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EDITORIAL

Editorial: Focus on Neuromorphic Circuits and Systems using Emerging Devices

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In the realm of neuromorphic computing, we delve into the latest advancements where innovative devices are reshaping the landscape. These emerging devices draw inspiration from biology and are revolutionizing how circuits and systems operate. Join us as we explore the frontiers of technology, where neuromorphic designs hold the promise of more efficient and adaptable systems, bringing us closer to the potential of human-like intelligence.

Saraswat and Ganguly [1]:
Saraswat and Ganguly explore the potential of scalable RRAMs based on PCMO for various applications, including neuromorphic computing and overcoming computational bottlenecks. It investigates the stochastic behavior of PCMO RRAMs, highlighting their unique characteristics of stochastic switching and deterministic control, which result in a 100× reduction in set time distribution drift. The study demonstrates improved performance in Boltzmann machines, solving problems 20× larger, and reducing device-to-device variability, making PCMO RRAMs suitable for stochastic recurrent neural networks.

Zheng *et al* [2]:
Zheng *et al* explore reservoir computing (RC) using a nonlinear MEMS resonator for efficient time-domain correlation processing. It builds an action recognition dataset and evaluates the RC hardware system's classification and prediction performance against universal datasets. The study demonstrates the feasibility of this approach, achieving a high success rate, paving the way for brain-inspired computing with microfabricated devices and integrated perception and computation in future applications.

Leroux *et al* [3]:
Leroux *et al* focus on leveraging spintronics devices with resonance-based synaptic communication to reduce power consumption in convolutional neural networks (CNNs). The study demonstrates how spintronic resonators can perform convolutions by rectifying radio-frequency signals and proposes spatial arrangements for parallel implementation. The architecture achieves results on MNIST dataset comparable to software CNN and holds promise for embedded applications, thanks to its ability to run CNNs efficiently with nano devices in parallel.

Desai *et al* [4]:
Desai *et al* explore domain-wall-synapse-based crossbar arrays for on-chip learning of CNNs. Through device-circuit-system co-design and co-simulation, they use 15-bit synaptic weights split between crossbar arrays. The arrays accelerate matrix-vector operations in CNNs and achieve high classification accuracy, with results influenced by device variations, bit precision, and weight update frequency.

Majumdar [5]:
Majumdar presents an efficient deep neural network (DNN) accelerator using analog synaptic weights controlled by ferroelectric (FE) domain dynamics. They benchmark novel synaptic devices, specifically poly(vinylidene fluoride-trifluoroethylene)-based ferroelectric tunnel junctions, demonstrating their linearity in weight updates. The results indicate ultrafast switching and low energy consumption. An integrated platform predicts conductance range for DNN tasks, achieving high accuracy on MNIST data. Challenges include limited dynamic conductance range, which is being addressed for improvement while maintaining linearity.

Siegel *et al* [6]:
Siegel *et al* address the energy efficiency challenges in sequence learning with machine learning models. It introduces a dedicated hardware implementation of a biologically inspired Temporal Memory using memristive crossbar arrays. Unlike traditional von-Neumann machines, this approach leverages memristive devices for both data storage and peripheral circuitry, promising greater energy efficiency. Simulation results demonstrate the model's effectiveness in training complex sequences and context-dependent prediction, with a focus on reduced energy consumption, and scaling potential is discussed.

Hernández-Balaguera *et al* [7]:
Hernández-Balaguera *et al* focus on perovskite memristors in neuromorphic electronics, particularly their potentiation effects. It proposes a detailed interpretation of these effects using nonlinear electrical circuits validated by impedance spectroscopy. The study reveals that ionic-electronic coupling creates a chemical inductor effect in these devices, leading to long-term synaptic enhancement. A quantitative electrical model explains this memory-based phenomenon, offering insights into material mimesis of neural communications and learning-memory functions in the human brain.

Ellis *et al* [8]:
Ellis *et al* introduce a methodology for harnessing stochastic effects in magnetic domain-wall motion in nanowires to create energy-efficient neural network hardware. It presents binary stochastic synapses with a gradient learning rule based on neuronal output distribution statistics. Depending on measurement frequency, the rule balances synaptic stochasticity and energy efficiency. Physical hardware tests demonstrate comparable performance to standard neural networks.

Wu *et al* [9]:
Wu *et al* introduce a voltage-gated conductance model for an artificial neuron that exhibits tonic, fast, and two types of intrinsic burst spiking. Spike generation is achieved with a single voltage-gated channel that exploits the conductance commutation properties of a two-terminal memristive device. The implementation is extremely simple using off the shelf electronic components, and employs a two-compartment bursting neuron model, similar to that of Pinsky-Rinzel.

This collection aims to offer fresh insights into the field of Neuromorphic Circuits and Systems utilizing Emerging Devices. The research underscores the significance of efficient hardware solutions, paving the way for enhanced energy efficiency and the emulation of biological neural computation.

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