

# Low power neuromorphic solutions for the health market



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*Improvements in battery technology and low-power communications, alongside the ubiquity of mobile computational resources in the form of smartphones, enable* ***smart wearable devices for healthcare****.*

*A wide range of sensing technologies are available, but more sensors means more data.* ***Transferring and storing data is expensive****, especially in continuous monitoring applications. More data collected means* ***more data to examine and diagnose****. Most of which is not pathological.*

*At the same time,* ***data analysis is energy-expensive****. Small power budgets for mobile medical devices limit local data analysis with traditional approaches.*

***Ultra low-power processors for digital health markers, designed by aiCTX****, enable continuous monitoring in health wearables. Pathological states are automatically identified, reducing data storage and transmission requirements, and facilitating faster diagnosis.*



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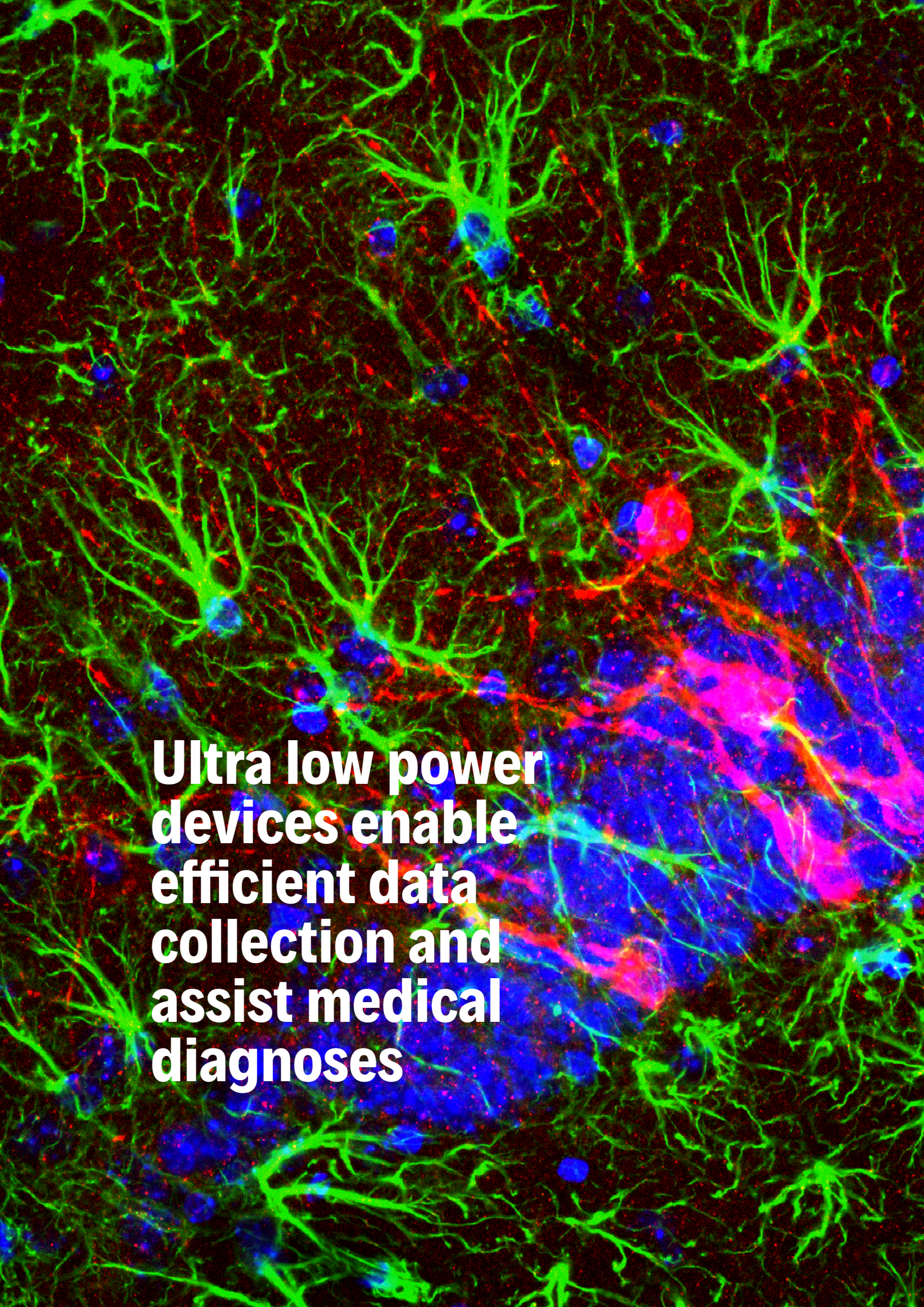
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Ultra low power devices enable efficient data collection and assist medical diagnoses

# Low-power real-time analysis for digital bio-markers

We are designing new solutions for **ultra low-power, real-time analysis of biological signals**. Our solutions generate real-time digital biomarkers for **close-to-the-sensor implementation** in new mobile health devices and wearables.

Our approach can be applied to a wide variety of bio-sensors, to build biomarkers for almost any application.

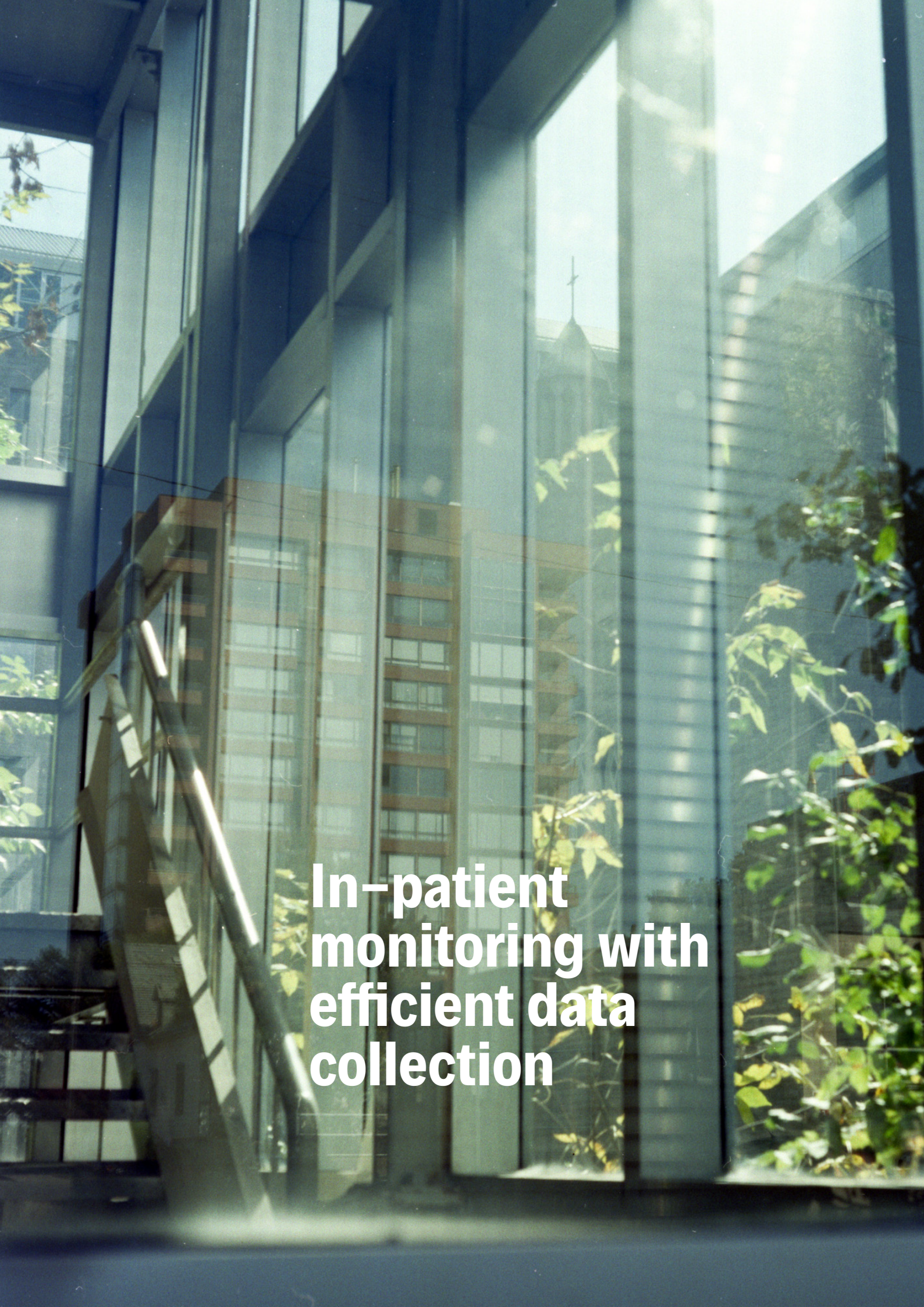
We design our systems to **recognise defined pathologies in bio-signals, in real-time**. Recognition of a pathological state can be used to trigger detailed data collection, meaning that pathological data is highlighted.

# In-patient monitoring

Efficient data collection, triggered by detection of pre-defined pathologies. Less data to trawl through means more efficient diagnosis per patient. The result is a concise set of records from a patient, with pathological states measured and highlighted for further diagnosis and analysis.

Non-invasive continuous monitoring can raise predefined alarms, both in and out of the ward.

Precise tuning for individual patients can be performed if desired. This increases the potential accuracy of detecting pathological states. A baseline recording from the patient is made in-office, and a wearable is given to the patient. The patient is then monitored continuously, with alarms or data collection triggered by detection of a desired pathological state.



# In-patient monitoring with efficient data collection



# Out-patient monitoring with good compliance

# Out-patient monitoring

Set-and-forget low-power devices require no recharging by the patient, and can be worn continuously. This means **better patient compliance, over longer durations**. Efficient low-bandwidth data collection highlights pathological events, raising an alarm or storing only pathological data for later analysis.

The wearable is returned to the office at the next appointment for data download and wireless recharging.

# In-field remote diagnosis

Robust low-power wearables can be used in the field. Pre-configured to identify pathological bio-markers, they efficiently collect data, identifying pathological events for immediate or remote diagnosis.

Assisted diagnosis can be performed by the device and associated analysis tools, or data can be collected for remote analysis. Pathological events are highlighted for faster diagnosis by a medical professional.

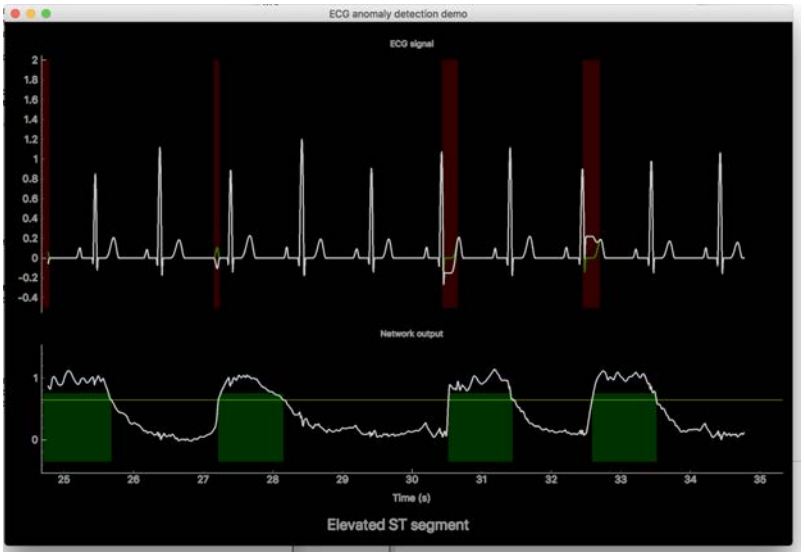


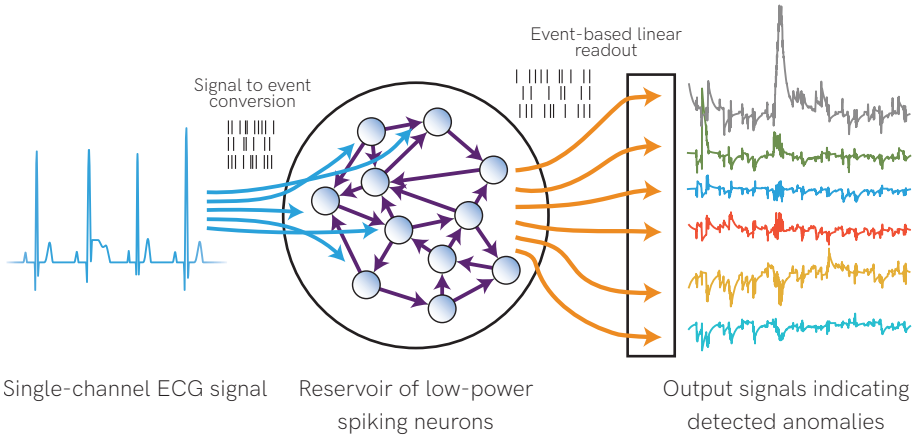
# Low-power robust data collection and analysis for in-field use


Network output
4
5
6
7
Time (s)

# Application: Real-time detection of anomalies in ECG traces

aiCTX has developed a proof-of-concept for ultra low-power analysis of ECG traces, using our neuromorphic hardware. Single-lead ECG signals are processed by a network of spiking neurons implemented in custom silicon. Pathological states are identified in real time. Our system raises a trigger signal when an anomaly is detected, which can be used as a trigger for recording a trace for further analysis in the cloud, or by a professional.






*The architecture of our proof-of-concept ECG analysis system. ECG signals are processed by a reservoir of 512 spiking neurons. Improved detection is achieved by training outputs to detect particular anomalies in ECG traces.*

## Implementation

A network of 512 spiking neurons receives as input a single-lead ECG signal. The variations in the ECG trace are analysed by the network, and collectively produce an output signal. We train the output signal to identify the presence of an anomalous component in the ECG trace, and raise a trigger-like event when an anomaly is present during single heartbeats.

## Performance

| Anomaly type | Sensitivity* | False positives† | MTBFP‡ |
|---|---|---|---|
| Inverted P wave | 95% | 0.125% | 13 mins |
| Absent P wave | 86% | 0.75% | 2 mins |
| Absent QRS complex | 82% | 0.94% | 2 mins |
| Inverted T wave | 99.9% | 0.125% | 13 mins |
| Elevated ST segment | 99% | 0.125% | 13 mins |
| Depressed ST segment | 85% | 0.25% | 7 mins |
| Overall detection | 92% | 1.1% | 1.5 mins |

**Detection accuracy per anomalous heartbeat. †False positives per nominal heartbeat. ‡Mean time between false positives, at 60 bpm heart rate.*



# Applications

Our ECG proof-of-concept is designed for **integration close to the sensor** in low-power medical devices. Our proof-of-concept solution can be adapted to multiple-lead ECG inputs. **Additional output signals can be selected according to medical needs.** For example, heart rate estimation or independent detection of specific anomalies can be selected.

### Implementation in a health wearable for use in hospitals

- Continuous, non-invasive monitoring of in-patients, both in and out of the ward
- Automated data pruning reduces data storage and transmission requirements
- Highlighted pathological states reduces cognitive load for diagnosis
- Ultra low-power design means longer operation between recharging

### Medical wearables for out-patient monitoring

- Low-power continuous monitoring means no recharging is required by the patient

- This "set and forget" approach means less for patients to remember, and better patient compliance
- Low-bandwidth data collection means more compact devices, and longer duration between return visits
- Anomaly detection can be used to raise alarms or to trigger data collection

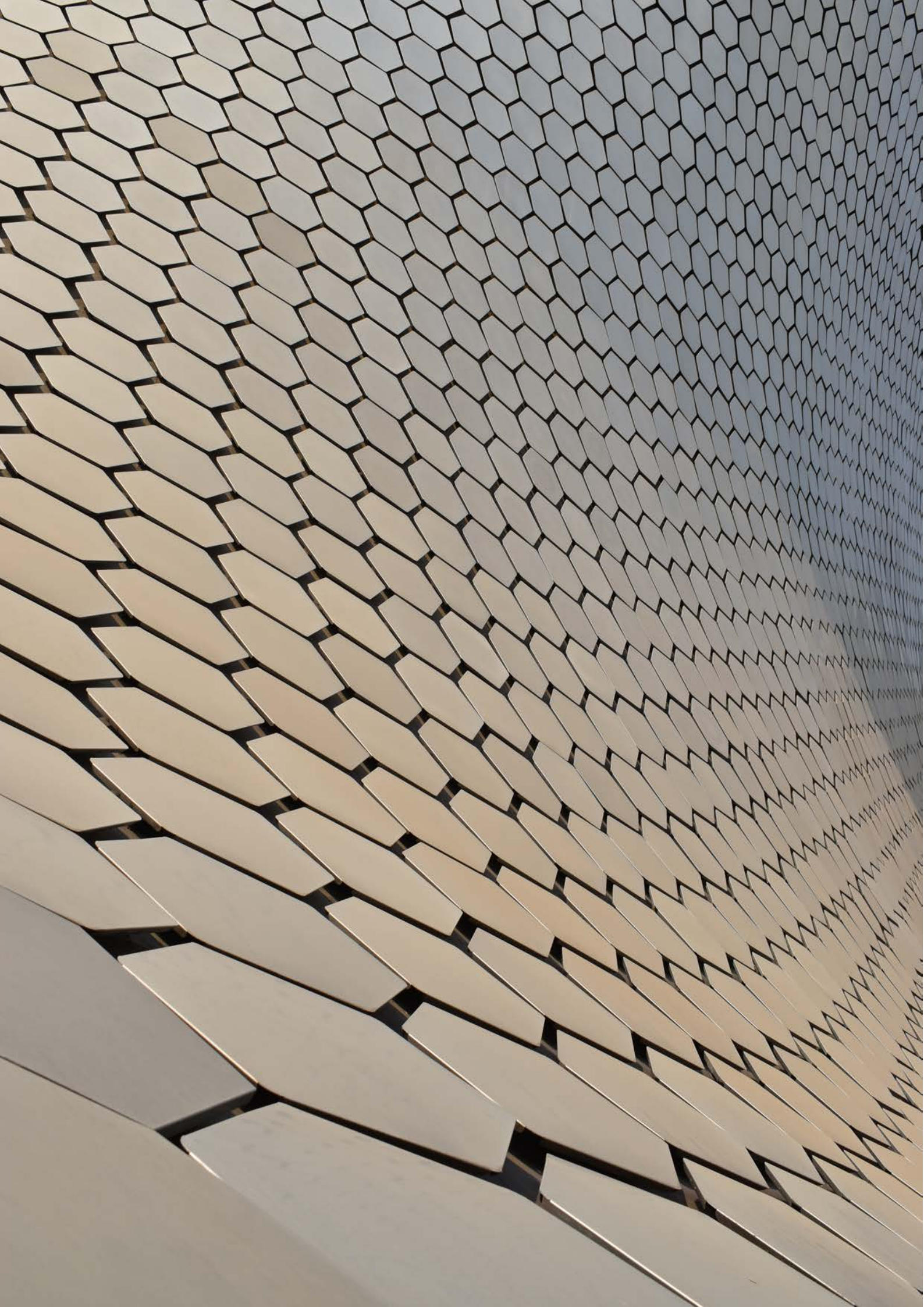
### Implementation in a robust low-power device for in-field use

- Ultra low-power design means longer operation between recharges, and/or more compact devices
- Smart data collection reduces network transmission, further lowering power consumption
- Automated data pruning assists remote diagnosis by reducing bandwidth costs
- Assisted diagnosis in-field by detecting and highlighting pathological states

### Full customization

Our general-purpose approach can be applied to a wide range of biological signals. We can design custom solutions for simultaneous monitoring of multiple signals, and deliver custom-designed hardware for any application.





# Technology: Neuromorphic Engineering

Neuromorphic means literally "like the brain". aiCTX is developing new classes of computing devices that make use of the **incredible power efficiency and real-time capability** of neural tissue.

We design custom chips that use the physical properties of silicon to efficiently emulate the behaviour of nerve cells. Our neurons receive and transmit signals using brief voltage pulses, **the same communication technique used in mammalian brains**. Silicon synapses (connections between neurons) mimic the chemical transmission of information between neurons in live tissue.

We connect our emulated neurons into communicating networks, that are configured to **process information in real time**.

## Benefits

Because our neurons are emulated using the physical properties of silicon, they require very little power to operate. Our Dynap-se chips can operate for **several months on a single AA battery**.

We distribute the storage of memory alongside the silicon neurons, with the result that comparatively **less data must be shuffled through**

our chips, compared with a classical CPU or GPU-based implementation. This further reduces the energy requirements of our hardware.

Our hardware communicates through events, in real time. Information is processed immediately when it arrives, using the timing of an input event to directly represent the time at which the event occurs. This provides three benefits:

- When no input is present, no energy-wasting computation occurs
- Processing of information is not delayed. In traditional frame-based image processing, in comparison, events can only be processed once an entire frame has been acquired.
- Our solutions process data in real time — no slower, no faster. As a result, our hardware is designed to interface directly with the real world.



## Differences from CPU/GPU simulation

Networks of neurons can be simulated using traditional von Neumann processors — the same CPUs that are in every computer and every phone. Standard processors are of course highly flexible, general-purpose computing devices, but that flexibility makes them less efficient in simulating networks of neurons. This is especially true when

one considers the massive parallelism in networks of neurons; CPUs are available with multiple cores, and usually implement some small-scale parallelism, but for large networks of neurons CPUs must sequentially simulate portions of the network in turn.

*“Our neuromorphic solutions are optimal for mobile and autonomous devices, where energy usage must be kept as low as possible”*

The use of GPUs for simulating neural networks has in recent years led to the commercialisation of deep learning — many-layered neural networks can now be trained and simulated in reasonable times. However, the energy usage required to train these architectures is increasing exponentially (**openai.com**). The massively parallel architecture of GPUs and TPUs (Tensor Processing Units) makes them well matched for simulating feedforward neural networks. Nevertheless, GPU architectures are designed for general-purpose computation, and so cannot reach the efficiency of special-purpose neuomorphic hardware for simulating neurons.

The simulation rate for CPU/GPU solutions usually scales with network complexity, with the result that these architectures are difficult to match to real-time processing. CPU/GPU solutions are a good match for applications where small energy budgets and real-time operation are not required. Our neuromorphic solutions are optimal for mobile and autonomous devices, where energy usage must be kept as low as possible. Our technologies are also ideally suited to real-time signal processing, especially on data that is fundamentally event-based.



# Technology: “Reservoir computing”

Reservoir computing is a method for using populations of simulated nerve cells (neurons), to extract desired information from a signal. In our case, the signals are either very simple (e.g. a recording from a single vibration sensor) or slightly more complex (simultaneous recordings from two or more ECG electrodes). Our approach is designed for these spatially “low-dimensional” inputs, rather than highly complex signals such as a video stream — we use other network architectures for these “high-dimensional” data.

A signal is passed to a population of several hundred simulated neurons (the reservoir), which are connected to each other in a complex pattern.

*“The input signal passes back and forward between neurons, combining with itself and with the signals already moving through the reservoir”*

The input signal passes back and forward between neurons, combining with itself and with the signals already moving through the reservoir. Signals remain in the reservoir for some time, as the input changes, meaning that different temporal components of signals can be examined simultaneously.

The complex patterns of activity that are produced within the reservoir can then be examined and compared to a desired output signal, during the training process. For example, we can inject ECG input signals corresponding to pathological heartbeat conditions, and train the reservoir to recog-

nise the difference between a normal heartbeat, and a pathological heartbeat.

We can also inject vibration signals into the reservoir, corresponding to normal, pre-failure and failure conditions of a mechanical device, and train the reservoir to identify when a component is not operating normally.

### Why "reservoir"?

The poetic name for our approach arises in analogy to a pebble tossed into a lake (or reservoir). The pebble causes ripples on the lake, which interact with the complex lake shore by reflecting in complicated ways. By examining the ripples on the lake surface, one can tell when and where the pebble was thrown. This information about the pebble persists for some time, and can interact with ripples from other pebbles tossed later into the same lake.

In this analogy, the pebble is the input signal, the lake is the population of simulated neurons, and the complex lake shore corresponds to the patterns of connections between neurons. The ripples on the lake surface represent the information about the input signal propagating within the population of simulated neurons.

### Further reading

- Wikipedia, "Reservoir Computing"
- Maass, Natschläger, and Markram, 2002. "Real-Time Computing Without Stable States." Neural Computation 14 (11) pp 2531–2560. DOI:10.1162/089976602760407955



# About aiCTX

aiCTX is a commercial spin-off from the Institute of Neuroinformatics, University of Zurich and ETH Zurich. We specialize in developing mixed-signal neuromorphic silicon hardware for neural simulation and signal processing; develop software for interfacing with and configuring neuromorphic hardware; and develop solutions to analyse and process bio-signals.

*“ aiCTX specializes in developing low-power neuromorphic silicon hardware ”*

aiCTX is developing approaches for bio- and industrial-signal processing, based on biologically-inspired neuronal architectures emulated on low-power neuromorphic hardware. The neuromorphic industry is growing rapidly, with significant contributions from large players such as Intel and IBM. Our advantages are our long experience in designing low-power neuromorphic circuits, and our experience in theory of neuromorphic and cortical computation.

aiCTX is also developing solutions for rapid event-driven processing of visual information, for application in industrial monitoring and automotive markets. We are building the first commercially available full-stack neuromorphic hardware solutions.

# aiCTX technology

## DynapSE2

Our new neuromorphic chip combines the **impeccable energy efficiency** of its previous generations with new features for **low latency, real-time end-to-end applications** for general purpose recurrent and reservoir networks. Its integrated biosignal amplifiers and the direct dynamic vision sensor bus make the DynapSE2 a **perfect fit for mobile health and robotic applications**. Each chip features 1k redesigned adaptive exponential integrate-and-fire analog ultra low-power spiking neurons and 65k enhanced synapses with configurable delay, weight and short term plasticity. The DynapSE2 enables **advanced biological processing schemas**, such as ampa, nmda and gaba channels, as well as conductance based dendritic computation to be utilised.

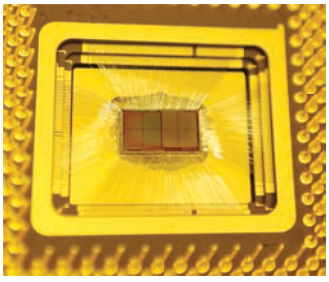


*Our DYNAP development kit is available for purchase. Build and test your own neuromorphic solutions using our spiking neuron HW emulators.*

The **innovative asynchronous low latency communication infrastructure** (patented) enables each neuron to communicate with up to 230k surrounding neurons and infinite scalability via relay neurons for truly large scale networks.

## DynapSEL

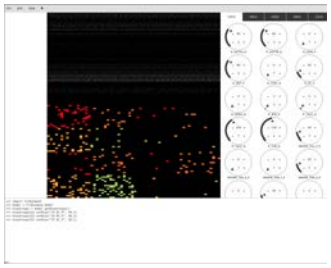
Our next-generation neuromorphic chip, DynapSEL, features 1k analog low-power spiking neurons and almost 80k configurable synaptic connections, including 8k synapses with integrated spike-based learning rules. In comparison with our nearest competitor, the TrueNorth



*DynapSEL spiking neuron emulator with plastic synaptic connections.*

chip from IBM, the DynapSEL features **8x the synaptic fan-in and 32x the fan-out**; these numbers are in the range of connectivity architectures observed in mammalian cortex, and permit networks with biologically realistic connectivity to be emulated using DynapSEL. In addition, the DynapSEL is considerably more energy efficient than TrueNorth, requiring less than a fifth of the energy expenditure per synaptic event and less than half the energy per neuron spike. This is combined with a speed advantage in favour of DynapSEL, resulting in more than **10 times the number of synaptic events per second per watt**.

## ctxctl software



*ctxctl software visualising the firing activity of a population of spiking analog neurons.*

**ctxctl** is the front end interface to the aiCTX toolchain, and cross-platform environment for interacting with our devices. It provides a Python API and data visualization tools for working with spiking neural networks.

# Key personnel

Dr. Ning Qiao, PhD — *CEO, CTO, co-founder*
Dr. Qiao is an expert analog and mixed-signal neuromorphic engineer, and holds the position of Chief Executive Officer at aiCTX. Dr Qiao designs next-generation mixed-signal neuromorphic circuits for rapid event-driven processing. He is the founder, CEO and CTO of aiCTX.

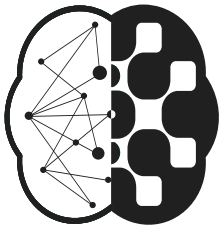


Prof. Dr. Giacomo Indiveri, PhD — *CSO, co-founder*
Prof. Dr. Indiveri is an expert neuromorphic engineer, with more than 20 years' experience in analog and mixed-signal hardware design, and extensive experience managing the development of neuromorphic computing hardware. He holds the positions of Chief Science Officer at aiCTX, as well as Director of the Institute of Neuroinformatics at the University of Zurich and ETH Zurich.



Dr. Kynan Eng — *Chairman, co-founder*
Dr. Eng is a co-founder and chairman of aiCTX. He has led startups to successfully closed funding rounds and product launches (YouRehab, iniVation), and has worked at companies including ABB, Alstom and a network management supplier for Telstra. He holds degrees in computer science and mechanical engineering from Monash University, and a PhD from the ETH Zurich, where he also led a research group investigating the neuroscience of virtual reality interactions.





Francois Stieger — *Board advisor*
Mr Stieger is an experienced executive, investor and board advisor. He has served in senior management roles at Verisign, Oracle, and Broadvision, where he was involved in the IPO and listing on NASDAQ. He is a former partner at Amadeus Capital and is currently active in S-Partners and in other investment vehicles.



Dr. Dylan Muir, PhD — *Senior R&D Engineer*
Dr. Muir is a specialist in architectures for neural computation. He has published extensively in computational and experimental neuroscience. At aiCTX he is responsible for directing development of neural architectures for signal processing. Dr. Muir holds a Doctor of Science (PhD) from ETH Zürich, and undergraduate degrees (Masters) in Electronic Engineering and in Computer Science from QUT, Australia.



Felix Bauer — *R&D Engineer, NN Architectures and Applications*
Mr Bauer is a physicist with strong mathematical and analytical background. He is experienced in working with neural network architectures, neural simulations and brain-machine interfaces. Mr Bauer holds a Master of Science degree and a Bachelor of Science degree in Physics, both from ETH Zurich, Switzerland.

# Forward-looking statements disclaimer

Certain information set forth in this document contains "forward-looking information", including "future oriented financial information" and "financial outlook", under applicable securities laws (collectively referred to herein as forward-looking statements). Except for statements of historical fact, information contained herein constitutes forward-looking statements and includes, but is not limited to

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4. sources and availability of third-party financing for the Company's projects;
5. completion of the Company's projects that are currently underway, in development or otherwise under consideration;
6. renewal of the Company's current customer, supplier and other material agreements; and
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