Research topics for thesis projects

Some of these research directions are based on Spiking Neural P Systems (SNPS), a computational model introduced in [4], which provides a general overview of its underlying mechanisms; others focus on Spiking Neural Networks (SNNs), for which a recent review can be found in [3]. For a clearer and more concise description encompassing SNPS, SNNs, and some of their potential applications, see [17].

A simulator capable of executing SNPS with anti-spikes and white holes has been developed (see [11]). A ready-to-use version, along with the paper describing its operation, is available at this **link**. Several of the proposed ideas directly reference this simulator.

In general, a cross-cutting and universally valid research avenue across all presented proposals involves evaluating the models on different datasets, both in terms of domain and data modality (e.g., time series, tabular data, or sequences). Although the image format remains the most suitable and natural fit for the architecture developed so far, adapting the model to diverse data structures represents an excellent opportunity for experimentation.

For a practical hands-on approach to working with SNNs for image analysis, a comprehensive tutorial is available **here**.

1 Biological Inspiration

Master's Thesis, SNPS or SNN

The human brain represents an extremely efficient processing system, capable of performing an enormous number of operations in parallel with remarkably low energy consumption compared to traditional computing architectures. While not optimal in terms of raw speed or numerical precision, it excels at complex tasks thanks to the highly distributed and adaptive nature of its neural networks.

However, most scientific literature and foundational neuroscience treatises describe sensory and anatomical pathways primarily from a medical or clinical perspective. Thus, a significant research gap exists in formally translating these biological processes (e.g., the visual pathway, the retina, or the primary visual cortex [6]) into algorithms for feature extraction and signal processing.

The objective of this proposal is to develop a biologically inspired model within the SNPS or SNN framework, conceived as an independent spiking network separate from the previously developed simulator.

Although the initial focus centers on the visual domain, the identified mechanisms can be extended and applied to other data modalities suitable for spiking networks, such as audio signals, video streams, time series, or text.

These studies require a solid understanding of the underlying neurophysiological principles and a willingness to delve into neuroscientific literature; the handbook *Principles of Neural Science* by Kandel et al. is recommended. A comprehensive work encompassing SNNs and brain-inspired computing is [18].

A similar effort was undertaken by M. Balzerani, who authored a document (*Towards Realism*) outlining several mechanisms worth investigating. This collection of insights was subsequently used to model part of the presented simulator.

1.1 Topological Extension via Self-Organizing Maps

To bring spiking models closer to real neuro-anatomical architectures, a natural extension involves introducing a physical, positional dimension to the neurons. Currently, in SNPS simulators, neurons are managed as abstract lists of coordinate-free nodes. By assigning each neuron a position in 2D (or 3D) space, the network's topology ceases to be a simple formless graph and acquires a genuine spatial geometry capable of reflecting biological structures or regions of brain tissue.

In this context, synaptic connectivity and link strengths can be modeled as a function of the physical distance between nodes. By incorporating dynamic movement or structural plasticity rules (creating, lengthening, or removing synapses based on firing activity), the network can achieve unsupervised self-organization, integrating the principles of Self-Organizing Maps [7]. This approach was recently applied to SNNs in [19].

2 Explainability of Frequency Chaos Game Representation

Bachelor's Thesis, extendable to Master's with 2.1, SNPS

The application of spiking models to the classification of genomic data represents a highly promising research area. In the work conducted by A. Ruggiero, available at this **link**, the SNPS simulator was evaluated on the classification of bacterial genomes (belonging to the genera *Aeromonas*, *Citrobacter*, *Helicobacter*, and *Streptococcus*). These genomes were converted into images using Frequency Chaos Game Representation (FCGR) [5]. While the model demonstrated strong performance, a systematic Explainable AI (XAI) analysis of its internal mechanisms when applied to FCGR matrices is currently lacking.

To provide a sense of the research direction, a related study was carried out by M. Ventura, who produced an XAI report focused on SNPS but applied to a different dataset.

The objective of this thesis is to conduct an in-depth explainability study on the SNPS network for FCGR, aiming to:

- Identify which convolutional kernels, synapses, and firing rules actually contribute to successful classification;
- Interpret the role of individual FCGR pixels (corresponding to k-mer frequencies in the genome) to understand which nucleotide regions and frequencies hold true biological relevance in distinguishing classes;
- Formalize metrics and visualization techniques to enhance the decision-making transparency of the spiking model [9].

2.1 Optimization for Generic FCGR

Once decision transparency and internal network dynamics are established through explainability analysis, the project can progress toward structural enhancement and broader application. Mastering firing mechanisms and feature selection on FCGR matrices allows overcoming the constraints of the original architecture, introducing greater computational complexity and superior generalization capabilities.

The goal of this phase is to evolve the network from a model optimized for a narrow case study (limited to the four bacterial genera considered in initial experiments) into a flexible framework highly adaptable to diverse genomic data types expressed in FCGR format.

Key development directions include:

- Extending the benchmark to a larger number of classes and testing on classification tasks with more homogeneous genome sizes, increasing the challenge for the network;
- Introducing additional processing layers, parallel convolution/pooling mechanisms, and advanced firing rules;
- Dynamically adapting network parameters (such as FCGR image resolution or quantization ranges) to maintain high performance despite structural variations in input data.

3 Comparison of Genomic Representations

Bachelor's or Master's Thesis, SNPS

Processing genomic data using Spiking Neural P Systems (SNPS) represents a promising research avenue, as outlined in the previous proposal. However, FCGR is only one of several strategies available to transform a DNA sequence (composed of the bases $\{A, C, G, T\}$) into a two-dimensional image. Indeed, various other methodologies exist in the literature aimed at converting biological sequences into visual representations. A few of these techniques include:

- **FCGR:** Used as the main baseline for comparison, evaluating its behavior and network response in line with the preliminary work mentioned above;

- **DNA Walk:** A mapping based on the work by Akbari et al. [1], who proposed a CNN-based classification approach. The nucleotide sequence is converted into a compact two-dimensional walk, transforming base trajectories into structured images for each species;

- **Hilbert Curve Mapping:** Arranging the sequence along a 2D Hilbert curve [2], a genomics technique used to preserve the spatial locality of nucleotides within the image matrix. This representation has also been combined with CNNs in prior work [16].

These serve merely as examples; the student is free to explore and implement alternative methods, such as Recurrence Plots [15]. The objective of this proposal is to evaluate how different sequence-to-image conversion techniques affect feature extraction capabilities and classification accuracy within the SNPS network.

As a natural follow-up, the next step would be to enhance the network and adapt it to each of the analyzed representations. There is also the option to incorporate an explainability analysis to investigate how the model adjusts to different input representations.

4 Comparison among SNPS, CNN, and SNN

Master's Thesis, SNPS, SNN, and ANN

The SNPS architecture developed for image classification, available at this **link**, was created by adapting the principles of a Convolutional Neural Network (CNN) into the spiking membrane computing formalism.

This thesis proposal aims to design a CNN model mirroring the structure of the SNPS, along with an equivalent Spiking Neural Network, thereby obtaining three structurally specular models grounded in three distinct computational paradigms:

1. **SNPS:** A discrete and synchronous spiking membrane system featuring firing and quantization rules. Optimization currently relies on linear/SVM classifiers applied to spike vectors extracted from intermediate layers;

2. **CNN:** A classical artificial convolutional network with real-valued weights, optimized via standard gradient descent (*Backpropagation*);

3. **SNN:** A neuromorphic spiking neural network based on dynamic membrane potentials and temporal events, optimized using algorithms designed for temporal processing, such as *Backpropagation Through Time* or *Spike-Timing-Dependent Plasticity*.

An aspect of major theoretical and practical interest lies in comparing the different training methodologies across these models, which differ radically from one another. The choice of dataset is flexible, provided it remains identical across all three networks. After defining the base models, a broader second

phase involves scaling up the three networks toward deeper and more complex architectures, analyzing how each training method responds to increasing model and dataset sizes.

4.1 Extension to Time Series for Water Stress Classification

As an extension of the architectural comparison among models, we propose applying these three methodologies to time series analysis, taking as a reference the recent work by Orellana-Martín et al., *Towards olive tree water stress classification with spiking neural P systems.*

The paper tackles the problem of detecting water stress in olive trees using temporal sensor data (e.g., fruit growth and leaf dynamics). While the model developed so far for image classification operates on static or spatial inputs, this thesis explores the processing of dynamic sequences by comparing the following strategies:

1. **SNPS Reservoir Computing:** Adapting the SNPS model into a dynamic recurrent reservoir with non-linear rules (NSNP) [8], where the network topology remains fixed and only the final readout layer is trained;
2. **Recurrent SNN:** Implementing a recurrent SNN trained on temporal sequences;
3. **1D CNN or RNN:** Real-valued artificial neural network architectures (e.g., 1D CNNs or LSTMs) for analyzing the same time series.

The objective is to evaluate how effectively the three approaches capture the temporal dependencies of sensory data and to compare key characteristics such as training complexity and memory footprint.

5 Computation and Minimization of Energy Costs

Bachelor's or Master's Thesis, SNPS or SNN

A central aspect in the adoption of spiking models is their energy efficiency compared to traditional Artificial Neural Networks (ANNs). However, to date, there is no consolidated and unified framework for computing and estimating energy consumption in SNPS and SNNs.

To analyze and compare energy consumption, a widely recognized method relies on counting elementary, energy-intensive operations:

- **ANN (MAC / FLOPs):** Traditional networks base their computational cost on *Multiply-Accumulate* operations, which require multiplications between real numbers (*Floating Point Operations*) with high energy consumption per operation;

- **SNN and SNPS (SOPs / AC):** Spike-based processing replaces multiplications with *Accumulate* (AC) operations or *Synaptic Operations* (SOPs), where the arrival of a discrete spike triggers only an integer addition of charge or synaptic weight.

A major challenge for SNPS is the lack of dedicated neuromorphic hardware for their direct execution. A practical approach consists in modeling their energy consumption by estimating Synaptic Operations and mapping their underlying mechanisms onto neuromorphic chips designed for SNNs (e.g., Intel Loihi 2 or SpiNNaker). This work will not be limited to the image-classification architecture developed so far, but will extend the comparison across different network structures and benchmark datasets to evaluate the impact of various design choices [12].

6 Federated Learning and Privacy-Preserving Training

Bachelor's or Master's Thesis, SNPS

The data used so far in preliminary experiments were already structured and ready for use. However, real-world application scenarios—such as processing clinical, genomic, or wearable device data—impose strict privacy constraints and prevent data centralization. In this context, Federated Learning (FL) represents an ideal framework for training models in a distributed fashion while keeping data localized on client devices [14].

SNPS offer a unique competitive edge for FL due to their remarkably low memory footprint. For more specific details, see the *Memory footprint* section of the paper available in the repository at the aforementioned **link**.

Instead of transmitting bulky datasets or risking sensitive data leakage, clients only send weight matrices or the discrete synaptic structure to the central server. Furthermore, while local nodes in SNNs and ANNs transmit real-valued floating-point weights, SNPS operate on discrete and boolean connections $\{-1, 0, +1\}$, enabling drastic compression of network traffic and distinct benefits for green FL [13].

Early attempts to formalize privacy-preserving and Federated Learning SNPS already exist—available at the GitHub repositories `https://github.com/miiip/Privacy-Presering-Spiking-Neural-P-System` and `https://github.com/miiip/Federated-LSNP`—linked to the work by Plesa et al. [10]. However, these approaches remain incomplete, highlighting an almost unexplored research niche.

The objective of this thesis is to design and evaluate an SNPS-based Federated Learning framework, addressing realistic scenarios characterized by non-IID data (unevenly distributed across clients) and constrained computational resources on local nodes.

Bibliografia

[1] Saeedeh Akbari Rokn Abadi, Amirhossein Mohammadi, and Somayyeh Koohi. "WalkIm: Compact image-based encoding for high-performance classification of biological sequences using simple tuning-free CNNs". In: *Plos one* 17.4 (2022), e0267106.

[2] Simon Anders. "Visualization of genomic data with the Hilbert curve". In: *Bioinformatics* 25.10 (2009), pp. 1231–1235.

[3] Sales G Aribe Jr. "Spiking Neural Networks: The Future of Brain-Inspired Computing". In: ().

[4] Mihai Ionescu, Gheorghe Păun, and Takashi Yokomori. "Spiking neural P systems". In: *Fundamenta informaticae* 71.2-3 (2006), pp. 279–308.

[5] Hannah Franziska Löchel and Dominik Heider. "Chaos game representation and its applications in bioinformatics". In: (2021).

[6] Richard H Masland. "The neuronal organization of the retina". In: *Neuron* 76.2 (2012), pp. 266–280.

[7] Dubravko Miljković. "Brief review of self-organizing maps". In: *2017 40th international convention on information and communication technology, electronics and microelectronics (MIPRO)*. IEEE. 2017, pp. 1061–1066.

[8] Hong Peng et al. "Reservoir computing models based on spiking neural P systems for time series classification". In: *Neural Networks* 169 (2024), pp. 274–281.

[9] P Jonathon Phillips et al. "Four principles of explainable artificial intelligence". In: (2021).

[10] Mihail-Iulian Plesa, Marian Gheorghe, and Florentin Ipate. "Privacy-preserving Linear Computations in Spiking Neural P Systems". In: *arXiv preprint arXiv:2309.13803* (2023).

[11] Tao Song et al. "Spiking neural P systems with white hole neurons". In: *IEEE transactions on nanobioscience* 15.7 (2016), pp. 666–673.

[12] Martino Sorbaro et al. "Optimizing the energy consumption of spiking neural networks for neuromorphic applications". In: *Frontiers in neuroscience* 14 (2020), p. 662.

[13] Dipanwita Thakur et al. "Green federated learning: A new era of green aware AI". In: *ACM Computing Surveys* 57.8 (2025), pp. 1–36.

[14] Yeshwanth Venkatesha et al. "Federated learning with spiking neural networks". In: *IEEE Transactions on Signal Processing* 69 (2021), pp. 6183–6194.

[15] Zuo-Bing Wu. "Recurrence plot analysis of DNA sequences". In: *Physics Letters A* 332.3-4 (2004), pp. 250–255.

[16] Bojian Yin et al. "An image representation based convolutional network for DNA classification". In: *arXiv preprint arXiv:1806.04931* (2018).

[17] Claudio Zandron. "An Overview on Applications of Spiking Neural Networks and Spiking Neural P Systems". In: *Languages of Cooperation and Communication: Essays Dedicated to Erzsébet Csuhaj-Varjú to Celebrate Her Scientific Career* (2025), pp. 267–278.

[18] Yi Zeng et al. "Braincog: A spiking neural network based, brain-inspired cognitive intelligence engine for brain-inspired ai and brain simulation". In: *Patterns* 4.8 (2023).

[19] Youdong Zhang et al. "Unsupervised spiking neural network based on liquid state machine and self-organizing map". In: *Neurocomputing* 620 (2025), p. 129120.