ESANN: Evolutionary Self-Assembling Neural Networks

Abstract

We introduce Evolutionary Self-Assembling Neural Networks (ESANN), a novel paradigm that unifies structural neuroevolution, biological neurogenesis, and dynamic architecture assembly. ESANN models begin with minimal neural configurations and progressively evolve deeper architectures through biologically inspired mechanisms. This system leverages a genetic encoding of neural structures (DNA), allowing architectures to dynamically self-assemble, grow, prune, and adapt through evolutionary cycles. Our approach demonstrates the potential of self-designing deep networks that construct and optimize their own topologies per task, minimizing manual architectural engineering and enabling task-specific adaptation.

1. Introduction

Neural architecture design remains one of the most critical challenges in deep learning. Traditional approaches require expert-driven architecture crafting, which often lacks adaptability across tasks. Inspired by biological neurogenesis and self-assembly mechanisms in nature, we propose ESANNan evolutionary framework that enables deep networks to grow, evolve, and assemble their own architectures automatically from encoded DNA blueprints.

2. Biological Inspiration and Motivation

ESANN is conceptually rooted in:

- Neurogenesis: Generation of new neurons during learning.

- Synaptic pruning: Removal of redundant or inefficient neural pathways.

- Self-Assembly: Spontaneous organization of structural systems guided by genetic code.

These biological phenomena are algorithmically modeled within ESANN through:

- Dynamic DNA encoding of layers,

- Mutation operators introducing growth/pruning,

- Evolutionary selection and crossover mechanisms,

- Automatic network construction from decoded DNA.

3. Methodology

3.1 DNA Representation

Each neural network is encoded as a DNA sequence representing:

- Layer types (Conv1D, Dense, Activation, Dropout),

- Layer parameters (kernel sizes, neuron counts, activation functions),

- Optional skip connections or normalization strategies.

3.2 Self-Assembling Network Construction

A custom NetworkBuilder reads this DNA and automatically assembles a PyTorch model:

- Layers are added sequentially,

- Reshaping handled dynamically,

- Final shape passed to a terminal classifier layer.

3.3 Evolutionary Pipeline

The ESANN evolutionary loop consists of:

1. Initial Population Generation Minimal networks (e.g., one or two layers).

2. Fitness Evaluation Task-specific loss (e.g., binary classification loss).

3. Selection Top networks selected by fitness.

4. Crossover New offspring DNA generated via gene-level recombination.

5. Mutation & DNA Repair Layer addition, pruning, or parameter mutation.

6. Self-Assembly & Evaluation New offspring networks are assembled and evaluated again.

4. Experimental Setup

We tested ESANN on a sentiment classification task using the IMDB dataset. Each generation comprised four individuals, evolved across five generations. The system successfully:

- Generated structurally diverse networks,

- Demonstrated progressive performance improvement,

- Maintained architectural feasibility through DNA repair logic.

Sample Output:

Generation 0 DNA Fitness: -0.91 to -0.62

Generation 4 DNA Fitness: -0.86 to -0.67

5. Key Contributions

- Self-Assembling Networks: PyTorch models built directly from encoded DNA.

- Neurogenesis & Structural Evolution: Networks grow new layers/neurons over time.

- Automated Architecture Search: Task-specific structural optimization.

- Robust DNA Repair: Ensures architectural feasibility post-crossover.

6. Impact and Future Work

ESANN opens a new pathway in neuroevolutionary research:

- Self-designing deep nets with minimal human intervention,

- Architectures that adaptively fit problem complexities,

- Evolution-based AI design frameworks for real-world adaptability.

Future Directions:

- Multi-objective fitness (speed, size, accuracy),

- Visualization of growth and pruning dynamics,

- Hybridization with reinforcement learning or foundation models.

7. Conclusion

ESANN offers a compelling synthesis of biology and computation. By enabling neural networks to self-assemble, grow, and adapt through evolutionary dynamics, we move toward an era where deep learning models can truly design themselvestask-specific, dynamic, and structurally intelligent.

References

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