Trends in Neuroscience and Education 38 (2025) 100248

Contents lists available at ScienceDirect

Trends in Neuroscience and Education

journal homepage: www.elsevier.com/locate/tine

Lu.i – A low-cost electronic neuron for education and outreach

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ARTICLE INFO

Keywords:
Education
Outreach
Low-cost PCB
Open hardware
Leaky integrate-and-fire
Neuron

ABSTRACT

With increasing presence of science throughout all parts of society, there are rising expectations for researchers to effectively communicate their work and for teachers to discuss contemporary findings in their classrooms. While the community can resort to established teaching aids for the fundamental concepts of most natural sciences, there is need for similarly illustrative demonstrators in neuroscience. We therefore introduce Lu.i: a parametrizable electronic implementation of the leaky integrate-and-fire neuron model in an engaging form factor. These palm-sized neurons can be used to visualize and experience the dynamics of individual cells and small networks. When stimulated with sensory input, Lu.i demonstrates brain-inspired information processing in the hands of a student. As such, it is actively used at workshops, in classrooms, and for science communication. As a versatile tool for teaching and outreach, Lu.i nurtures the comprehension of neuroscience research and neuromorphic engineering among future generations of scientists and the general public.

1. Introduction

Expanding our understanding of the brain is among the central frontiers of modern science and yet implies some of the longest standing questions humanity has posed to itself. Their fundamental nature induces an intrinsic curiosity about the progress of neuroscience, artificial intelligence, and brain-inspired technology. In contrast to this demand, the repertoire of tangible demonstrators to communicate principles and recent achievements in brain research is limited [1]. In comparison, other fields can build on many centuries of experience to convey their essential concepts through physical demonstrators and live experiments.

In our current understanding, the fundamental principles of information processing in nervous systems lie in neuronal dynamics and synaptic interactions. A strong intuition for these mechanisms is, therefore, the foundation for understanding and investigating more complex processes and emerging phenomena. In the following, we thus present Lu.i – an analog electronic implementation of the leaky integrate-and-fire (LIF) neuron model targeted for educational use as well as scientific outreach. Lu.i features current-based synaptic inputs that enable the formation of simple spiking neural networks (SNNs) and offers control over many parameters, including the time constants and the synaptic weights. The printed circuit board (PCB) visualizes the time-continuous dynamics of the emulated membrane potential and allows interfacing with digital and analog periphery for advanced experiments. It has been optimized for low-cost production, long battery life, and intuitive operation.

2. Neuron and synapse dynamics

Neurons are a family of electrically active cells that compute and communicate by exchanging action potentials. Each cell receives such signals via its synapses and integrates them over time. Once a neuron has accumulated enough input, it becomes active and communicates this by itself sending a spike to other neurons.

Lu.i implements the LIF neuron model, arguably the simplest abstraction that still captures these fundamental properties of neuronal information processing: time-continuous computation, spatio-temporal integration, and event-based communication. This model was originally put forward by Louis Lapicque (`/lu.i la'pik/`) in [2], after whom the PCB was fittingly named. In contrast to models based on specific ion channel dynamics like the one by Hodgkin and Huxley [3], LIF captures essential neuron dynamics in a single state variable: It describes the evolution of a neuron's membrane potential $V_{\mathrm{mem}}(t)$ by the differential equation

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https://doi.org/10.1016/j.tine.2025.100248
Received 24 September 2024; Received in revised form 24 January 2025; Accepted 25 January 2025
Available online 31 January 2025

$$\tau_{\mathrm{mem}} \frac{\mathrm{d}V_{\mathrm{mem}}(t)}{\mathrm{d}t} = -[V_{\mathrm{mem}}(t) - V_{\mathrm{leak}}] + I_{\mathrm{syn}}(t)/g_{\mathrm{leak}}, \quad (1)$$

where τ_{mem} denotes the membrane time constant, g_{leak} the leak conductance, and V_{leak} its resting potential. $I_{\mathrm{syn}}(t)$ subsumes the time-dependent synaptic currents stimulating the neuron. This differential equation describes a membrane potential which continuously decays to the resting state. It is, however, augmented by a reset condition to mimic the hyperpolarization following the action potentials observed in biological neurons: Whenever the membrane potential crosses the threshold ϑ, the neuron emits a spike. This efferent signal is accompanied by a reset of the membrane potential, where the latter is simply clamped to V_{reset} for the refractory period. For an exemplary time evolution of these dynamics see Fig. 3A.

Lu.i implements current-based synapses with postsynaptic currents following exponential kernels with time constant τ_{syn}. This additional temporal filter mimics the kinetics of synaptic ion channels: Each presynaptic spike j, arriving at time t^j_{pre} at synapse i, triggers an exponentially decaying current

$$I^j_{\mathrm{syn}}(t) = w_i \cdot \exp\left(-\frac{t - t^j_{\mathrm{pre}}}{\tau_{\mathrm{syn}}}\right) \quad \text{for } t > t^j_{\mathrm{pre}}, \quad (2)$$

where w_i denotes the weight of the respective synapse i. This weight variable models the strength of synaptic interaction, its sign corresponds to the positive and negative effect of excitatory and inhibitory neurotransmitters, respectively. The total synaptic current then results as a sum over the individual contributions from all synapses i and spikes j.

In biological neurons, the membrane potential typically resides between -80 mV and 0 mV. The temporal dynamics are, however, independent of that absolute voltage scale, and are instead mainly governed by the time constants. We on the one hand chose to slow down the temporal dynamics to a scale that can be visually well perceived and interacted with by experimenters. On the other hand, we opted to reduce the full complexity of the parameter space by fixing two of the potentials, namely the threshold ϑ and reset potential V_{reset}, leaving the leak potential V_{leak} as a free, adjustable, parameter.

3. Electronic implementation

Lu.i realizes the LIF dynamics through a set of analog electronic circuits (Fig. 2) and thus forms a physical model thereof. It exposes the neuronal time constants τ_{mem} and τ_{syn}, the leak potential V_{leak} and all synaptic weights w_i as user-settable parameters (Fig. 3B). The membrane is accessible through a board-edge connector and its voltage – as well as spike events – are visualized by on-board LEDs.

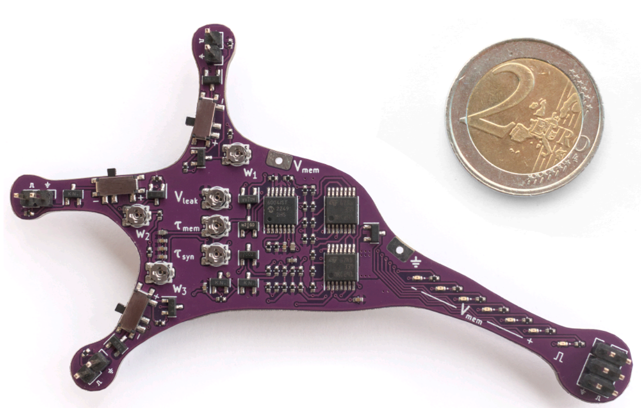

Fig. 1. A single Lu.i neuron PCB, with a 2-Euro coin for scale. To relay information from one neuron to the other, excitatory and inhibitory synapses can be formed by wiring the axonal output (right) to one of the three dendritic terminals (left).

Internally, Eq. (1) is rendered by the combination of capacitor C_{mem} and potentiometer g_{leak}, which form an RC integrator with adjustable time constant τ_{mem} (Fig. 2A). Without external stimuli, V_{mem} decays towards the resting potential V_{leak}, which we generate by the combination of an adjustable voltage divider with a subsequent unity gain buffer. The leak potential can thus be set between 0 V and the supply voltage V_{DD}. The spike mechanism is implemented by continuously comparing the membrane potential to the threshold, which was chosen as $\vartheta = V_{\mathrm{DD}}/2$ to guarantee sufficient voltage headroom for the comparator (Fig. 2D). Once the membrane reaches this threshold, the comparator trips, indicating a spike and causing a membrane reset. To avoid instabilities, it is fitted with a hysteresis circuit that temporarily reduces the comparator's reference potential to $V_{\mathrm{DD}}/4$ during the onset of a spike. At that point, the capacitor C_{ref} is discharged and the connected comparator trips, thus shorting the membrane to $V_{\mathrm{reset}} = 0$ V via the transistor Q_{reset} to implement the refractory period. R_{ref} and C_{ref} determine the fixed refractory time of approximately 15 ms, which starts once V_{mem} is discharged below $V_{\mathrm{DD}}/4$, where the threshold comparator releases. The control signal for Q_{reset} is re-used as the neuron's axonal output, with a pulse width equivalent to the refractory time.

Lu.i features three synapses implementing the current-based model with an exponential kernel as introduced by Eq. (2). Each of them possesses a tunable weight and can be switched between excitation and inhibition. The synapses share a common synaptic time constant τ_{syn}, which is adjustable over a broad range. For an area- and cost-effective implementation, we minimize the amount of components per synaptic connection: Events from presynaptic neurons control the gate of the n-channel MOSFET Q_{low} (Fig. 2B). Depending on the selected polarity $S_{\mathrm{sign},i}$, this transistor either directly discharges the shared synaptic integrator or indirectly charges it via the p-channel MOSFET Q_{high}. For each event, this synaptic trace is in- or decremented by a fixed amount of charge proportional to the respective weight $g_{\mathrm{w},i}$ which can be configured through a potentiometer. The time constant $\tau_{\mathrm{syn}} = C_{\mathrm{syn}}/g_{\tau_{\mathrm{syn}}}$ of the integrator can be similarly tuned (Fig. 2C). Especially in light of the additional filter introduced by the membrane, the resulting temporal behavior closely approximates the instantaneous response of the original model. The synaptic current I_{syn} is derived from the integrator state through a V-I conversion stage. As such, it consists of two voltage-controlled current sources – each built from a resistor, a MOSFET, and an operational amplifier. Q_{push} and Q_{pull} operate in a push-pull configuration and generate two antagonistic currents. Their difference is proportional to the deflection of the integrator and corresponds to the total postsynaptic current I_{syn} that stimulates the membrane.

Lu.i displays its state through a set of LEDs. Six of them form a bar that visualizes the membrane potential, and a seventh LED indicates efferent spikes with a flash. This interface is sketched in Fig. 3A for various states of the neuron. The voltmeter is implemented through a set of comparators and a resistor ladder to generate the respective reference potentials. While these circuits take up significant area on the PCB, they have been omitted from the schematic for clarity. This intuitive on-board interface enables standalone operation and the visualization of network activity and signal propagation therein. Experimentation with external equipment is, however, encouraged and allows more detailed insights into the neuron dynamics. For that purpose, the emulated membrane is accessible through a pad at the board edge for interfacing with, e.g., current sources and oscilloscopes.

The PCB is powered from a single CR2032 coin cell, which we chose for its small form factor, wide availability, and comparably high capacity at low cost. All voltage references of the circuit are derived relative to this supply voltage of nominal 3 V. The temporal dynamics are thus, on first order, invariant to the battery voltage. This ensures mostly stable operation across the entire lifetime of the cell, which results in approximately 24 h of continuous use. Lu.i can be powered down completely through a switch on its back side.

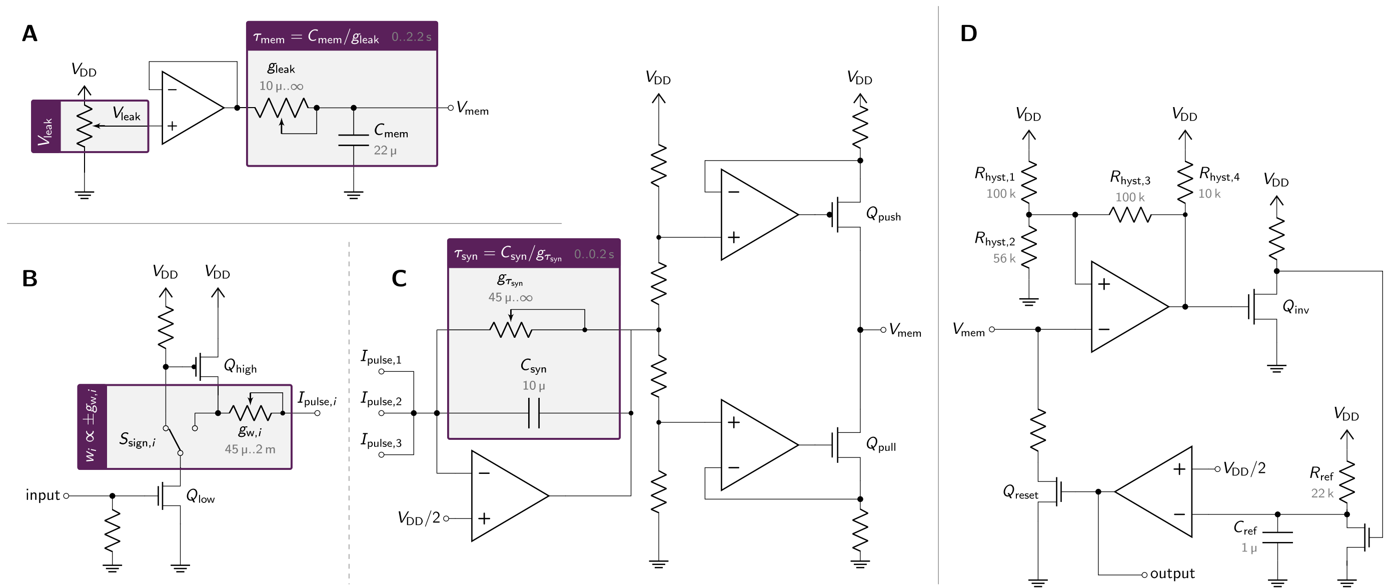

Fig. 2. Schematic of the LIF emulation circuit implemented in Lu.i. (A) Membrane capacitance and leak conductance. (B) Current-based synaptic input circuits. This circuit is instantiated three times, once per synapse. (C) Synaptic integrator and voltage-to-current conversion circuit. (D) Threshold, reset, and refractory circuit. The spike output pulse is derived from the neuron's reset signal and of equivalent duration. The purple boxes relate all user-settable parameters to their representation in the circuit.

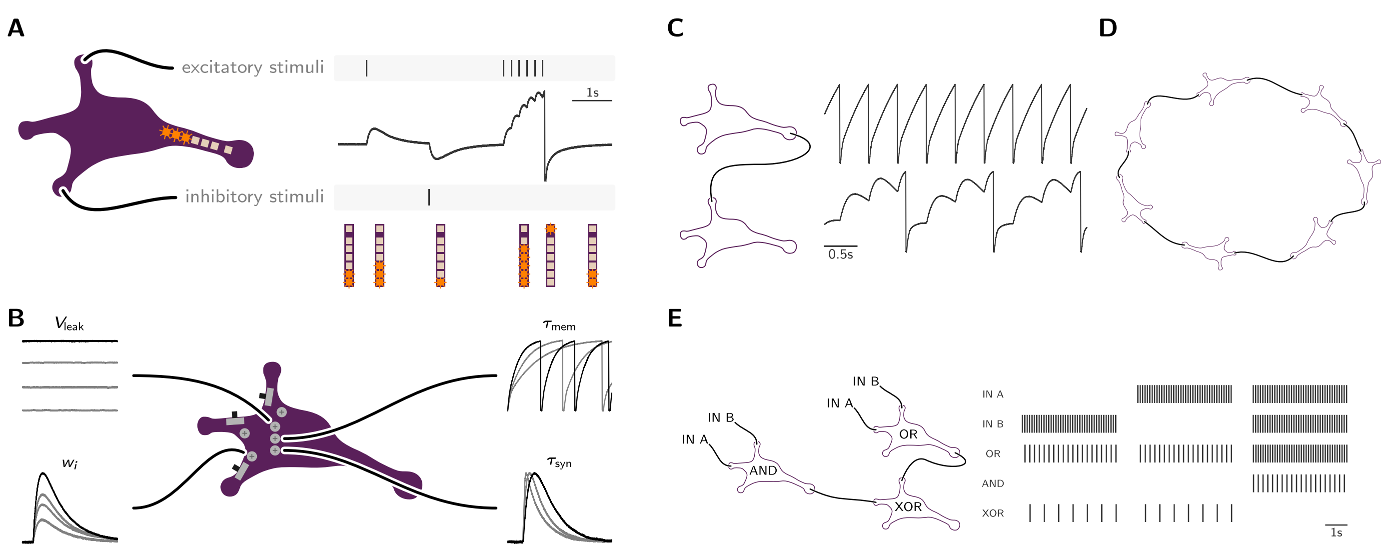

Fig. 3. Exploration of single-cell and network dynamics with Lu.i. (A) A single Lu.i neuron receiving multiple excitatory and a single inhibitory events. The depicted trace is an analog recording of V_{mem} on the board. It shows how stimuli are integrated on the membrane, which continuously leaks back to the resting potential. If the threshold ϑ is reached, the neuron sharply resets and emits a spike. For applications without an oscilloscope at hand, each Lu.i neuron features a bar of LEDs to display the current membrane potential as well as axonal spikes (top LED, flashing). (B) Tuneable neuron parameters on Lu.i. Each model parameter is represented by a small potentiometer (cf. Fig. 1), all three synaptic weights are individually configurable in sign and strength. The traces showing the influence of τ_{syn} have been normalized in amplitude. (C) Analog recording of the membrane potential V_{mem} of two Lu.i neurons. The top trace shows the dynamics of a circuit that is configured with $V_{leak} > \vartheta$ and emits spikes at regular intervals. This neuron projects onto a second one (bottom trace), which is excited by these events, integrates the post-synaptic current and – eventually – also spikes. (D) Wiring diagram of a closed, circular delay chain built from seven Lu.i neurons. (E) Spike recording of three Lu.i boards, configured to represent rate-based AND, OR and – combined – XOR gates. For panels (A) and (E), the input events are presented by an external microcontroller.

While aiming for an intuitive and appealing form factor, the PCB has been strongly optimized for low-cost fabrication. This is reflected in the selection of components as well as the layout, which only relies on a simple two-layer PCB. As a result, we achieved a unit price of around US $3 (excluding the battery) already for batches below 1000 Lu.i neurons. As the backside only contains the battery holder and an optional power switch, fabrication costs can be further reduced by restricting automated assembly to the top layer.

4. Exploring neural computation with Lu.i

Lu.i was designed to illustrate two of the fundamental aspects of biological neurons: spatio-temporal accumulation of input and event-based communication, both of which are captured by the LIF model. These aspects can be demonstrated in a set of experiments of increasing complexity, some of them shown in Fig. 3.

The first property – leaky integration of input – can be seen in Fig. 3A: The membrane potential rises after weak excitatory stimuli and

Fig. 4. Lu.i has played an integral role at various events all over the world for teaching and outreach applications, including: Nacht der Forschung (Switzerland, 2022), CapoCaccia Workshop toward Neuromorphic Intelligence (Italy, 2023), TReND in Africa (Ghana, 2023), and Deutsche SchülerAkademie (Germany, 2023).

decays back to the resting potential, similarly with inhibitory input. The resulting trajectories are shaped by the adjustable time constants τ_{syn} and τ_{mem}. These determine the time scales on which consecutive inputs are integrated and stacked. Only when the threshold is reached, an efferent spike is triggered and visible externally. On Lu.i, these dynamics can be observed using an on-board LED strip visualizing the membrane state and spike output, as shown in Fig. 3A. Neurons compute through this combination of analog integration and thresholding, for example by performing spatio-temporal coincidence detection. Exploring the impact of the model parameters on this computation – in case of coincidence detection on the sensitivity or detection window – is a worthwhile educational exercise: When Lu.i receives two spikes with a certain time difference, the neuron's parametrization determines whether an output spike is emitted. With short time constants, it becomes active only for inputs close to each other, whereas longer time constants result in a larger detection window. These temporal dynamics fundamentally determine the timescale on which information is processed.

In contrast to the local computation on their membranes, neurons communicate through temporally sparse spike events. This signal propagation can be demonstrated in a simple two-neuron network (Fig. 3C), where a synaptic connection is formed by a cable between the presynaptic axon and a postsynaptic dendrite. By choosing a resting potential above the threshold, the first neuron can act as a regularly firing spike source to the second. As before, the stacking of excitatory stimuli and the reset upon threshold crossing can be observed on the membrane of the postsynaptic cell. The behavior of both neurons is clearly visible using the built-in LEDs without an external oscilloscope. Already in this simple setup, the influence of the synaptic parameters can be explored: For example, the combination of a short synaptic time constant and a strong excitatory weight can be used to trigger one spike for each incoming event. Increasing the synaptic time constant, while lowering the weight, can lead to a delayed propagation of single spikes. This can be used to build delay chains, which vividly illustrate the finite propagation speed of neural signals. Once these chains are closed (Fig. 3D), their activity becomes self-sustained.

Fig. 3E shows a more complex example, where rate-based AND, OR and – in combination – XOR gates are implemented using three Lu.i neurons. In this case, the OR (AND) gate is implemented by a single neuron that has been tuned to fire for at least one (two) active presynaptic neurons. The output of the OR neuron excites the XOR cell, with the AND neuron acting inhibitorily.

While the inputs A and B can be presented using Lu.i neurons (e.g., in leak-over-threshold configuration), we have used an external microcontroller to stimulate the network in Fig. 3E. With a pulse duration of 15 ms and a signal level of approximately 2.5 V, Lu.i's event output signal can be detected by most 3.3 V and 5 V microcontrollers. The event inputs on Lu.i are compatible with signal levels from 1.8 V to 20 V, allowing to interface with a great variety of sensors and devices.

Due to its simplicity, the XOR network is attractive in educational and outreach environments. Inspired by existing literature, more complex networks have emerged from collaborations of researchers across all areas of neuroscience, including realtime sound localization [4], a balanced random network [5], a ring attractor model [6], an echo localization latch [7], and – with preprocessing of the analog signals – a brightness change detection circuit. Lu.i has been used repeatedly to teach a younger audience about fundamentals of neuroscience and physical computing, also in combination with a subsequent transition to neuromorphic systems made accessible through the european research initiative EBRAINS. Within the first two years, Lu.i has been used at more than 20 workshops held by lecturers not affiliated with the group of authors. Across all described applications, it was used to compellingly illustrate fundamental topics across a wide range of research areas from robotics to systems neuroscience.

5. Discussion

This manuscript presents Lu.i, a palm-sized electronic neuron with versatile applications for teaching and scientific outreach. It can be used to illustrate the dynamics of individual neurons under different parametrizations and their interaction in small spiking neural networks (Fig. 3). Featuring various connectivity options as well as on-board visualization aids, Lu.i can be used stand-alone or in combination with external equipment, like oscilloscopes, current sources, or microcontrollers.

Lu.i complements a range of pedagogical tools spanning from experimental to computational neuroscience [8,9]. Among those are guided experiments on tissue and living animals, which are arguably the most natural way to convey biological concepts but always imply ethical and logistical challenges. Simulation-based curricula, on the contrary, trade immediacy with ease-of-use and simplicity, even when considering graphical user interfaces [10,11]. Reducing experimentation on living tissue in accordance to the 3R principles [12] while keeping the benefits of interactive teaching [13], the concept of tangible hardware has been put forward before [14–18]. As another effort in this direction, Lu.i combines an inviting interface with an analog yet accurate implementation of the LIF model. The latter is sufficiently complex and flexible to allow illustration of fundamental biological phenomena as well as the concept of physical computation. The PCB is optimized for cost-effective manufacturing to ease acquisition especially for educational institutions. With its engaging form factor, Lu.i has been welcomed at various conferences and workshops, leading to adoption by teachers and tutors in classrooms (Fig. 4). As such, the project received enthusiastic responses initiating collaborations across both different areas of expertise and from pupils to faculty.

The Lu.i project is available as open hardware[2] and undergoes active development. The circuits are continuously improved and future versions might be accompanied by additional extensions, such as sensory spike sources or actuators. In conjunction with the above-mentioned collaborations on courses and workshops using Lu.i, a curriculum of teaching material and feedback is being collected to nurture adoption among teaching personnel.

Funding

The presented work has received funding from the Manfred Stärk Foundation, the EC Horizon 2020 Framework Programme under grant agreement 945539 (HBP) and Horizon Europe grant agreement 101147319 (EBRAINS 2.0), the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy EXC 2181/1-390900948 (Heidelberg STRUCTURES Excellence Cluster), and the VolkswagenStiftung under grant number 9C840.

Ethical statement

Not applicable.

CRediT authorship contribution statement

Yannik Stradmann: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Conceptualization. **Julian Göltz:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Conceptualization. **Mihai A. Petrovici:** Writing – review & editing, Supervision, Funding acquisition. **Johannes Schemmel:** Writing – review & editing, Supervision, Funding acquisition. **Sebastian Billaudelle:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank the Manfred Stärk Foundation for sponsoring the first batch of Lu.i neurons in preparation for the Nacht der Forschung (Bern, 2022), Andreas Baumbach for his dedicated support during early development and prototyping, Laura Kriener for patiently tutoring Lu.i users and passionately building functional networks, Matthias Penselin and Nazarii Bogachuk for bringing the project into school classrooms, the Human Brain Project for sponsoring subsequent production batches, Björn Kindler for his administrative and public relations support, Barbara Webb, Ben Efron, Chenxi Wen, Robin Dietrich, Sarah Hamburg, Shreyan Banerjee, and Yulia Sandamirskaya for pioneering experiments during the CapoCaccia Workshop toward Neuromorphic Intelligence 2023, Saray Soldado-Magraner for taking Lu.i to Ghana and her photos thereof, the Deutsche SchülerAkademie for kindly authorizing the use of a group photo, Maxime Zimmermann for representing Lu.i at the FENS Forum 2024, and the anonymous reviewers for their comprehensive and constructive feedback that considerably improved this manuscript. Finally, we'd like to thank the NeuroTMA and ElectronicVisions groups for their continuous support and inspirational atmosphere.

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