Modeling the brain with generative approaches: An overview

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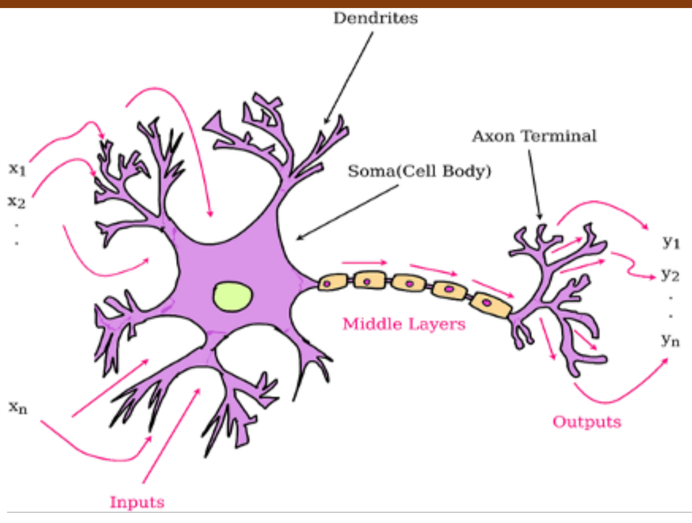
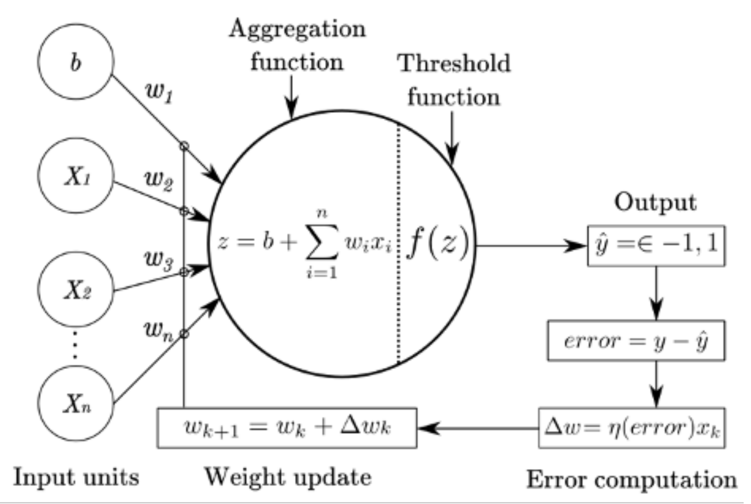
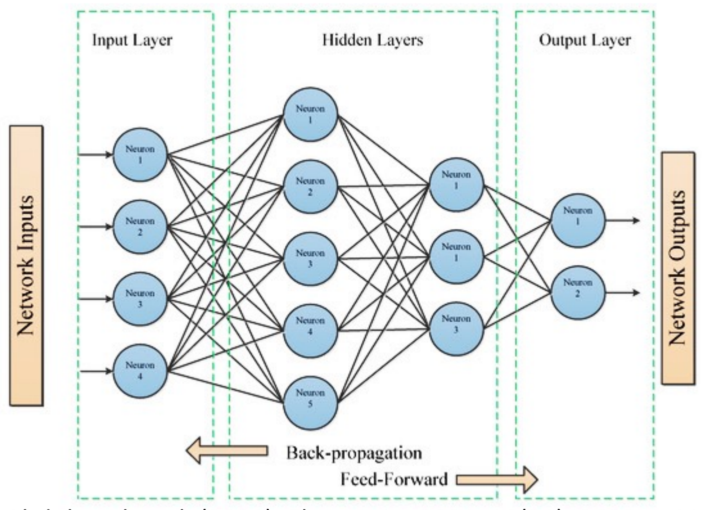
Introduction



Thakur et al. (2023), Artif Intell Rev, 56, p. 14671



Bishop and Bishop (2024), Springer eBooks



Abdolrasol et al. (2021), Electronics 2021, 10(21), 2689, p.11

Generative models provide a powerful framework to reproduce and study neural processes, aiming to deepen our understanding of perception, memory, and consciousness. Since the introduction of the perceptron in the 1950s, the idea of interpreting the brain as a computational system has gained prominence, laying the foundation for artificial neural networks inspired by the structure and function of biological neurons.

Objectives

- Review the current state of brain simulation research.
- Identify the most prominent computational models used in brain simulations.
- Distinguish the degree of bio-plausibility of each model.
- Analyse the strengths and limitations of each model.

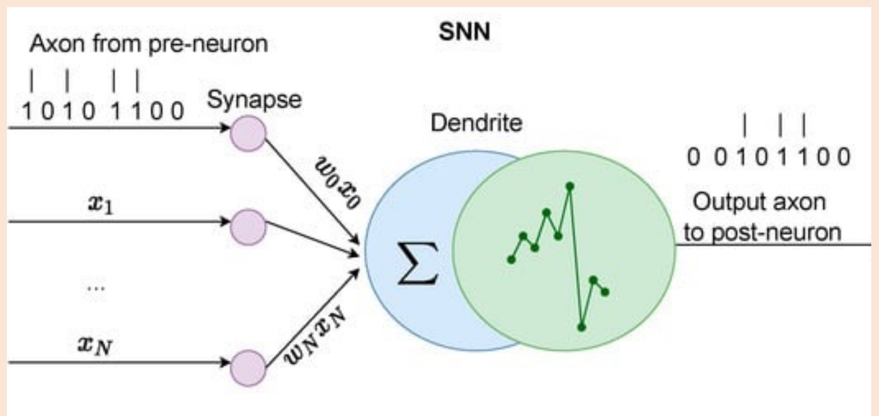
Project typology

This work is a comprehensive overview of the main computational generative models developed for brain simulation. A literature review has been conducted to identify and analyse the most relevant and widely used models in the field.

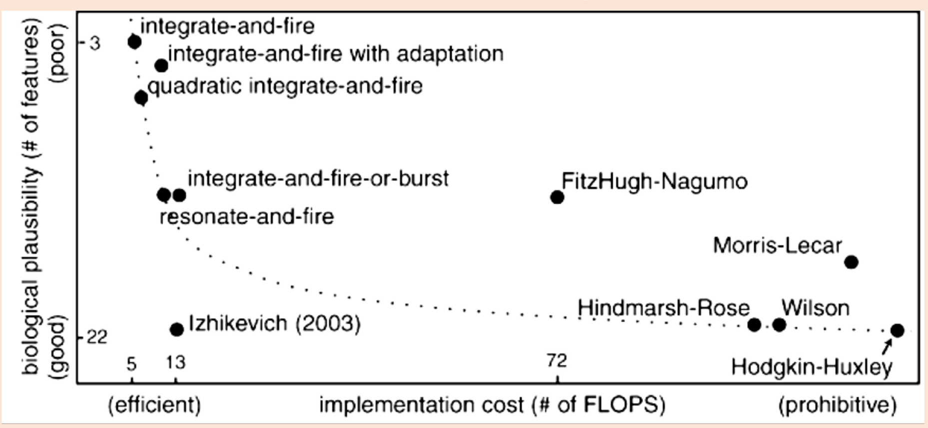
Biophysical models

Spiking Neural Networks (SNNs)

SNNs are biologically inspired models that mimic how neurons communicate using discrete electrical spikes, allowing for more realistic temporal processing.



Yamazaki et al. (2021), Brain Sciences, 2022, 12(7), 863, p.5



Izhikevich (2004), IEEE Transactions on Neural Networks, 15(5), p.. 1066

Strengths

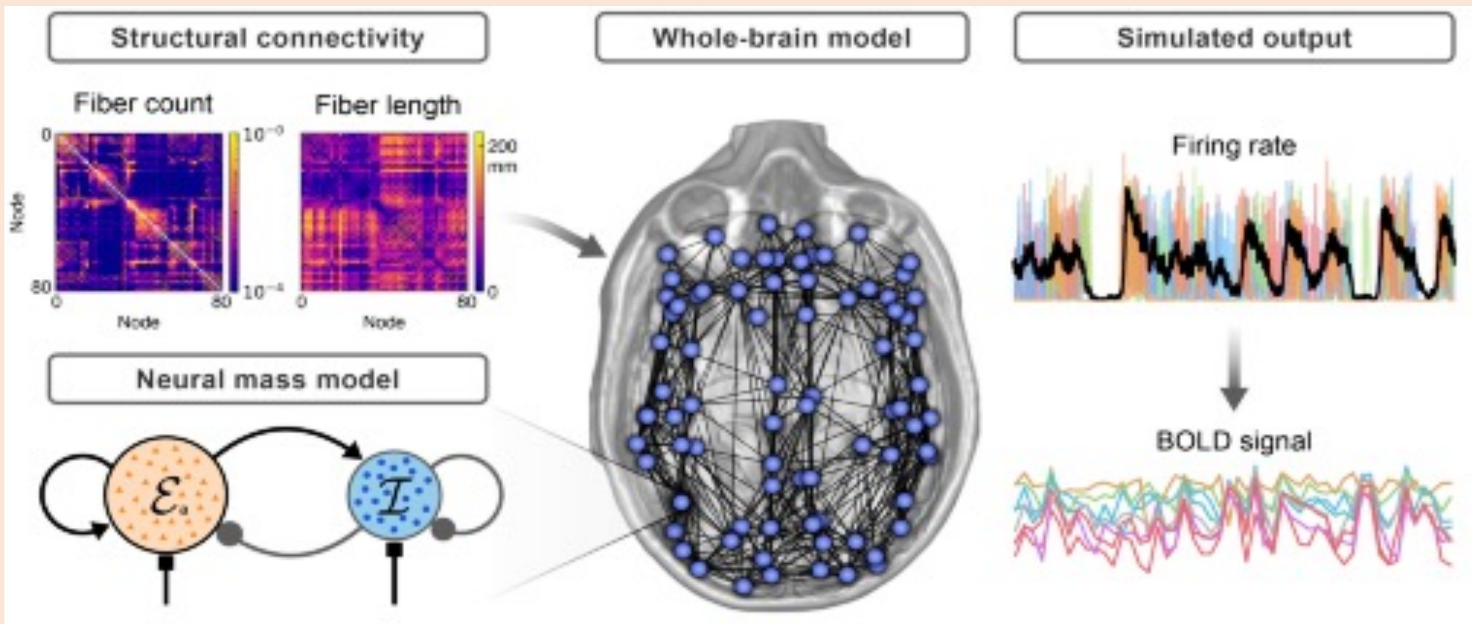
- Temporal dynamics
- Energy efficiency

Limitations

- Training complexity
- Parameters sensitivity

Neural mass models

Neural mass models simulate the average activity of large populations of neurons to capture macroscopic brain dynamics efficiently.



Cakan, C., Jajcay, N., & Obermayer, K. (2021), Cognitive Computation, 15(4), p.1132-1152

Strenghts

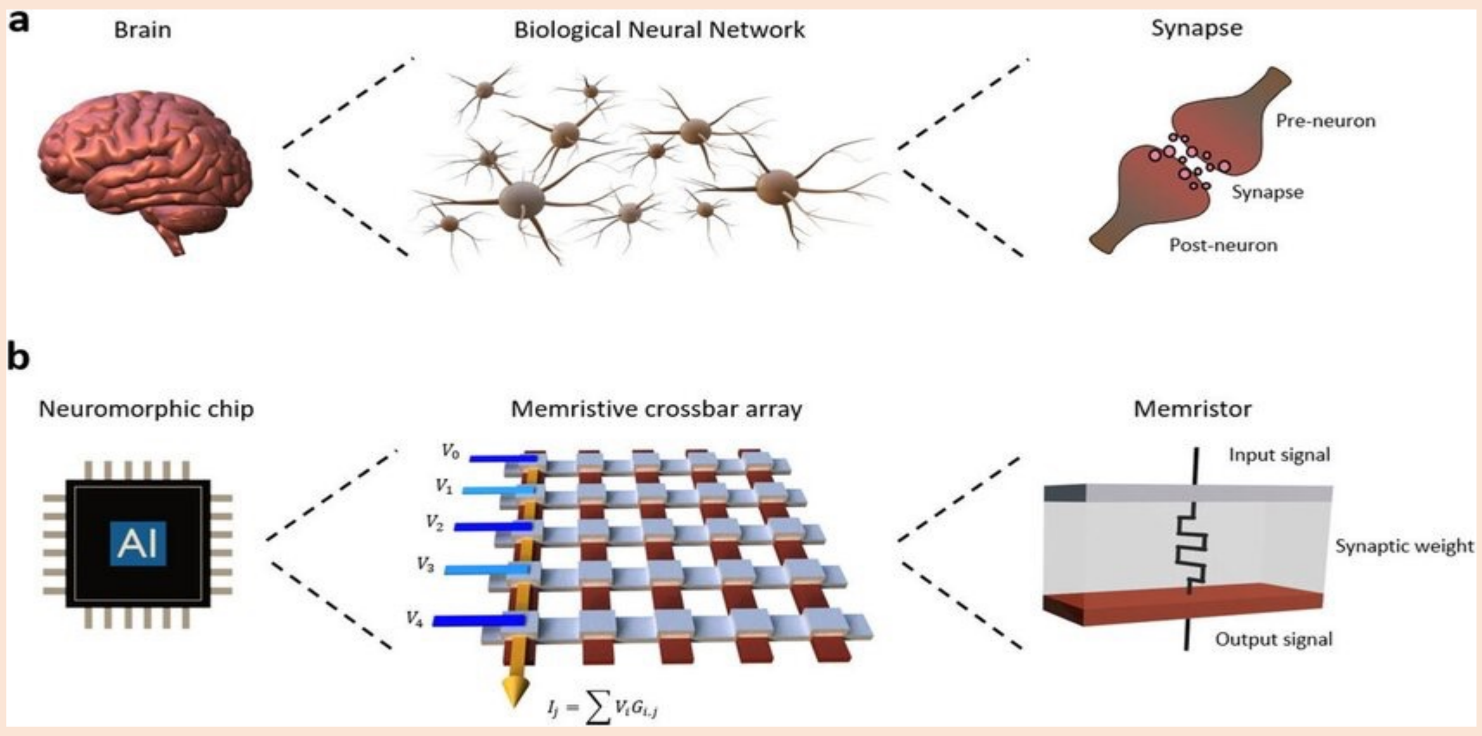
- Captures population dynamics
- Computationally efficient

Limitations

- Low biological detail
- Limited individual neuron resolution

Neuromorphic engineering

Neuromorphic engineering designs hardware inspired by the brain's architecture to emulate neural processing efficiently, providing a platform for the effective implementation of biophysical models

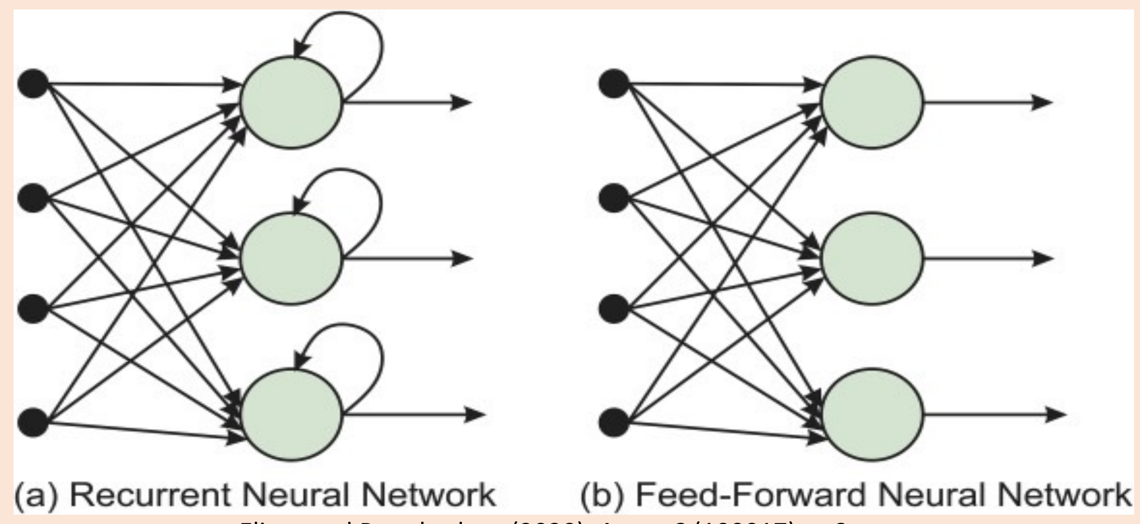


Salinas et al., (2022), Materials Research Letters, 11(5), p. 305-326

Agnostic models

Recurrent Neural Networks (RNNs)

RNNs are artificial models with feedback connections that allow them to process sequential and temporal data by maintaining a memory of previous inputs.



Eliasy and Przychodzen (2020), Array, 6 (100017), p.6

Strengths

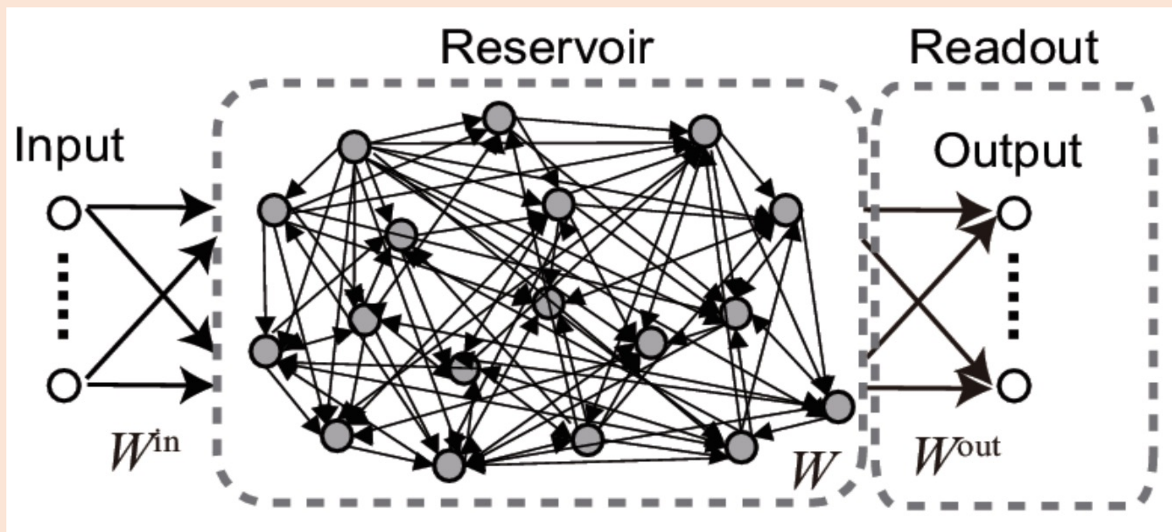
- Handles temporal data
- Capture sequence dependencies

Limitations

- Vanishing/exploding gradients
- Limited long-term memory

Reservoir Computing (RC)

RC is a neural computation framework that uses a fixed, dynamic network to project inputs into high-dimensional space, where simple readout layers can extract meaningful patterns over time.



Tanaka et al. (2019), Neural Networks, 115, p.100-123

Strenghts

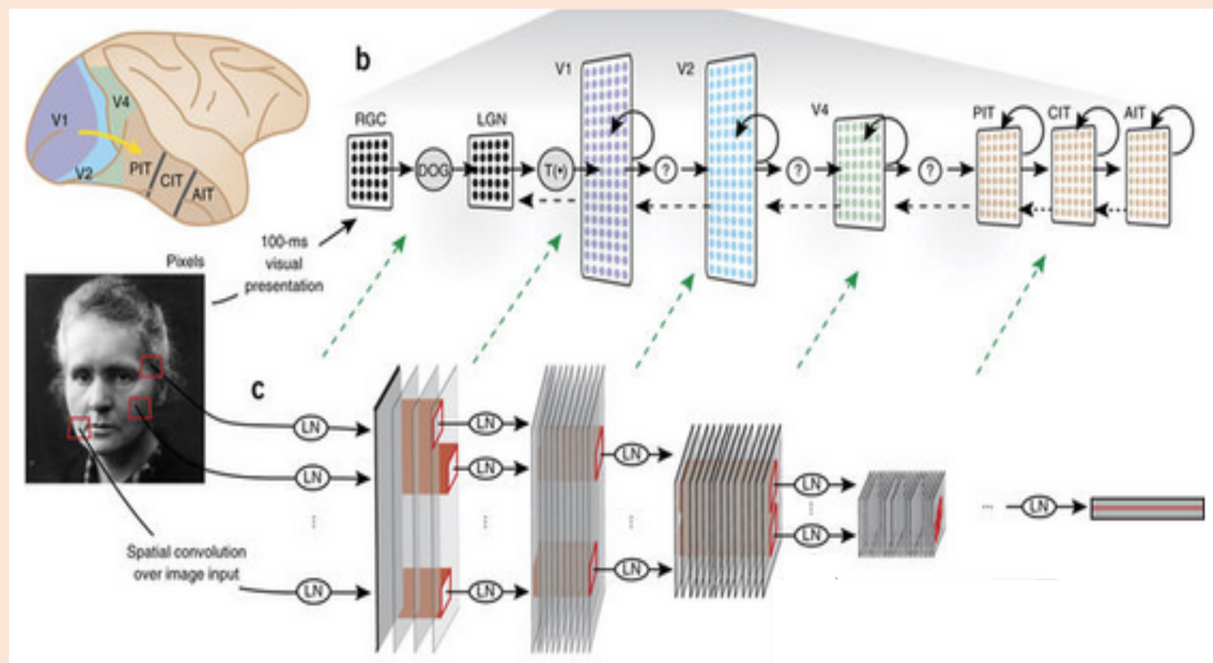
- Efficient temporal processing
- Easy training of output layer

Limitations

- Fixed reservoir limits adaptability
- Less interpretable dynamics

Convolutional Neural Networks (CNNs)

CNNs are neural architectures inspired by the visual cortex, designed to efficiently extract spatial hierarchies of features from input data using convolutional filters.



Yamins and DiCarlo (2016), Nature Neuroscience, 19, p.356

Strenghts

- Visual feature extraction
- Efficient for image data

Limitations

- Limited temporal processing
- Low biological realism

Discussion and conclusions

Biological plausibility and computational efficiency present a trade-off between biophysical and agnostic models in brain simulation.

- Bridging the gap → Hybrid and hierarchical modelling: Balanced biological realism and computational efficiency
- Large-scale efforts → Blue Brain Project (cortical microcircuit reconstruction); Human Brain Project (Tools, data integration)
- Future perspectives → Quantum computing (computational power, complex neural states) and neuromorphic engineering
- Questions: Can we simulate without body-brain interaction? How much abstraction is acceptable before it limits understanding?

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