All Roads Lead to TinyML: The Rome of Efficient Machine Learning in Engineering

Dinuka Sahabandu[1], Nushara Wedasinghe[2], Madusha Weerasooriya[2], Asiri Gawesha Lindamulage[3*], Sanka Mohottala[2*]

1) University of Washington, USA 2) Sri Lanka Institute of Information Technology, Sri Lanka
3) Open University of Sri Lanka, Sri Lanka

*sanka.mo@sliit.lk

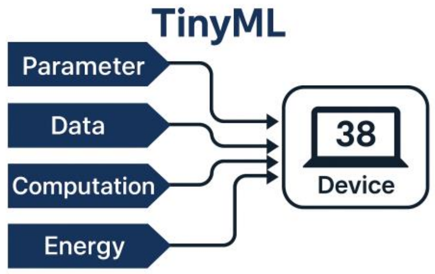
Connecting Connectme-Inspired ANNs with the TinyML Landscape

Purpose

- Convergence point of multiple efficiency paradigms — parameter, data, computation, energy, and connectivity.
- Binary classification application

My Role in the Roadmap

- **Focus:** on Connectome-based Artificial Neural Networks (ANNs) and Spike Neural Networks (SNNs).
- **Key Link:** Brain-inspired architectures (e.g., EleganṡAI) embody multiple efficiencies naturally — high connectivity sparsity, event-driven computation, and parameter parsimony — making them ideal for TinyML integration.



- **Relevance to Others' Work:**
  - Complements **compression** by exploiting structural sparsity from the connectome.
  - Enhances **parameter efficiency** through biologically-constrained architectures.
  - Supports **energy efficiency** via SNN event-driven processing.
  - Informs **deployment** through neuromorphic hardware compatibility.
- Connectome-based Artificial Neural Networks (ANNs)and Spiking Neural Networks(SNNs).

Takeaway

Brain-inspired models are not just another "road" to TinyML – they are the evolutionary blueprint from which all emergency strategies can learn.

Bardis, F., et al. — *"EleganṡAI: From the connectome of a living organism to artificial neural networks."* **Neurocomputing**, 2024.

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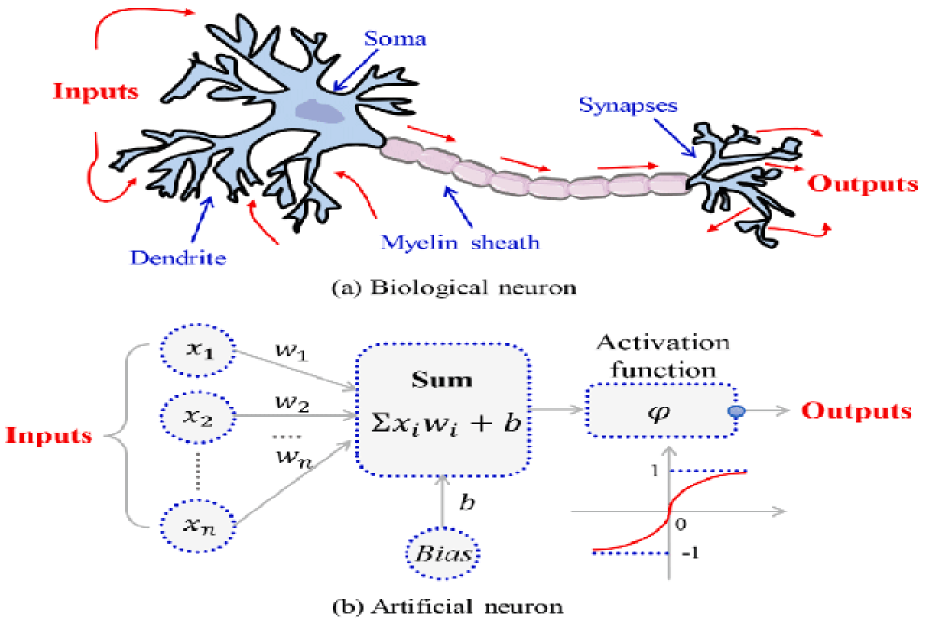
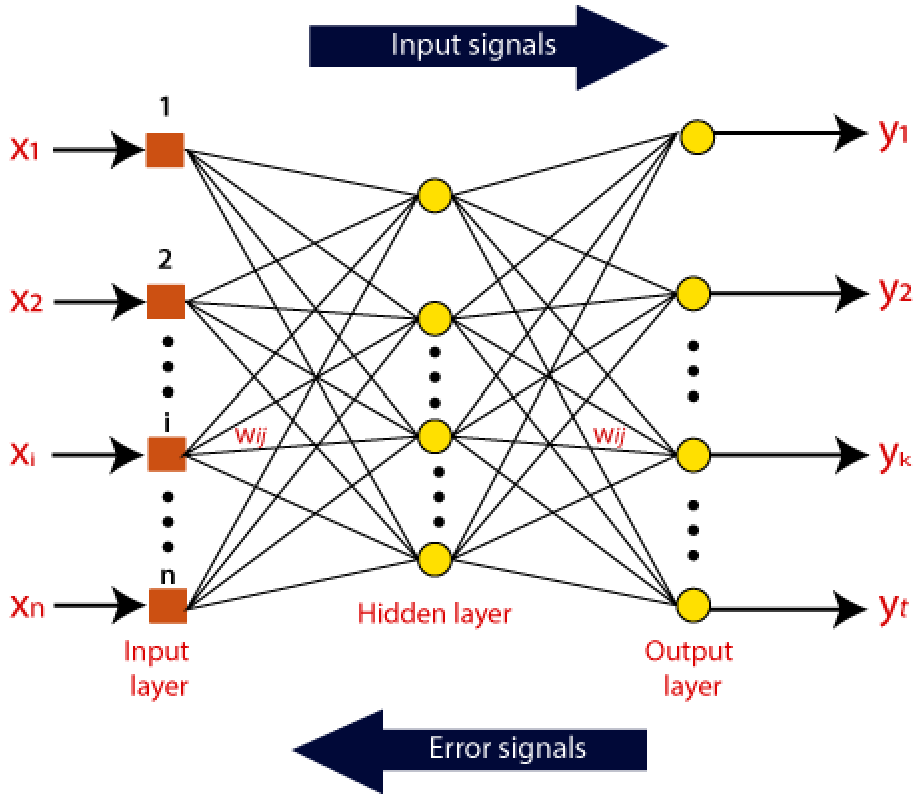
Bio-Inspired Artificial Neuron





I. Alnaib and A. Alsammak, Advance Artificial Neural Networks. Sep. 2022.

Artificial Neural Networks (ANNs)

Overview

Definition: ANNs are computational models inspired by biological neurons, designed to recognize patterns and solve complex tasks.

Structure: Composed of layers of interconnected nodes (neurons) – typically including an input layer, one or more hidden layers, and an output layer.

Functioning:

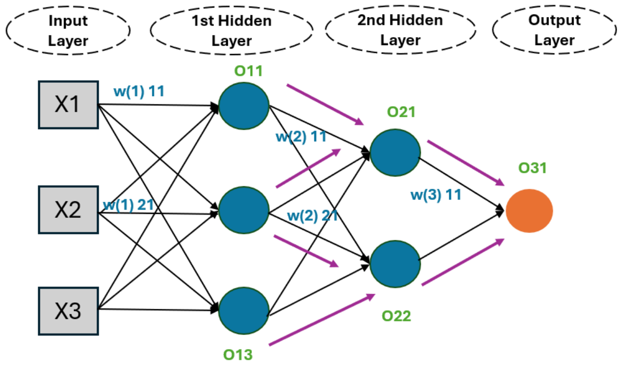
Each neuron processes inputs and passes information to subsequent layers.

Neurons are connected via weights that adjust based on learning to optimize output accuracy.

Not Outdated: Despite being an early AI approach, ANNs remain relevant and widely used.

Modern Architectures: CNNs and RNNs, key DL models, are advanced extensions of ANNs.

Behavior



Learning Process:

- Uses algorithms like **backpropagation** to adjust **weights** and minimize error.

Applications

- Image Recognition
- Natural Language Processing
- Predictive Analytics
- Speech Recognition
- Cybersecurity
- Robotics and etc.

ANs: Inspired, Not Replicated

1. **Simplified Representation:** ANs abstract brain processes; biological neurons are far more complex.

2. **Functional Differences:** ANs use math-based weights; and lack neuroplasticity and neuron-like spikes.

3. **Structural Differences**: ANs have fixed layers; unlike the brain's interconnected, hierarchical networks.

4. **Origins**: Developed from mathematical models, not detailed brain studies, for engineering tasks.

Hardware Limitations

•**Computational Power:** Requires costly, high-performance GPUs/TPUs.
•**Energy:** High training power consumption.
•**Slow inference:** not ideal for real-time.
•**Scalability:** Expensive, complex distributed setup.

Software Limitations

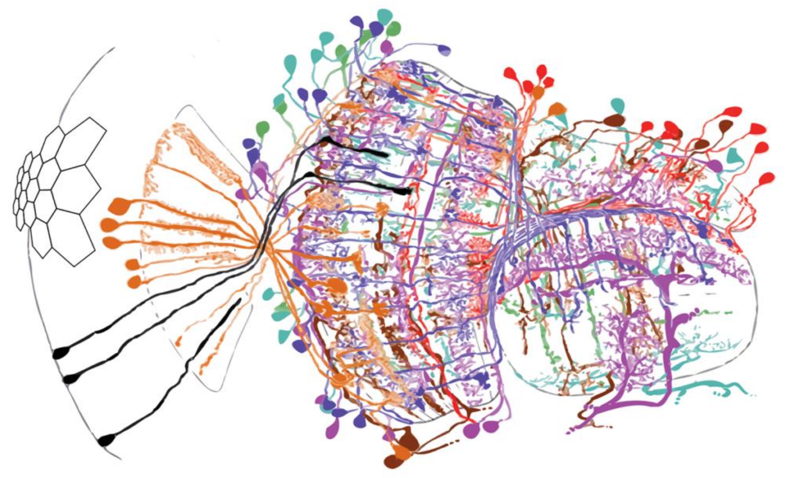
•**High complexity:** Neural networks need heavy computation and resources.
•**Framework limits:** Some don't support custom designs or special hardware.
•**Data needs:** Require large labeled datasets, often scarce.
•**Maintenance:** Need strong infrastructure, monitoring, and updates.

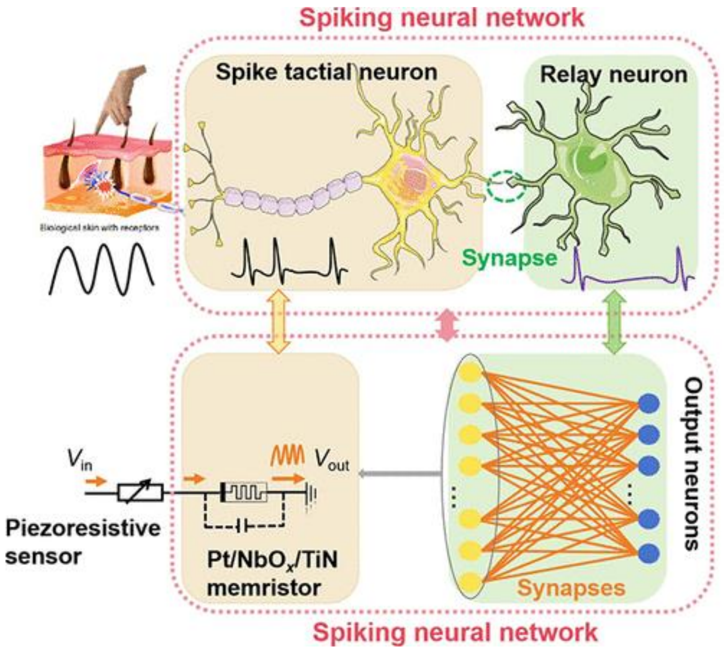
Bio-Plausible Neurons/Neural Networks

Types

Bio-plausible neural networks have two types,

1. Spiking Neurons (SNs).
2. Biological Connectome-Based Neural Networks.





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https://doi.org/10.53053/BWTN6816

Spiking Neural Network (SNNs) CODE

Core Concept

Third-generation neural networks

- Event-driven processing

Coding Schemes

- Rate coding
- Temporal coding
- Population coding

Learning Paradigms

- STDP (Spike-Timing-Dependent Plasticity)
- Supervised
- Unsupervised learning
- Reinforcement learning

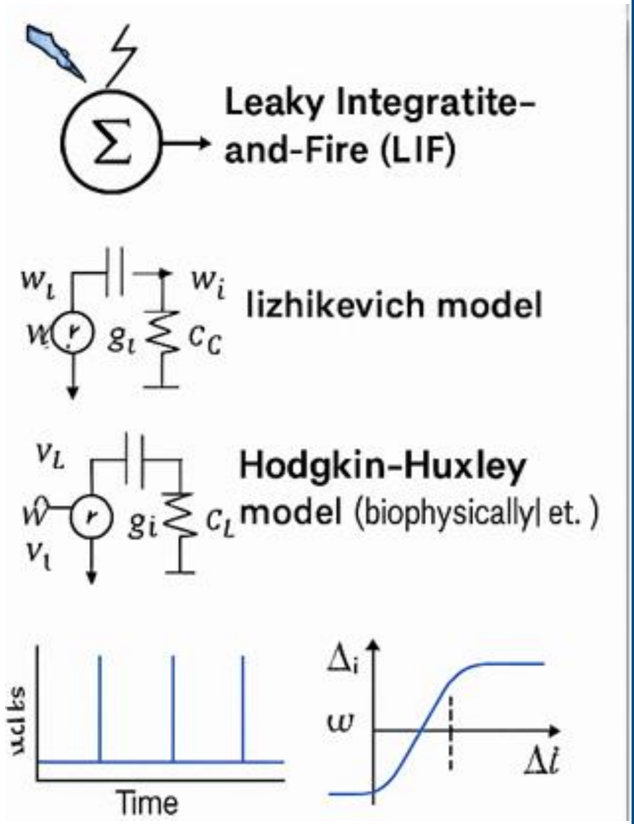
Research Directions

Hybrid models

Bio-inspired learning rules

Applications – Event-based vision (DVS), tactile sensing, auditory processing, robotics.

Theoretical neuroscience links – Understanding brain computation.



Advantages

Energy efficiency – Event-driven computation suitable for neuromorphic hardware (e.g., Loihi, SpiNNaker, TrueNorth).

Temporal information processing – Ideal for time-series and sensory event data.

Sparse representation – Lower memory footprint.

Challenges

- **Training difficulty** – Non-differentiability of spikes.
- **Lack of large-scale SNN datasets and benchmarks.**
- **Hardware–algorithm co-design** required for real gains.
- **Scalability** – Efficient mapping on neuromorphic hardware.

Biological Connectome-Based Neural Networks

Concept
- AI models whose architecture, connectivity, and dynamics are inspired or directly derived from biological connectome data.

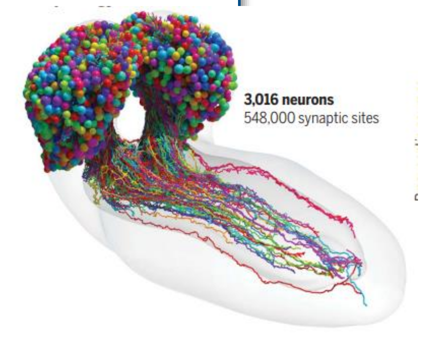
Foundation: Built using neuron–synapse maps from organisms (e.g., C. elegans, Drosophila melanogaster).
- **Goal:** Leverage biological wiring efficiency, modularity, and functional specialization to improve AI adaptability and efficiency.

Data Sources
- **Electron Microscopy (EM) Reconstructions** – nanoscale mapping of synapses.
- **Tracing & Registration Tools** – CATMAID, FlyWire, Neuroglancer.

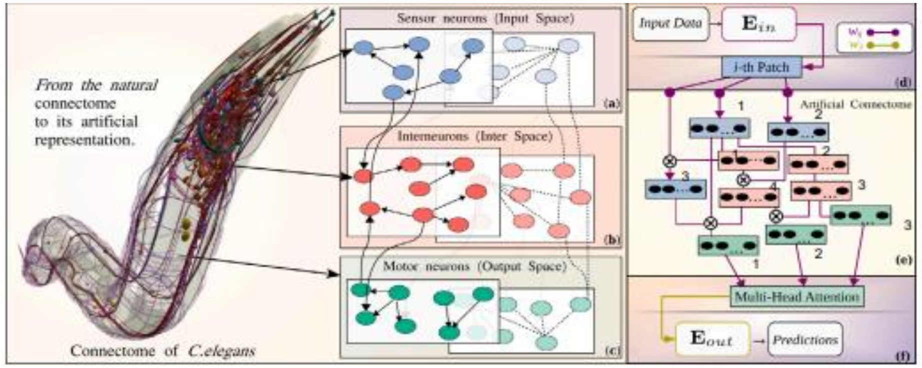
Example Datasets:
  - *C. elegans* – 302 neurons fully mapped.
  - Drosophila larva brain – ~3,000 neurons, >500,000 synapses.

Research Directions
Connectome-to-Computational Model Translation, Multi-Scale Modeling, Neuroevolution, Comparative Connectomics, Neuromorphic Hardware Implementation

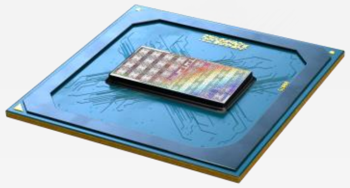
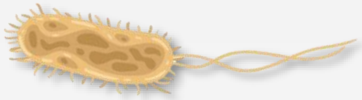
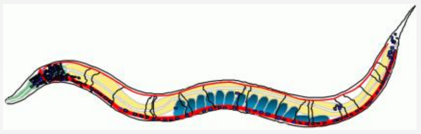
Advantages
- Data Efficiency
- Energy Efficiency
- Inductive Biases
- Functional Robustness



Challenges
- Incomplete Data
- Noisy Biological Data
- Functional Mapping Gap
- Simulation Costs



Background & Motivation

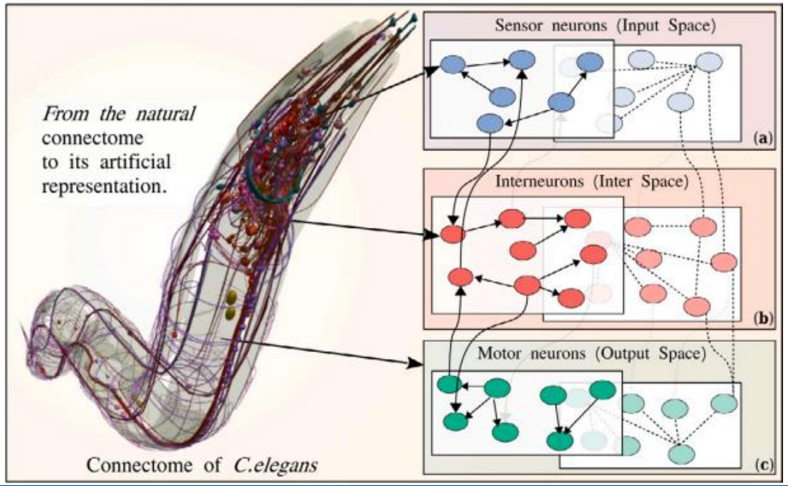
	Human brain	Loihi 2	Bacteria	C Elegan
				
# Computing units	100 B neurons	1 M neurons	100-11000 genes	~302 neurons
Storage	~2500 Tb	24 MB	~1.2 MB	~7000 genes
Size	1300 cm^3	31 mm^2	~0.4 - 3 μm^3	~1 mm (length), ~0.5 mm^3 volume
Power consumption	20 W	100 mW	<0.1pW	~10–20 μW
Comp. unit density	$7.7x10^4$ mm^{-3}	$3.2x10^4$ mm^{-2}	5 $x10^{12}$ mm^{-3}	~600 mm^{-3} (302 neurons / ~0.5 mm^3)

Biological Connectome-Based Neural Networks

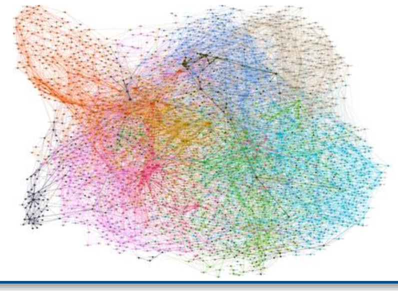
To date, the complete connectomes—detailed maps of all neural connections—have been mapped for the following organisms:

- **Caenorhabditis elegans** (a nematode worm) - **“Successfully converted to ANN”**
- **Drosophila Larva** (fruit fly)
- **Platyneresis Dumerilli** (Marine Worm)

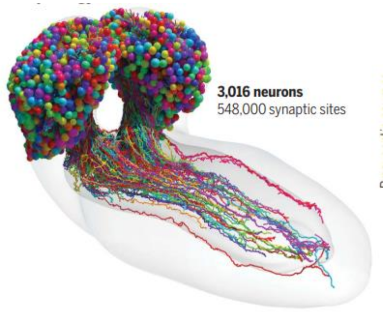
C Elegan



Platyneresis Dumerilli



Drosophila Larva



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Elegans-AI: How the Connectome of a Living Organism Could Model Artificial Neural Networks

Authors: Francesco Bardozzo, Andrea Terlizzi, Claudio Simoncini, Pietro Lió, Roberto Tagliaferri

Journal: Neurocomputing, 2024

Elegans-AI Repo

Background, Motivation, and Core Concept

Background & Motivation

- Biological connectomes represent neuron-level wiring diagrams
- C. elegans is fully mapped: 302 neurons, ~7,000 synapses
- **Aim:** Translate biological wiring efficiency into AI architectures

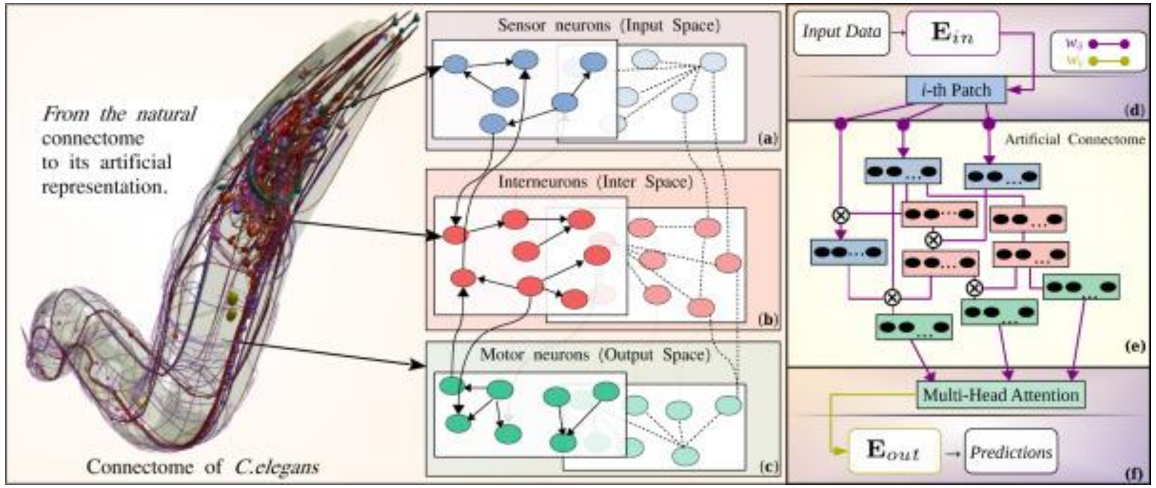
Core Concept

- Elegans-AI Models: AI inspired by C. elegans topology

  1. Convert biological connectomes to artificial representations
  2. Embed connectomic topologies in deep learning & reservoir networks
  3. Structural explainability via motifs

Methodology

C. elegans Connectome → AI Mapping



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- Architecture Construction: Map connectome graphs into ANNs
- Maintain small-world & motif structures
- Learning: Deep Connectomic Networks, Reservoir (Echo-State Transformers)
- Explainability: Analyze heterophilic vs. homophilic connections.

Elegans-AI

Key Features

- Bio-inspired priors as topological constraints
- Neurodynamic memory (short/long term)
- Connectomic motifs as inductive biases
- Evolutionary optimization embedded

Experimental Setup

Benchmarks: CIFAR-10, CIFAR-100, MNIST Unsup
- Comparisons: Randomly rewired & bio-plausible networks
Metrics: Accuracy, parameter efficiency, memory

Results

Accuracy: 99.99% (CIFAR-10 & CIFAR-100), 99.84% (MNIST Unsup)

Efficiency:

- Fewer trainable parameters vs. DNNs
- Reservoir networks' strong performance
- Small-world topology boosts learning

Architecture Components

M1: Deep Connectomic Network (DCN)

Concept:

- Instead of training all connections, the connectome is used as a **reservoir** (fixed recurrent structure).
- Only the **readout layer is trained**, reducing training cost and improving stability.

Implementation:

- Biological connectome → reservoir structure (fixed recurrent graph).
- External inputs injected into the reservoir (mimicking sensory neuron activation).
- Outputs read from specific nodes mapped to motor/output neurons.
- Training is restricted to **linear readout weights**, making it computationally efficient.

Strengths:

- Provides **short- and long-term memory** via recurrent loops.
- Very **parameter-efficient** and **energy-efficient** (good for neuromorphic hardware).
- Achieves **state-of-the-art accuracy** (99.99% CIFAR-10/100, 99.84% MNIST Unsup) with **much fewer parameters**.

Limitations:

- Less flexible than fully trainable DCNs.
- Performance highly dependent on how input/output mappings are chosen.

Results over Metrics

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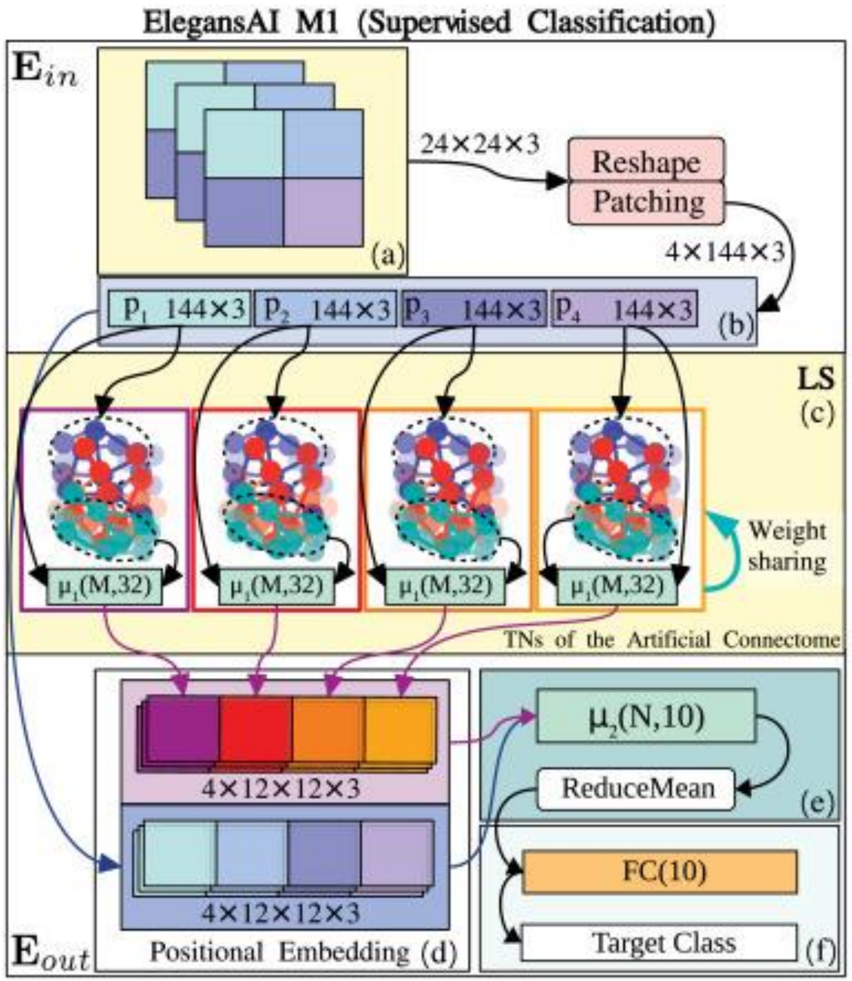

Elegans-AI *M1* vs. SOTA models for *Cifar10* and *Cifar100*.

Model	Cifar10		Cifar100	
	Top-1 Acc.	Trainable params	Top-1 Acc.	Trainable params
Elegans-AI M1 DNN (ours)	**99.9**	107M	**99.9**	313M
Elegans-AI M1 ESN (ours)	**99.9**	5K	**99.9**	34M
EfficientNet V2-L (SAM) [97]	99.1	121M	96.08[a]	120M
ViT-H/14 [34]	99.5[a]	632M	–	–
μ2Net [38]	99.5[a]	111K	94.95[b]	100K
ViT-L/16 [34]	99.4[b]	307M	–	–
CaiT-M-36 U 224 [36]	99.4	86M	–	–
CvT-W24 [35]	99.4	276.7M	94.09	276.7M
BiT-L [96]	99.4	928M	93.51	928M
ViT-B [103]	99.3	928M	–	–
Heinsen Rout.+BEiT-l. 16 224 [67]	99.2	309.5M	93.8	309.8M
ViT-B/16 [104]	99.1	86M	93.9	86.5M
CeiT-S [105]	99.1	24.2M	–	–
AutoFormer-S 384 [106]	99.1	23M	–	–
TNT-B [107]	99.1	65.6M	–	–
DeiT-B [37]	99.1	86M	–	–
EfficientNetV2-L [33]	99.1	121M	92.3	121M
BPSR SNN ResNet [28]	90.74	260.7M	–	–
Swin-L + ML-Decoder [108]	–	–	95.1	–
ViT-B-16(ImageNet-21K-PT) [109]	–	–	94.2	87M
Astroformer [110]	–	–	93.36	161.75M
CaiT-M-36 U 224 [36]	–	–	93.1	86M
ViT-L(attn fine-tune) [103]	–	–	93.0	306M
TResNet-L-V2 [111]	–	–	92.6	77.1M
EfficientNetV2-M [33]	–	–	92.2	55M
BiT-M(ResNet) [96]	–	–	92.17	235M

Highest accuracy is in **bold**.
[a] The second-best.
[b] The third-best.

Architecture Components

M2: Connectome-Based Reservoir Network (Echo-State Inspired)

Concept:

- Uses the biological connectome as a **fixed recurrent reservoir**, inspired by **echo-state networks**.
- Only the readout layer is trained, lowering training cost and improving stability.

Implementation:

- Connectome graph → reservoir structure with fixed recurrent loops.
- Inputs injected into the reservoir, simulating sensory activations.
- Outputs mapped from designated motor/output neurons.
- Training limited to linear readout weights, keeping computation lightweight.

Strengths:

- Same efficiency benefits as M1.
- Strong **temporal dynamics** from echo-state formulation.
- Excellent **memory retention** with low cost.

Limitations:

- Less flexible than fully trainable networks.
- Performance strongly depends on **input/output mapping choices**.
- May underperform on tasks requiring adaptive recurrent dynamics beyond fixed wiring.

Results over Metrics

Table 1
Elegans-AI $M2$ vs. SOTA models for MNIST Unsup.

Model	Top-1 Acc.
Elegans-AI $M2$ DNN (ours)	**99.8**
IIC [100]	99.3[a]
Sparse Manifold Transform [41]	99.3[a]
Elegans-AI $M2$ ESN (ours)	98.5[b]
SubTab [42]	98.3
Stacked Capsule Autoencoder [39]	98.0
Self-Organizing Map [43]	96.9
Bidirectional InfoGAN [99]	96.6
Adversarial Autoencoder [40]	95.9
CatGAN [98]	95.7
InfoGAN [102]	95.0
PixelGAN AE [69]	94.7
Model	**F1 (%)**
Elegans-AI $M2$ DNN (ours)	**99.3**
DenMune [101]	96.6[a]
Elegans-AI $M2$ ESN (ours)	94.9[b]

Highest accuracy is in **bold**.
[a] The second-best.
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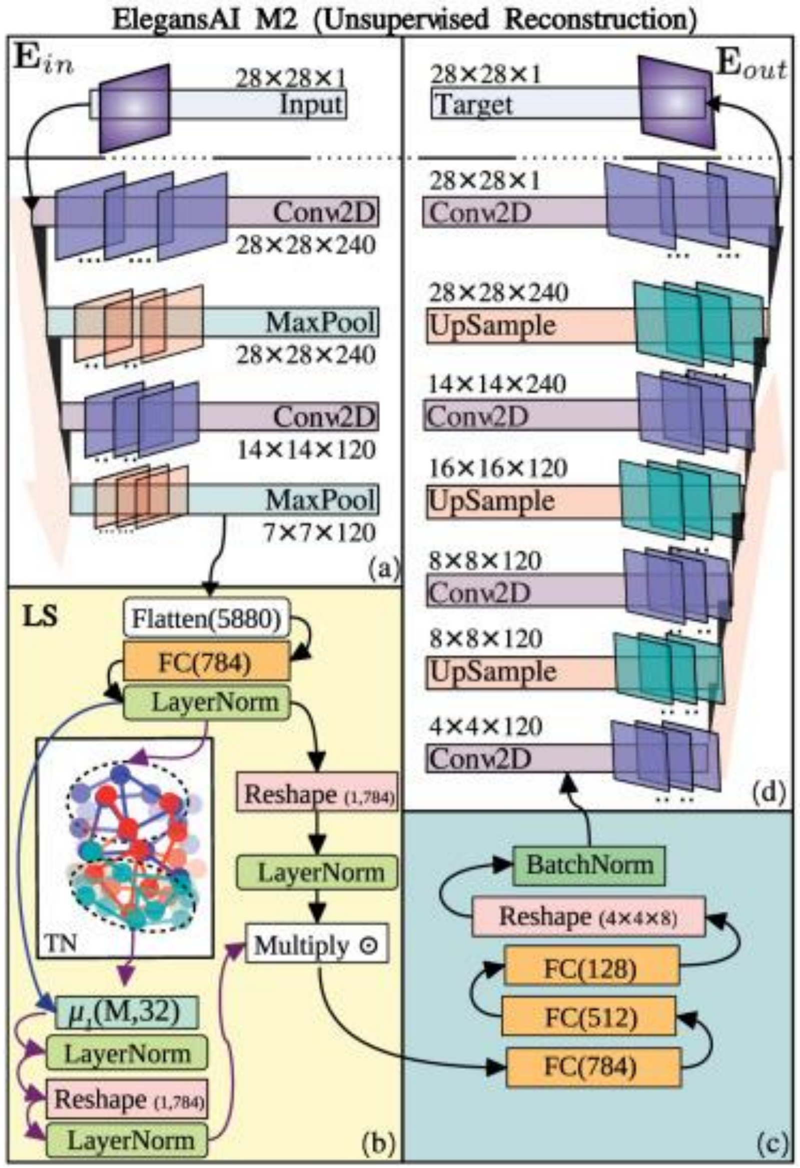

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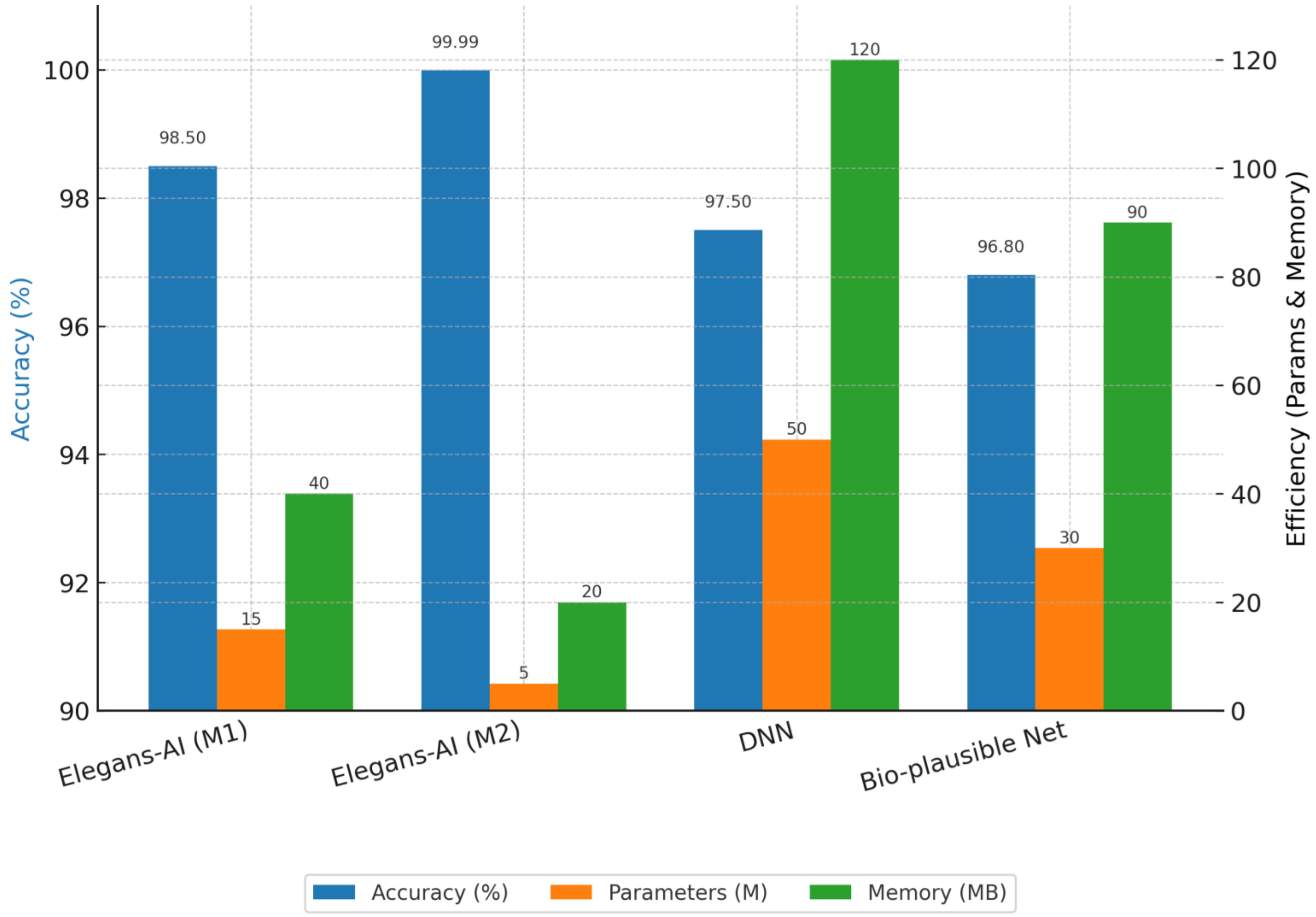

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Strengths and Contributions

Advantages

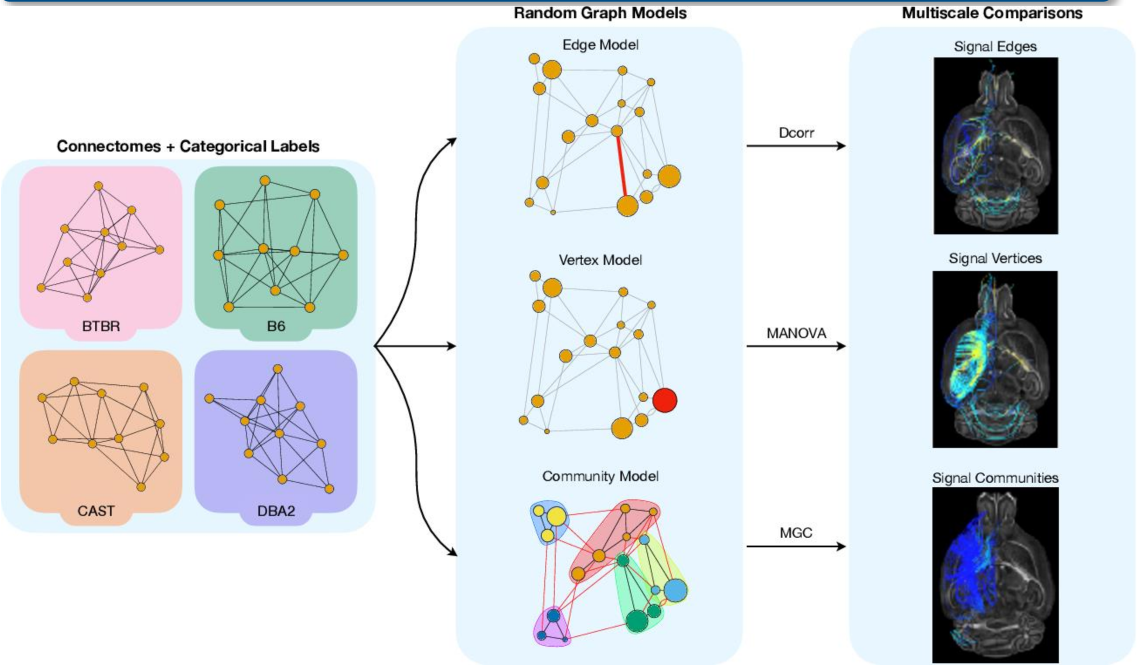
- Data efficiency with fewer parameters
- Topology-driven generalization
- Structural explainability
- Bio-aligned with evolutionary design

Challenges & Limitations

- Scaling beyond C. elegans
- Biological noise vs. artificial precision
- Limited general-purpose applicability
- Hardware demands

Future Directions

- Larger connectomes: Drosophila
- Hybrid ANNs, SNNs, and BCNNs
- Neuromorphic implementations
- Comparative connectomics for AI principles



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FlyWire

github.com

Welcome to CATMAID — CATMAID 2021.12.21 documentation

Thank You