subsequent discussions.

The core function of a neuron is forming electrical impulses, called action potentials or spikes, typically through integrating stimuli from pre-neurons. The generation of action potentials depends on the structure and electrochemical properties of neurons. A typical biological neuron consists of a soma (cell body), dendrites, and an axon (Figure 1A),²⁶ all enclosed by a lipid bilayer membrane. The soma gives rise to two types of protrusions—dendrites and an axon—that establish connections within neural networks and integrate input signals from synapses. Dendrites receive incoming spike signals from the axon terminals of presynaptic neurons through synaptic clefts, while axon propagates action potentials to postsynaptic neurons. Furthermore, this membrane separates the intracellular and extracellular

environments and maintains the membrane potential, which is the voltage difference across the membrane. The membrane potential is dynamically regulated by ion channels embedded in the membrane, primarily voltage-gated sodium (Na⁺) and potassium (K⁺) channels.²⁷ The selective inflow and outflow of these ions allow the neuron to switch between different electrical states and initiate action potentials. The generation of an action potential consists of four stages: resting, depolarization, repolarization, and hyperpolarization (Figure 1B). At rest, the membrane potential is stable and the neuron remains inactive. When excitatory inputs raise the membrane potential to exceed the threshold, Na⁺ channels open and Na⁺ ions flow into the cell, causing depolarization.²⁸ As the membrane potential continues to rise, K⁺ channels open, allowing K⁺ to flow out and counteracting further depolarization. This is followed by Na⁺ channel inactivation and membrane repolarization. Finally, excess K⁺ efflux causes hyperpolarization, during which the neuron enters a refractory period and cannot fire again. Stronger inputs usually increase the firing rate, enabling neurons to encode stimulus intensity through spike frequency. Therefore, within a single neuron, information is propagated along the axon as electrical signals (action potentials). Upon reaching the axon terminal, these action potentials trigger the opening of another key ion channel—voltage-gated calcium (Ca²⁺) channels. The influx of Ca²⁺ ions then prompt the release of chemical signals (neurotransmitters) from synaptic vesicles into the synaptic cleft. Neurotransmitters diffuse across the synaptic cleft and bind to receptors on the postsynaptic neuron membrane, where the chemical signals are converted back into electrical

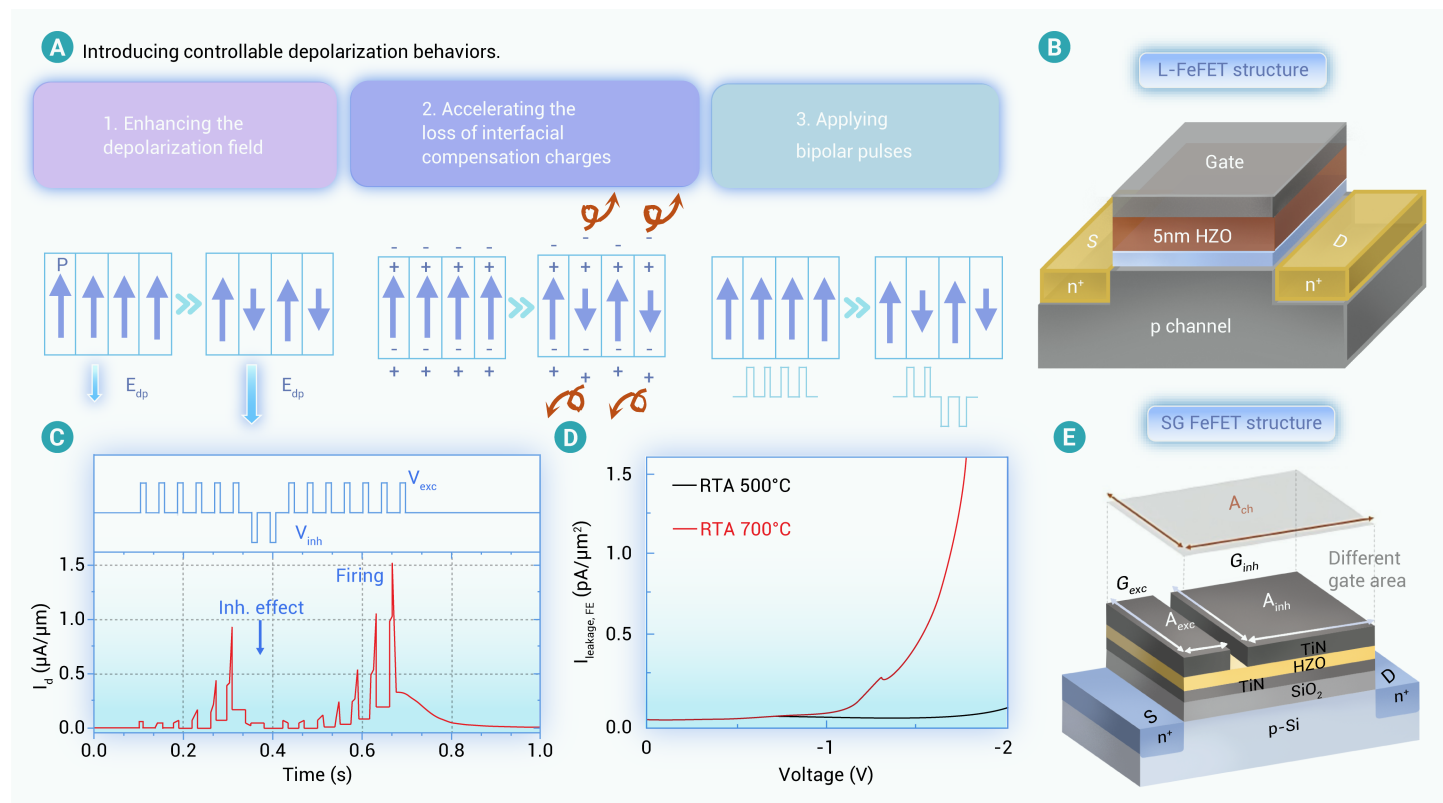


Figure 2. The device design and LIF implementation of ferroelectric neurons (A) Schematic of three approaches for introducing depolarizing behavior in ferroelectric LIF neurons. (B) Schematic of designed L-FeFET with a 5 nm Hf_{0.5}Zr_{0.5}O₂ (HZO) layer. (C) Excitatory and inhibitory pulses modulate neuronal firing behavior in opposing directions. Reproduced with permission.⁴³ Copyright 2019, IEEE. (D) Manifestations of polarization degradation in HZO layers with different annealing temperatures. (E) Schematic of designed SG FeFET. Reproduced with permission.⁴⁴ Copyright 2022, IEEE.

signals (postsynaptic potentials). Thus, information transmission in neurons is an electrical-chemical-electrical signal conversion process. In the brain, numerous neurons are interconnected in this manner to form a vast neural network for information processing and computation. Furthermore, neural networks can learn and remember through synaptic plasticity, adaptively adjusting the strength and structure of connections to optimize their computational capabilities. Different brain regions specialize in processing specific types of information and performing distinct functions, while the brain as a whole can efficiently process multiple complex tasks in parallel.

To replicate the functionalities of the biological neurons, a variety of artificial neuron models have been developed, including the McCulloch-Pitts (MP) model,²⁹ the Hodgkin-Huxley (HH) models,³⁰ the FitzHugh-Nagumo (FHN) model, the Morris-Lecar (ML) model,³¹ the integrate-and-fire (IF) model,³² and the LIF model, etc., differing in complexity and biological plausibility. The HH model provides highly biologically accurate description of ion-channel dynamics but involves high computational cost. The MP model, as a pioneering binary threshold model, captures the logical abstraction of neuronal firing but lacks temporal and dynamic characteristics. The FHN and ML models are simplified forms of the HH model that retain nonlinear excitability with fewer variables, yet they still rely on coupled nonlinear differential equations. This limits their suitability for large-scale circuit-level implementation compared with the simpler LIF model. The IF model further reduces computational complexity but ideal subtypes neglect the leakage behavior of membrane potential, leading to unrealistic accumulation of charge. Among them, the LIF model achieves an optimal trade-off between biological plausibility, computational efficiency, and ease of hardware implementation, making it extensively adopted in neuromorphic systems.⁷ The LIF model offers a compact and effective framework for modeling essential neuron behaviors, including leaky, integration, and threshold-driven spiking. The membrane potential relaxes between the input pulses, exhibiting "leaky" behavior; The neuron receives the input pulses, which assist in elevating its membrane potential toward threshold to achieve "integration".³³ The threshold-driven spiking

occurs when input signals are sufficient to exceed the neuronal threshold, which triggers an output spike.⁴ The LIF model can also be extended to incorporate features such as the refractory period and strength-modulated firing frequency. The hyperpolarization stage of the action potential causes the neuron to temporarily enter in a state where it cannot generate another action potential, called the refractory period.³⁴ Strength-modulated firing frequency is usually manifested by adjusting pulse parameters. As the strength of input stimulus increases, e.g., higher pulse amplitude, wider pulse width, or higher input pulse frequency, the firing frequency also rises.³⁵ Moreover, when embedded in appropriate network architectures, LIF neurons are capable of supporting spatiotemporal information integration. Spatiotemporal integration is the integration of non-synchronous signals from different synapses. In addition to spatiotemporal integration, there are non-simultaneous events occurring through the same synapse and simultaneous events occurring across different synapses, to achieve temporal integration and spatial integration respectively.³⁶ Temporal integration of input signal can be simply expressed as the stimuli of different frequencies applied to the LIF neurons. For example, when one is subjected to an external injury, biological neurons will transmit both low and high frequency signals corresponding to the temporal dimension of information processing.²¹ Similarly, spatial integration of input signal can be simply expressed as the stimuli of different amplitudes applied to the LIF neurons. Spatiotemporal integration, in contrast, involves both temporal and spatial dynamics, where presynaptic spikes with different amplitudes and arrival times jointly trigger a postsynaptic spike. As a result, this interaction establishes spatiotemporal complex dynamics similar to those in biological neural networks, making it essential for spike-timing-dependent logic and neuromorphic computation.³⁵

To obtain these functions, an LIF neuron typically consists of three functional components: a summator for input spikes, an activation function, and an output spike generator,³⁷ as shown in Figure 1C. LIF neurons serve as a foundation for many SNNs implementations.

DEVICE IMPLEMENTATION OF FERROELECTRIC LIF NEURONS

Ferroelectric materials have the inherent characteristics of spontaneous and switchable polarization.³⁸ The cumulative polarization switching in ferroelectric device under repeated voltage pulses can easily emulate the integration function of LIF neurons, making them promising candidates for emulating the dynamic behavior of biological neurons.³⁹ On the other hand, the intrinsic non-volatility of ferroelectric materials hinders the natural decay of polarization and prevents the realization of leaky behavior. Therefore, introducing volatility into ferroelectric devices is critical for simulating neuron dynamics.⁴⁰ The main strategies to achieve volatility include constructing depolarization field and inducing antiferroelectric phase. This section focuses on the implementation of LIF functionalities through introducing volatility in the ferroelectric neurons.

Ferroelectric LIF neurons based on depolarization behaviors

To achieve volatility, a variety of material-level approaches have been developed to modulate their retention characteristics by introducing controllable depolarization behaviors. One approach is to enhance the depolarization field by reducing the ferroelectric layer thickness or inserting thick buffer layers, both of which destabilize the polarization state (left panel of Figure 2A).⁴¹ Another approach involves reducing the crystallinity of the ferroelectric layer to form partially crystalline films comprising mixed ferroelectric and non-ferroelectric phases. Such microstructures promote defect formation and oxygen vacancy accumulation, thereby accelerating the loss of interfacial compensation charges, which eventually shortens the polarization retention time (middle panel of Figure 2A). In addition to material-level approaches, leaky behavior can also be promoted through pulse engineering (right panel of Figure 2A). Applying input voltage pulses with alternating polarity can dynamically disrupt the polarization buildup and mimic the temporal decay processes in neuronal membranes. These technologies enable leaky integration behavior in ferroelectric artificial neurons.

Based on the above material-level approaches, Chen et al.⁴² demonstrated a leaky ferroelectric field-effect transistor (L-FeFET) using a 5 nm $\text{Hf}_{0.5}\text{Zr}_{0.5}\text{O}_2$ (HZO) ferroelectric layer, which is sufficiently thin to enhance depolarization field. Additionally, annealing at 450°C induces partial crystallization of the HZO layer, further reducing retention time and accelerating polarization degradation to achieve the leaky effect. The cumulative polarization enables output spike generation when the device channel is sufficiently conductive.

Luo et al.⁴³ also designed an L-FeFET using a partially crystallized 5 nm $\text{Hf}_{0.5}\text{Zr}_{0.5}\text{O}_2$ ferroelectric layer (Figure 2B), which facilitates the realization of leaky behavior. Then an LIF neuron with excitatory and inhibitory input connections was designed, implemented using this L-FeFET, an n-channel field-effect transistor (nFET), and a resistor R_0 . In this design, the nFET functions as a gating switch that selectively conducts the inhibitory input to the gate of the L-FeFET. By applying excitatory (positive) and inhibitory (negative) voltages to the gate of L-FeFET through low resistance R_0 and nFET, respectively, and utilizing polarization switching and back-switching of the ferroelectric layer to reduce or increase threshold voltage, enabling different firing behaviors (Figure 2C). Furthermore, Lee et al.⁴⁴ controlled the crystallization temperature of $\text{Hf}_{0.5}\text{Zr}_{0.5}\text{O}_2$ ferroelectric layer at 700°C, resulting in a partially crystalline ferroelectric film. This microstructure promotes defect formation and accelerates the loss of interface compensating charges, which degrades the retention performance of the FeFET to achieve volatility and enable leaky behavior (Figure 2D). They further developed a split-gate FeFET (SG FeFET) based on a metal (TiN)-ferroelectric ($\text{Hf}_{0.5}\text{Zr}_{0.5}\text{O}_2$)-metal (TiN)-insulator (SiO_2)-semiconductor (p-Si) (MFMIS) stack (Figure 2E). This structure features two independently addressable gates with significantly different ferroelectric areas, creating asymmetric capacitances ($C_{\text{exc}} \ll C_{\text{inh}}$). The resulting imbalance enables excitatory and inhibitory inputs to modulate threshold voltage in opposite directions. By pairing the SG FeFET with a current stopper nFET, the system achieves an energy-efficient, self-resetting neuron that combines compact design with bio-inspired dynamics. Therefore, FeFET LIF neurons often require peripheral transistors and resistors to implement LIF functionality.

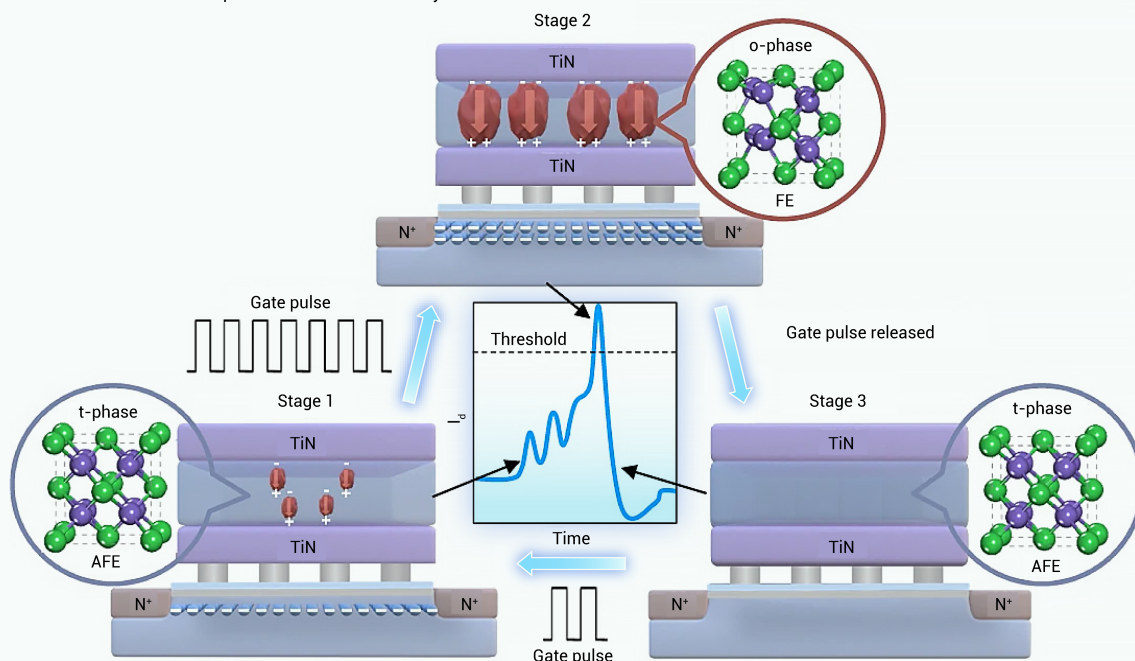
Antiferroelectric LIF neurons based on volatile antiferroelectric-ferroelectric phase transition

Compositionally modification induced antiferroelectric phase is another essential strategy to achieve volatility. For example, by carefully adjusting Zr content of the $\text{Hf}_{1-x}\text{Zr}_x\text{O}_2$ (HZO) film, antiferroelectric phase can be obtained.^{45,46} Under an external electric field, the antiferroelectric tetragonal (t)-phase transforms into a metastable ferroelectric orthogonal (o)-phase.⁴⁷ Once the electric field is removed, the metastable ferroelectric phase returns to antiferroelectric phase, resulting in inherent volatility (Figure 3A), enabling the leaky behavior within a single device.⁴⁸

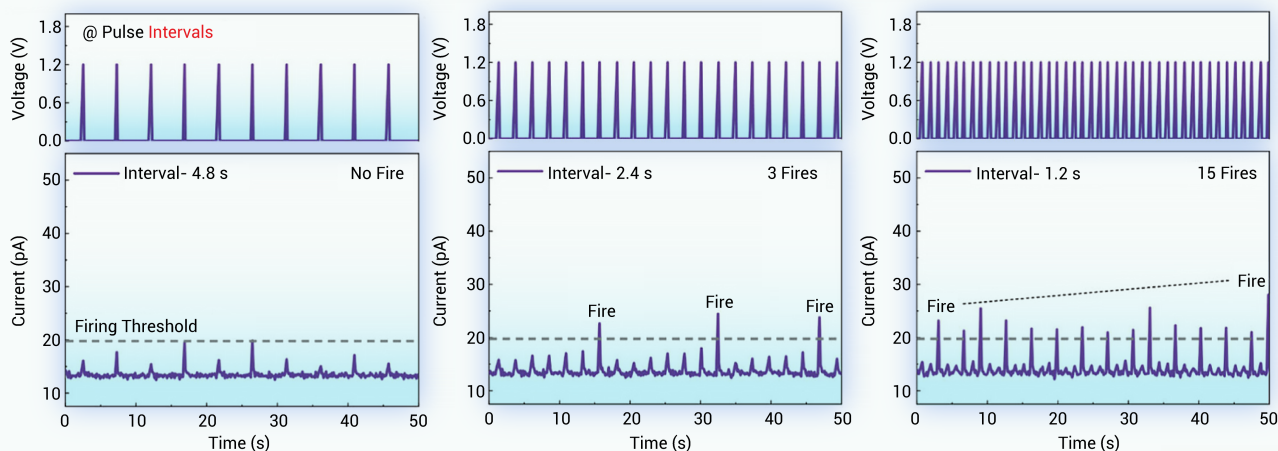
Many antiferroelectric LIF artificial neurons have been reported. Xu et al.⁴⁹ demonstrated a simple two-terminal $\text{W}/\text{Hf}_{0.1}\text{Zr}_{0.9}\text{O}_2/\text{W}$ device, in which the antiferroelectric layer $\text{Hf}_{0.1}\text{Zr}_{0.9}\text{O}_2$ is employed to emulate neuronal dynamics based on the reversible antiferroelectric-ferroelectric phase transition. Repeated input pulses cause a gradual transformation from antiferroelectric phase into ferroelectric phase. This process accumulates polarization switch, endowing the device with integration behavior. After stimulus removal, the spontaneous ferroelectric-antiferroelectric phase transition provides a depolarization effect, enabling leaky behavior. A fixed current threshold is set, once the integrated current surpasses the threshold, a current spike is generated, emulating threshold-driven spiking behavior. This mechanism also supports interval-modulated leaky behavior (Figure 3B) and strength-modulated integration process at different pulse amplitudes (Figure 3C). For shorter intervals, less charge is released during the idle period, making it easier to reach the firing threshold. When the pulse interval is wider enough, the current cannot reach the threshold anyway. This feature represents the filtering capability of the neuron for weaker input signals, which corresponds to the temporal filtering and noise-suppression function in biological neurons and neuromorphic systems.¹⁹ Pulses with higher amplitudes form more electric field-induced ferroelectric phases, accelerating charge integration and increasing the firing frequency. This phenomenon indicates that the neuron performs high-precision computation under sufficient stimuli intensity, corresponding to intensity-dependent rate coding in the brain and thus favorable for performing high-precision tasks.¹⁹ However, excessively high amplitude enables the neuron to fire with a single input pulse, which compromises the resolution of input pulse detection in the LIF neuron and subsequently degrades network performance.⁵⁰

In addition to two-terminal devices, due to the relatively simple implementation mechanism of antiferroelectric LIF neurons, a single AFeFET can typically implement LIF functionality, while a few require the assistance of transistors and resistors. Cao et al.¹⁹ further demonstrated the CMOS compatibility of antiferroelectric field-effect transistor (AFeFET) neurons by integrating $\text{Hf}_{0.2}\text{Zr}_{0.8}\text{O}_2$ antiferroelectric layer into the gate stack of a standard MOSFET, forming a three-terminal device (Figure 4A). Compared to two-terminal devices, this three-terminal architecture demonstrates enhanced signal controllability. Its gate allows precise tuning of electric field strength and duration, making antiferroelectric-ferroelectric phase transition process to be carefully adjusted, thereby the polarization accumulation speed and leakage degree is easily controlled. Consequently, the neuron exhibits tunable integration speeds with respect to input pulse amplitude and width (left and middle panel of Figure 4B). Stronger inputs lower the required pulse count for firing and increase the firing rate. Moreover, pulse intervals modulate leaky behavior: longer intervals lead to greater charge loss, making firing more difficult (right panel of Figure 4B). This three-terminal AFeFET neuron achieves ultra-low power consumption, high endurance, excellent uniformity, and scalable architecture within a CMOS-compatible framework. Based on the same principle, Sun et al.⁵¹ employed an AFeFET consisting of $\text{Hf}_{0.2}\text{Zr}_{0.8}\text{O}_2$ antiferroelectric layer and an amorphous-indium-gallium-zinc-oxide (a-IGZO) channel (Figure 4C), and tailored circuit structure to construct a more functionally enriched LIF neuron. Moreover, their design incorporated both excitatory and inhibitory inputs, simulating biologically inspired synaptic integration. Furthermore, they integrated the neuron with FeFET synapses to construct SNNs.

A Ferroelectric-antiferroelectric phase transition and volatility



B Interval-modulated leaky behavior



C Amplitude-modulated integration process

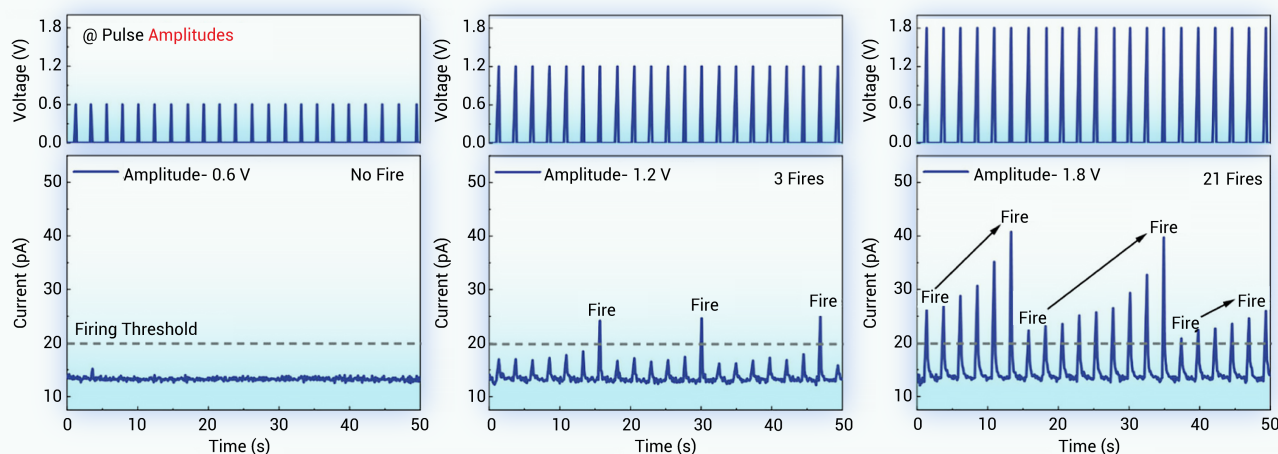


Figure 3. Field-induced programmable neuron response via antiferroelectric-ferroelectric phase transition and volatility (A) Schematic of field-induced antiferroelectric-ferroelectric phase transition and volatility in AFeFET neuron. Reproduced with permission.¹⁹ Copyright 2022, The Authors. (B) Interval-modulated leaky behavior in W/Hf_{0.1}Zr_{0.9}O₂/W capacitor-based neuron. (C) Strength-modulated integration process at different pulse amplitudes in W/Hf_{0.1}Zr_{0.9}O₂/W capacitor-based neuron. Reproduced with permission.⁴⁹ Copyright 2024, American Chemical Society.

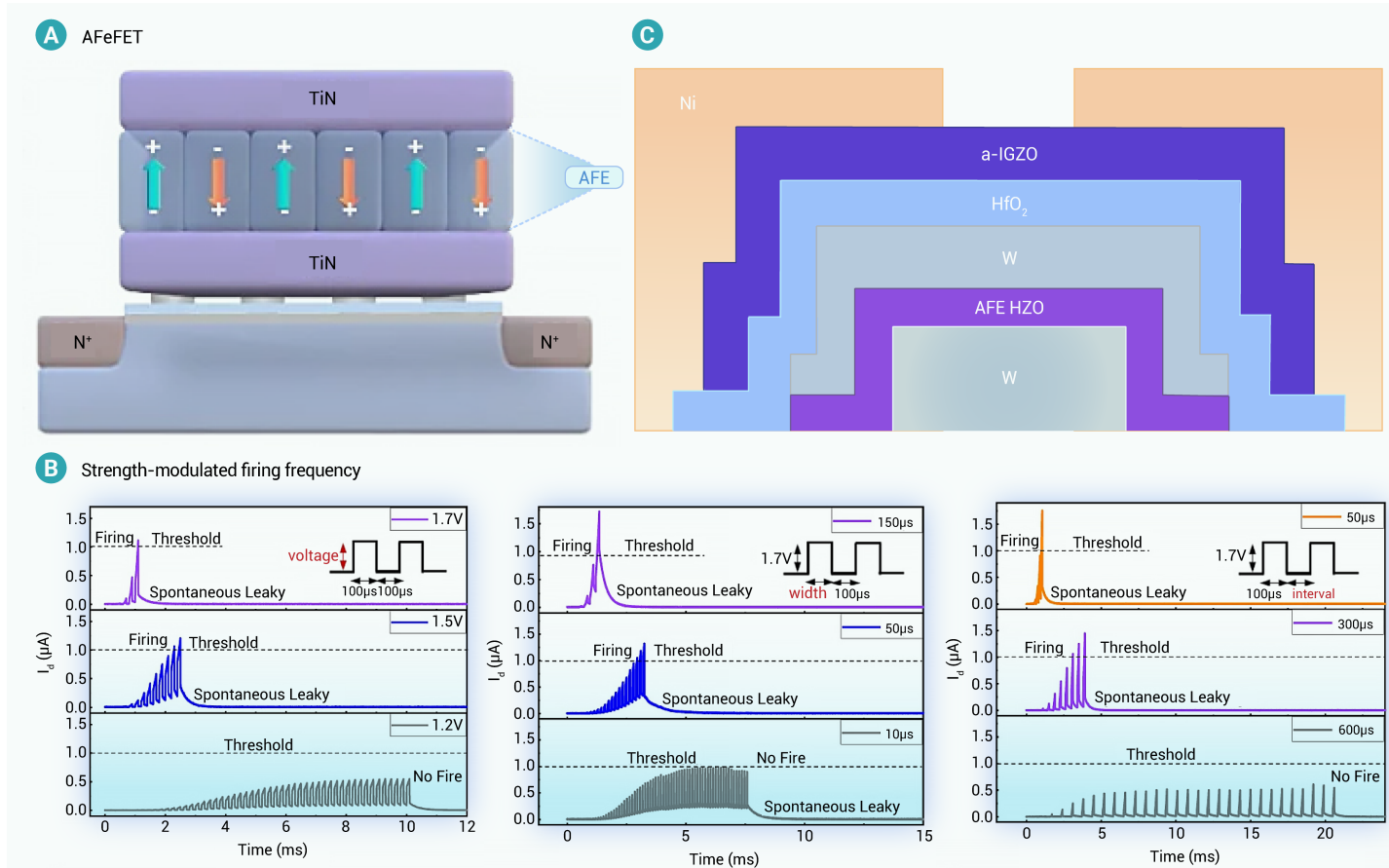


Figure 4. The device design and LIF implementation of antiferroelectric neurons (A) Schematic of designed AFeFET by integrating $\text{Hf}_{0.2}\text{Zr}_{0.8}\text{O}_2$ antiferroelectric layer into the gate stack of a standard MOSFET. (B) The strength-modulated firing frequency of the AFeFET under different gate pulse amplitude/width/interval. Reproduced with permission.¹⁹ Copyright 2022, The Authors. (C) Schematic of designed MFMS AFeFET with $\text{Hf}_{0.2}\text{Zr}_{0.8}\text{O}_2$ antiferroelectric layer and a-IGZO channel. Reproduced with permission.⁵¹ Copyright 2022, IEEE.

KEY PERFORMANCE METRICS OF FERROELECTRIC LIF NEURONS

For artificial neurons, hardware cost, energy consumption and endurance are key performance metrics that determine their practical viability. To clearly demonstrate the comprehensive advantages of ferroelectric neurons, this section briefly describes their key performance metrics.

Hardware cost

The hardware cost of an artificial neuron primarily depends on the constituent hardware required to construct neurons or implement their functionalities. Table 2 lists the ferroelectric device and corresponding hardware architecture for implementing LIF neurons. Overall, ferroelectric neurons generally offer lower hardware cost compared to traditional CMOS-based neurons as ferroelectric materials themselves can serve as an effective capacitor, eliminating the need for discrete passive components, thereby reducing circuit complexity and area consumption.

Compared to other types of neurons that often require additional capacitors, resistors, or feedback circuits to emulate leakage and reset, the device-level volatile ferroelectric neurons and antiferroelectric neurons allow natural decay after stimulus removal. This enables leaky behavior within a single device, eliminating the need for external circuits, greatly reducing peripheral overhead, exhibiting inherently low hardware cost. Such advantages make these kinds of neurons ideal candidates for area-efficient and scalable neuromorphic systems. For example, Huo et al.⁴⁰ demonstrated reconfigurable n/p-FeFETs via an MFMS structure, by integrating ferroelectric $\text{Hf}_{0.5}\text{Zr}_{0.5}\text{O}_2$ with an ambipolar WSe_2 channel (Figure 5A). In this design, the p-FeFET exhibits volatile behavior due to the electron self-compensation effect in the ambipolar WSe_2 materials. Leveraging this volatility, the study implemented a capacitance-free LIF neuron. In addition, Xu et al.⁴⁹ presented a compact neuron

consisting of a two-terminal antiferroelectric capacitor (Figure 5B). This structure eliminates the need for transistors or capacitors, offering the simplest and most integrable architecture. Cao et al.¹⁹ further developed a single three-terminal AFeFET neuron to implement LIF behavior, where integration, leakage, and firing are all achieved through internal polarization dynamics without the external components. However, if more complex functionality is desired, such as selective excitatory/inhibitory input handling or the controllable refractory period, more elaborate device architectures become necessary.

Ferroelectric devices without volatility, typically require additional peripheral circuits to emulate leakage functions and reset, therefore increasing hardware cost. Nevertheless, they can still achieve hardware efficiency if their architectures are carefully designed to minimize circuit overhead and leverage intrinsic device physics. Chen et al.⁴² proposed a L-FeFET exhibiting fast polarization degradation, which implements an LIF neuron in combination with a resistor. This L-FeFET performs integration and leakage functions, while the resistor converts the channel current into a voltage signal to trigger output spikes when the L-FeFET becomes sufficiently conductive. Luo et al.⁴³ developed an LIF neuron consisting of an L-FeFET, a transistor and a resistor (Figure 5C). This neuron enables stochastic firing, leaky integration, and excitatory/inhibitory response via polarization switching dynamics of partially crystallized ferroelectric films. The transistor supports input selectivity and gain control. However, a negative supply voltage is needed to implement the inhibitory function, which adds routing cost. These neurons also incur increased structural complexity and area overhead when more advanced functionalities are integrated, such as excitatory/inhibitory control or dual-mode operation. Therefore, it is important to strike a balance between neuromorphic functionality and hardware cost.

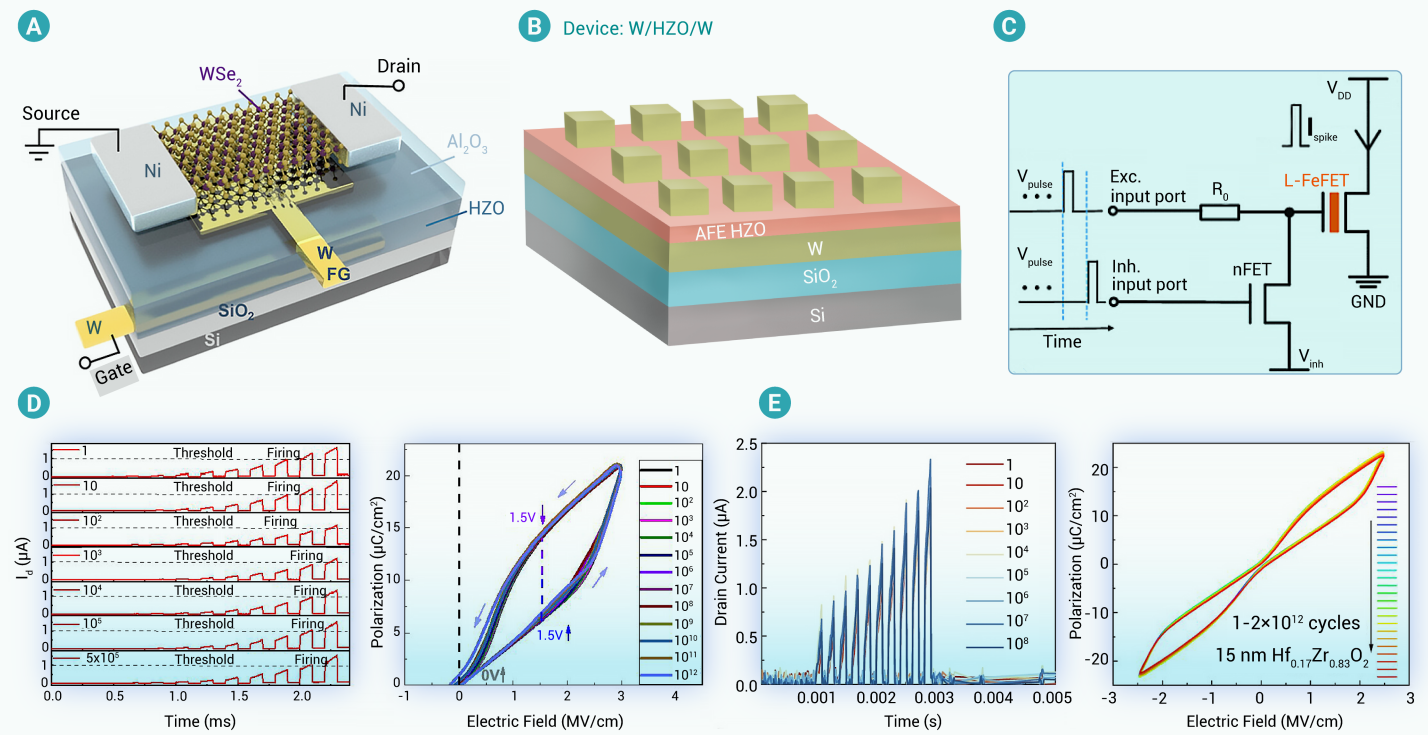


Figure 5. The hardware cost and endurance of ferroelectric neurons (A) Schematic of reconfigurable n/p-FeFETs by integrating ferroelectric Hf_{0.5}Zr_{0.5}O₂ with an ambipolar WSe₂ channel. Reproduced with permission.⁴⁰ Copyright 2024, American Chemical Society. (B) Schematic of the W/Hf_{0.1}Zr_{0.9}O₂/W neuron. Reproduced with permission.⁴⁹ Copyright 2024, American Chemical Society. (C) The LIF neuron circuit consists of an L-FeFET, a transistor and a resistor. Reproduced with permission.⁴³ Copyright 2019, IEEE. (D) The endurance of the AFeFET neuron and the TiN/Hf_{0.2}Zr_{0.8}O₂/TiN structure. Reproduced with permission.¹⁹ Copyright 2022, The Authors. (E) The endurance of the MFMIS AFeFET neuron and the capacitor with 15nm Hf_{0.17}Zr_{0.83}O₂. Reproduced with permission.⁴⁸ Copyright 2025, The Authors.

Energy consumption

The firing energy of neuromorphic neurons is calculated using the following equation:

$$E_{\text{firing}} = V_{\text{pulse}} \times I_{\text{firing}} \times t_{\text{pulse}} \quad (1)$$

Where V_{pulse} is the amplitude of the applied pulse, I_{firing} is the actual current during firing, and t_{pulse} is the width of the applied pulse.⁴⁹ Table 2 presents some energy consumption values for implementing ferroelectric LIF neurons. Neuromorphic neurons aim at achieving energy consumption comparable to or even lower than that of biological neurons, typically in the femtojoule (fJ) per spike range.⁵² Ferroelectric-based neurons have demonstrated energy consumption within this range.^{19,49} This superior efficiency is attributed not only to the ultra-low energy required for polarization switching but also to their compact hardware architectures. The device structure, which eliminates the need for integration capacitors and leakage components, play a crucial role in energy performance.^{19,48-50} For example, the two-terminal Hf_{0.1}Zr_{0.9}O₂ antiferroelectric neuron eliminates the transistor gate, achieving an ultra-low energy consumption of 1.36 fJ/spike, which ranks among the lowest reported values.⁴⁹ When a transistor gate is included, as reported in the AFeFET-based neuron in Ref.¹⁹, the estimated energy consumption remains a low level of 37 fJ/spike, still significantly outperforming metal-insulator transition (MIT) and CMOS counterparts. In another case focusing on AFeFETs, Gao et al.⁴⁸ achieved energy consumption of 0.1 pJ/spike by adjusting pulse scheme applied to a single AFeFET device. Furthermore, in schemes where antiferroelectric devices are combined with transistors and resistors to implement LIF neurons, device integration leads to a certain increase in energy consumption. Furthermore, the LIF neuron composed of an a-IGZO AFeFET paired with one transistor and one resistor has energy consumption of 15 pJ/spike.⁵¹ In another scheme, the LIF neuron formed by using a double-gate (DG) morphotropic phase boundary-based thin-film transistor (MPBTFT) together with one transistor and two resistors achieves an energy consumption of 1.95 pJ/spike.⁵⁰ Even if using non-volatile ferroelectric devices to emulate spiking behavior, which requires gate voltage control and series resistance, the low driving voltage ensures this device more energy-efficient than those

based on other materials. Therefore, ferroelectric neurons combine low-energy polarization mechanisms with simplified architectures, offering substantial reductions in energy consumption.

Endurance

The endurance of neuron devices refers to the number of firing behaviors it can withstand without significant deterioration. Among various kinds of hardware neuron implementations, antiferroelectric neurons demonstrate outstanding endurance, as shown in Table 2. For instance, Cao et al.¹⁹ reported an AFeFET neuron can stably fire 5 × 10⁵ cycles without significant deterioration (left panel of Figure 5D). Notably, the TiN/Hf_{0.2}Zr_{0.8}O₂/TiN structure in the AFeFET neuron, which is the endurance bottleneck of the AFeFET, exhibits exceptional endurance exceeding 10¹² cycles (right panel of Figure 5D). Similarly, Gao et al.⁴⁸ demonstrated an MFMIS AFeFET neuron with the MoS₂ channel, exhibiting reliable firing performance up to 10⁸ cycles, showing minimal cycle-to-cycle variations (left panel of Figure 5E). Extended endurance measurements on the capacitor component with 15nm Hf_{0.17}Zr_{0.83}O₂ of the AFeFET demonstrate sustained performance over 10¹² cycles without breakdown (right panel of Figure 5E).

In contrast, ferroelectric neuron devices usually exhibit lower endurance compared with the antiferroelectric counterparts. The FeFETs with doped HfO₂ ferroelectric layers, particularly those adopting a metal-ferroelectric-insulator-semiconductor (MFIS) gate stack, often suffer from limited cycling stability, typically capped at 10⁴-10⁶ program/erase operations.⁵³⁻⁵⁶ Degradation usually manifests after approximately 10⁵ cycles. This endurance limitation arises not from the ferroelectric material itself, but rather from structural and interfacial reliability issues. Charge trapping and defect generation at dielectric/semiconductor interfaces, which can be exacerbated by high electric field stress, are the dominant mechanisms responsible for endurance degradation.⁵⁷⁻⁵⁹ As a result, the endurance of FeFETs is highly sensitive to device architecture, voltage amplitude, and pulse scheme. Optimizing device structure provides an effective approach to enhancing the endurance of ferroelectric neurons. A notable example is the ambipolar WSe₂/HZO-based FeFET reported by Huo et al.⁴⁰, which achieved over 10⁵ stable spiking cycles.

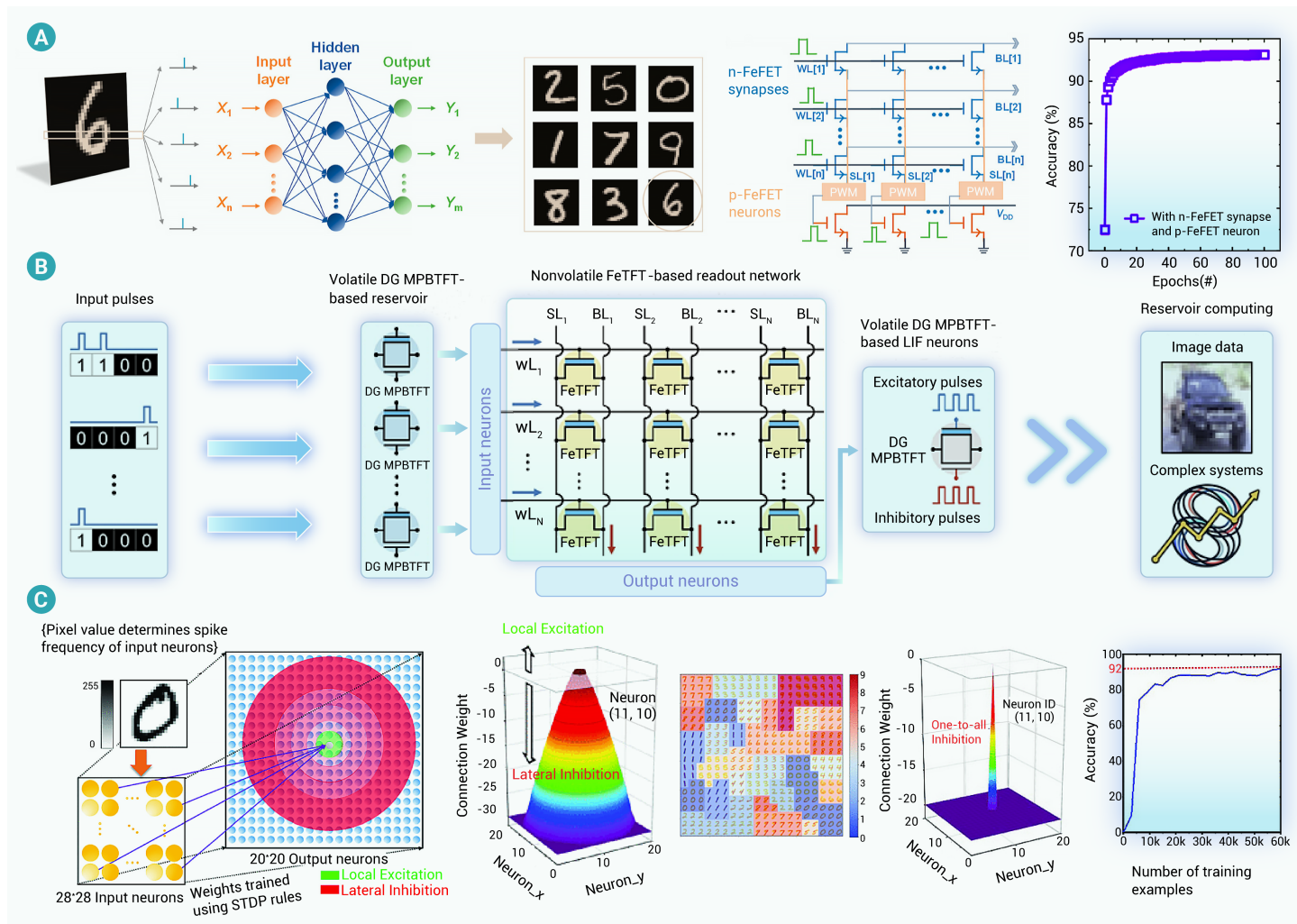


Figure 6. The applications of ferroelectric LIF neurons (A) Schematic of the spike-based neuromorphic computing system and hardware implementation of a three-layer SNN based on n-FeFET synapses and p-FeFET neurons, which achieves a test accuracy of 93.8% after 20 training epochs.⁴⁰ Copyright 2024, American Chemical Society. (B) Schematic of an analog reservoir computing system built with DG MPBTFT-based physical reservoirs and LIF neurons, and an FeTFT-based synaptic readout network.⁶² Copyright 2024, the Authors. (C) Schematic of an unsupervised SNN based on L-FeFET neurons with excitatory and inhibitory input connections achieved biomimetic clustering through self-organizing map learning and reached an inference accuracy of 92% with WTA learning.⁴³ Copyright 2019, IEEE.

The enhanced endurance in this case is mainly due to the robustness and controllability of the MFMS FeFET structure integrated with ambipolar WSe₂ channel and the high-quality of Hf_{0.5}Zr_{0.5}O₂ layer.

Comparison of ferroelectric LIF neurons based on ferroelectric type and antiferroelectric type

The LIF neurons based on ferroelectric materials typically need to introduce depolarization behavior by enhancing the depolarization field, accelerating the loss of interfacial compensation charges, or applying voltage pulses with alternating polarity, making its implementation mechanism relatively complex. Moreover, the non-volatility of ferroelectric materials typically requires transistors and resistors to implement leakage and reset, which makes the circuit complexity of ferroelectric type LIF neurons relatively high. Consequently, this requirement for peripheral circuits limits the further improvement in integration density and energy efficiency. In contrast, antiferroelectric type LIF neurons based on simple ferroelectric-antiferroelectric phase transition of antiferroelectric materials have inherent volatility, allowing a single device to achieve LIF functions, with only a few requiring transistors and resistors to assist in achieving more complex functions. However, antiferroelectric type LIF neurons require more precise material preparation, such as precise control of Zr content in HZO materials to stabilize the antiferroelectric phase. To more clearly demonstrate their advantages and limitations, Table 1 systematically compares ferroelectric type and antiferroelectric type LIF neurons in terms of implementation mechanisms, circuit complexity, and

key limitations. A detailed comparison in terms of hardware architecture, energy consumption, and endurance between ferroelectric type and antiferroelectric type LIF neurons^{19,40,42-44,48-51,60-62} is summarized in Table 2.

Comparison of ferroelectric LIF neurons with other LIF neurons

Apart from ferroelectric materials, other devices such as Mott memristors, diffusive memristors and spintronic devices also used for realizing LIF neuron functions. This section compares key performance metrics as well as operating mechanisms of these types of LIF neurons with ferroelectric ones, aiming to comprehensively assess the characteristics of different technical routes.

Mott memristors utilize Mott insulator materials such as NbO_x and VO₂ as functional layers, and typically simulate LIF neurons behaviors through the MIT induced by temperature or electric field changing. The integration process is achieved by metallic sites accumulating under electrical pulses. The firing action is generated when accumulated metallic regions form a conductive filament across the device. The leakage behavior is realized through metallic regions relaxing back to an insulating state during pulse intervals.⁶³ Mott memristor-based LIF neurons typically have the advantages of fast and stable switching characteristics and the ability to emulate various biological neuron behaviors.^{14,64} However, the high instantaneous current of mA level results in high power consumption, which presents challenges for low-power neuromorphic systems where energy efficiency is critical.⁶⁴

Diffusive memristors typically implement LIF neuron behavior through the formation and rupture of conductive filaments caused by the migration of

Table 1. Comparison of LIF neurons based on ferroelectric and antiferroelectric materials.

Property	Ferroelectric type	Antiferroelectric type
Implementation mechanism	Introducing depolarization behaviors.	Utilizing the volatile antiferroelectric-ferroelectric phase transition.
Circuit complexity	Usually requiring peripheral transistors and resistors to implement LIF functionality.	A single device can implement LIF functionality.
Key limitations	Complex circuits limit integration density and energy efficiency.	Precise preparation process is necessary to stabilize the antiferroelectric phase.

metal ions or oxygen vacancies.⁶⁵ The integration process is implemented through the oxidation of metal atoms at the active electrode and their migration toward the inert electrode under an external electric field, forming a conductive filament. The firing action occurs when the conductive filament connects two electrodes, causing a resistance switch. The leakage behavior is achieved by the spontaneous rupture of the conductive filament when the external electric field is weakened or removed. Diffusive memristors typically have the advantages of simple structure, low standby power consumption, and high scalability. However, their switching behavior can be highly variable due to stochastic filament growth, leading to cycle-to-cycle resistance scatter, which presents challenges for reliable neuromorphic hardware implementations.⁶⁴ Furthermore, diffusive memristors show relatively poor endurance due to the excessive injection of active metal ions after several operations.⁶⁶

Spintronic-based LIF neurons usually achieve the LIF neurons behaviors through controlled motion of magnetic domain walls or skyrmions. The integration process is achieved when input current pulses drive the movement of domain walls/skyrmions. And in the absence of driving, they relax back in the opposite direction due to internal gradients or fields.⁶⁷⁻⁷¹ The firing behavior is realized when domain walls or skyrmions reach a critical position. Spintronic devices typically have the advantages of ultralow power consumption, high scalability, low footprint area and high endurance.⁷²⁻⁷⁴ However, spintronic devices have a limited number of different resistance states and a small on/off ratio due to the upper limits of fundamental physical properties such as the spin polarization of magnetic materials.⁷⁵

Compared with other types of LIF neurons, ferroelectric devices are compatible with CMOS processes, enabling high-density integration. In terms of energy consumption, ferroelectric LIF neurons typically outperform Mott and diffusive memristors, while being comparable to spintronic counterparts. Furthermore, ferroelectric LIF neurons exhibit superior endurance to that of Mott memristors and diffusive memristors, which demonstrates greater application potential. In comparison to other types of LIF neuron schemes, the ferroelectric-based approach is distinguished by a compelling profile of advantages, making it a highly promising candidate for scalable neuromorphic computing systems.

OPTIMIZATION STRATEGIES FOR FERROELECTRIC LIF NEURONS

Enhancing the performance of ferroelectric-based LIF neurons requires a synergistic optimization of materials engineering, device architecture, and pulse control strategies, with the purpose of building ferroelectric-based neurons with high reliability, low power consumption, and rich functional capabilities.

Materials optimization can be achieved by regulating the concentration and distribution of defects (such as oxygen vacancies), adjusting film thickness, and refining crystallization techniques. Oxygen vacancies are an important type of defect, which can act as charge trapping centers that degrade device endurance. Interface engineering, such as introducing interfacial TiO_{2-x} layers through controlled oxidation or plasma treatments, has been shown to reduce vacancy-induced defects and improve cycling stability.⁷⁶⁻⁷⁹ Moreover, reducing the thickness of HZO and partial crystallization can induce volatility that mimic the “leaky” behavior of biological neurons. This approach enables emulating more neuron functionalities within a single device because of the natural decay without external circuitry, dramatically reducing hardware complexity and energy consumption.

Device architecture optimization involves the design of novel device structures to achieve more neuron functionalities and reduce hardware volume/area. For instance, Sun et al.⁵¹ developed an a-IGZO AFET neuron

that combines the advantages of HZO and a-IGZO channel. The intrinsic volatility of the antiferroelectric HZO enables tunable leaky behaviors without external capacitors, while the a-IGZO channel supports the integration of both excitatory and inhibitory inputs, resulting in a compact and multifunctional neuromorphic device. Moreover, this structure provides excellent cycling endurance due to the high-quality HZO/a-IGZO interface, which reduces charge trapping and suppressing interface degradation. Thus, the combination of a-IGZO and AFET enables efficient, compact, and durable neuromorphic neurons, making it well-suited for high density neuromorphic systems. In another example, Kim et al.⁶² prepared a volatile DG transistor with both a bottom-gate (BG) and a top-gate (TG). The device was fabricated using an IGZO thin-film transistor and an HZO (Hf: Zr=3: 5) thin film near the phase boundary between the ferroelectric o-phase and t-phase within an MFIS structure. The HZO film exhibits high polarization magnitude at low voltages and intrinsic relaxation, which is crucial for simulating LIF neuron behaviors. Additionally, the DG architecture of the device allows separate handling of excitatory and inhibitory pulses. This device structure offers high area efficiency and functional versatility in implementing LIF neurons.

Lastly, optimized pulse control allows fine-tuned emulation of biologically plausible neuronal behaviors. By applying a reset pulse immediately after the firing event, the FeFET neuron can be brought back to its OFF state. By tuning the electrical pulse parameters, the refractory period can be precisely programmed, aligning the device's spike dynamics with the time constants.⁸⁰ Such programmable dynamics can be achieved without altering the device structure, offering flexible and efficient neural function through electrical control.

THE APPLICATIONS OF FERROELECTRIC LIF NEURONS

Ferroelectric LIF neurons, known for their tunable performance and ease of hardware integration, have been successfully applied in neuromorphic computing systems. They have demonstrated outstanding performance across a wide range of applications, from classical static pattern recognition to complex temporal signal processing.

In the classic MNIST handwritten digit recognition task, systems integrating ferroelectric LIF neurons with ferroelectric synapses have become a mainstream solution. Leveraging approach such as time-to-first-spike encoding, STDP, and supervised temporal backpropagation, efficient information processing is achieved in SNNs with different architectures. For example, a three-layer SNN utilizing WSe₂ n/p-FeFET-based synapses/neurons achieved an accuracy of 93.8% (Figure 6A),⁴⁰ while a two-layer SNN using AFET LIF neurons reached a high accuracy of 96.8%, maintaining stable performance.¹⁹

Beyond static image recognition, ferroelectric LIF neurons have been extended to dynamic signal processing tasks, leveraging their excellent temporal signal processing capabilities. In one demonstration, an efficient analog reservoir computing system was constructed using volatile ferroelectric MPBTFTs as physical reservoirs and LIF neurons, combined with non-volatile ferroelectric synapses in the readout network (Figure 6B).⁶² This system successfully performed sine/square waveforms classification (with a normalized root mean squared error as low as 0.0044), Hénon map prediction (with a normalized root mean squared error as low as 0.035). Notably, it was also successfully applied to the prediction of confirmed COVID-19 cases (with a normalized root mean squared error as low as 0.28), highlighting its potential for sophisticated temporal data processing capabilities. Additionally, an unsupervised SNN constructed with ferroelectric LIF neurons featuring excitatory and inhibitory connections achieved biomimetic clustering through

Table 2. Comparison of key performance metrics of ferroelectric type LIF neurons and antiferroelectric type LIF neurons.

Type	Ferroelectric device ^a	Hardware architecture ^b	Energy consumption	Endurance	Ref.
Ferroelectric	n/p-FeFET	p-FeFET	—	$>10^5$	40
Ferroelectric	L-FeFET	L-FeFET+1R	—	—	42
Ferroelectric	L-FeFET	L-FeFET+1T1R	420pJ/spike	—	43
Ferroelectric	SG FeFET	FeFET+1T	—	—	44
Ferroelectric	FeFET	FeFET+1T4R2C	360pJ/spike (simulation)	—	60
Antiferroelectric	AFFeFET	AFFeFET	37fJ/spike	$>10^{12}$	19
Antiferroelectric	AFFeFET	AFFeFET	0.1pJ/spike	$>10^{12}$	48
Antiferroelectric	Capacitor	Capacitor	1.36fJ/spike	$>10^9$	49
Antiferroelectric	AFFeFET	AFFeFET+1T1R	15pJ/spike	$>10^9$	51
Antiferroelectric	DG MPBTFT	MPBTFT+1T2R	1.95pJ/spike	$>10^{10}$	50
Antiferroelectric	AFFeTFT	AFFeTFT	—	—	61
Antiferroelectric	DG MPBTFT	MPBTFT+1R+2Op-Amp	250pJ/spike	$>10^8$	62

^an/p-FeFET = n-type/p-type ferroelectric field-effect transistor

L-FeFET = Leaky-FeFET

SG FeFET = Split-Gate FeFET

AFFeFET = antiferroelectric field-effect transistor

DG MPBTFT = Double-Gate Mixed/Morphotropic Phase Boundary-based thin-film transistor

AFFeTFT = antiferroelectric thin-film transistor

^bp-FeFET = p-type FeFET

R refers to resistor, T refers to transistor, and C refers to capacitors.

Op-Amp refers to operational amplifier. Op-Amp = amplifier or comparator

self-organizing map learning and reached an inference accuracy of 92% with WTA learning, without the need for additional inhibitory layer neurons, significantly enhancing hardware integration character (Figure 6C).⁴³

In conclusion, the applications of ferroelectric LIF neurons have expanded from classic pattern recognition classification to advanced fields such as dynamic time-series prediction and biomimetic unsupervised learning. These applications fully validate their potential in high-performance and low-power neuromorphic computing, providing a feasible path for achieving multi-functional and highly integrated intelligent systems.

CHALLENGES AND PROSPECTS

In summary, ferroelectric/antiferroelectric-based LIF neurons exhibit compact device structure and ultra-low energy consumption, making them one of the most promising candidates for neuromorphic neurons. This review provides a comprehensive overview of their developments and applications in neuromorphic computing.

From a device perspective, the ferroelectric devices are inherently non-volatile and thus require enhanced depolarization fields, increased leakage currents, or additional peripheral circuits to induce leaky behavior and spontaneous reset. However, these strategies often compromise device endurance or increase hardware complexity. In contrast, antiferroelectric devices exhibit intrinsic volatility, enabling basic LIF neuron functionality in a single device. Furthermore, more sophisticated neuronal behavior can be achieved with minimal peripheral circuitry, offering a viable path toward compact and energy-efficient neuromorphic systems.

Despite growing progress, ferroelectric-based neuron technology remains in its early stage and faces multiple challenges before it can be widely adopted in high-performance neuromorphic systems. First, key performance metrics, such as hardware cost, energy consumption, and endurance, must be improved to ensure system reliability and scalability. Addressing this requires a deeper understanding of the underlying physical mechanisms, including interface trap formation, charge injection dynamics, and oxygen vacancy distribution, which can guide material selection and process optimization. Second, multifunctional neuron devices are necessary to explore.

On one hand, incorporating more complex neuronal functions, such as adaptive behaviors, would allow more biologically realistic models. On the other hand, ferroelectric-based neurons with multimodal response capabilities, which are responsive to stimuli such as light, temperature, and pressure, will promote the development of perception-computation fusion systems. Moreover, advances in ferroelectric synapses must proceed in parallel to realize fully ferroelectric artificial neural networks.

Overall, although challenges remain, ferroelectric-based artificial neurons offer unique and irreplaceable advantages for neuromorphic computing. Future development will require coordinated innovation across materials, devices, and circuit designs to bridge the gap between proof-of-concept demonstrations and practical deployment.

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AUTHOR CONTRIBUTIONS

L.Z. and L.Z. supervised and revised the manuscript. M.L. wrote the draft. M.L., J.W., H.F. and C.C. edited the manuscript. All authors contributed to the article and approved the submitted version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

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DATA AND CODE AVAILABILITY

No new data and code were created or analyzed in this review.