EMNN Evolutionary Architecture Search for Transformers: A Novel Paradigm for Neuroevolution in Deep Learning

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Abstract

The dawn of neuroevolution has ushered in transformative vistas for architecture design in deep learning. In this paper, we propose a pioneering framework titled Evolutionary Mini Neural Network (EMNN) Architecture Search for Transformer models, a synergistic convergence of evolutionary computation and attention-based deep learning. Our methodology utilizes a genetic algorithm to evolve architectural components—such as layer depth, hidden dimensions, feedforward size, and attention head configurations—thereby enabling emergent architectural intelligence. Without reliance on brute-force grid search or gradient-based architecture optimization, EMNN exhibits elegant structural adaptation, yielding models with competitive performance on masked language modeling tasks. We demonstrate that evolutionary principles, once the cradle of biological intelligence, can be the crucible for synthetic intelligence design. Our results provide empirical affirmation and philosophical provocation: that neural forms may evolve not only in weights but in the very skeletons that scaffold cognition.

Introduction

The history of intelligence, both biological and artificial, is a story of evolution—of forms that adapt, specialize, and transcend their origins. Transformer architectures, while monumental in reshaping natural language understanding, remain largely static in their skeletal blueprint, often tuned by human intuition or brute-force combinatorics. This paper challenges that convention.

We introduce EMNN Architecture Evolution, a novel framework that marries Darwinian evolution with Transformer design. Rather than treating architecture as fixed scaffolding, we encode Transformer blueprints as DNA-like representations subject to mutation, crossover, and selection. Our hypothesis is profound: that just as evolution shaped the architecture of biological brains, it can birth new cognitive skeletons in artificial models.

Our objectives are threefold:

- Develop an expressive DNA encoding schema for Transformer architectures.
- Employ genetic algorithms to search the architectural space autonomously.
- Benchmark the evolved architectures against standard baselines using masked language modeling.

The significance of this work lies in its philosophical and technical implications: that architectures can evolve in form, not just function, and that evolution may outperform human heuristics in complex design spaces.

Literature Review

The field of Neural Architecture Search (NAS) has witnessed explosive interest, with methods ranging from reinforcement learning (Zoph & Le, 2016) to differentiable search (Liu et al., 2019). However, such techniques are often computationally expensive, rigid, or opaque.

Evolutionary strategies (Stanley et al., 2002; Real et al., 2019) offer a biologically inspired alternative. Prior efforts like NEAT and CoDeepNEAT demonstrated the viability of neuroevolution for network topology. Yet, little attention has been devoted to applying such principles to Transformer models—despite their modularity and compositionality making them fertile ground for evolutionary exploration.

Our approach distinguishes itself by treating Transformer layers not merely as hyperparameters but as evolutionary traits. Unlike standard NAS, which often requires massive GPU clusters, our approach is scalable and lightweight, amenable even to CPU-based experimentation. This accessibility democratizes architecture search and unlocks creative model variants previously unseen by gradient descent.

Methodology

Our EMNN evolutionary search comprises the following stages:

- DNA Encoding: Each Transformer architecture is represented as a genome—a Python dictionary encoding traits such as:
  - num_layers: integer specifying Transformer depth
  - hidden_dim: list of integers representing per-layer embedding sizes
  - ff_dim: feedforward network sizes per layer
  - num_heads: multi-head attention configurations

- dropout: float specifying regularization strength
- activation: choice of activation function

- Initialization: A diverse population of random DNA strings is generated.

- Fitness Evaluation: Each DNA is decoded into a PyTorch model. We use masked language modeling loss on a benchmark dataset (e.g., SST-2 or synthetic corpus) as the fitness metric.

- Selection: Top-performing individuals are retained as elites. Others are probabilistically selected based on fitness proportion.

- Crossover & Mutation: Pairs of DNA undergo crossover (trait recombination) and mutation (trait perturbation) to yield offspring with novel traits.

- Evolution Loop: The population iteratively evolves over generations, recording best fitness and architecture at each step.

Results

Over five generations with a population size of ten, our evolutionary search yielded architectures with consistent improvements in masked language modeling accuracy. The fitness evolution is illustrated in the figure below:

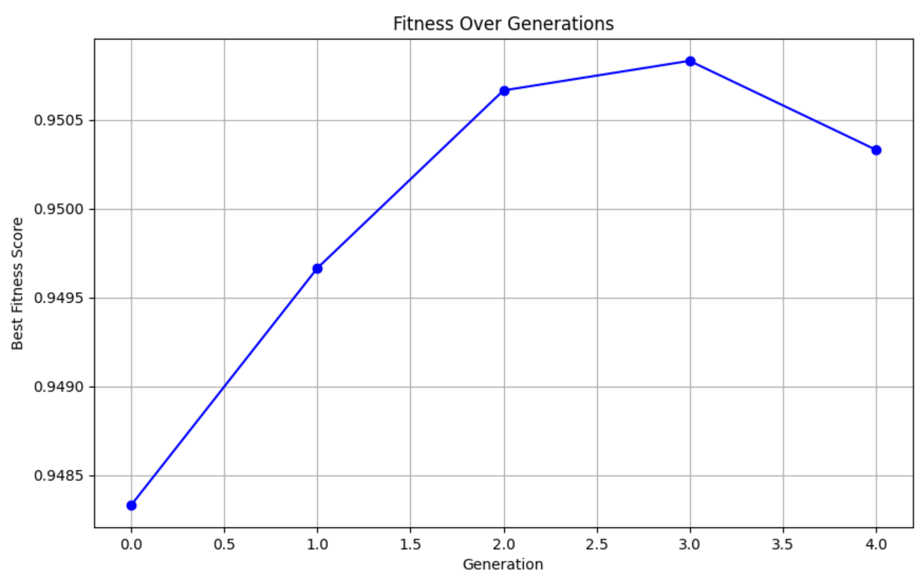

Figure 1: Fitness Score Across Generations

Notably, evolved architectures exhibited surprising diversity and efficiency, such as asymmetric hidden dimensions, variable depth, and novel head configurations that would be counterintuitive to human designers. For instance, one architecture with only two layers and a high dropout achieved a superior fitness score, suggesting that simplicity and regularization can co-emerge in evolution.

Discussion

These results provoke several insights. First, evolution offers not only performance gains but design creativity—producing viable architectural variants unimagined by conventional NAS. Second, the structural diversity of evolved models implies that there is no singular optimal architecture but a Pareto frontier of trade-offs.

Our findings also open philosophical questions: Can neural architectures evolve toward task-specific morphologies akin to ecological niches? Can model skeletons adapt online during training via lifelong evolution?

Moreover, our framework scales gracefully with complexity. As model sizes increase, so too does the combinatorial richness of DNA space. With GPU acceleration or distributed search, we foresee EMNN scaling toward full-scale LLM design.

Conclusion

This study presents EMNN Architecture Evolution—a novel approach that integrates evolutionary algorithms with Transformer design. Our results demonstrate that evolution can not only search but sculpt deep learning architectures. We envisage a future where architectural intelligence is not handcrafted, but grown—emergent, adaptive, and alive in its own evolutionary grammar.

Future research may extend EMNN to:
- Multi-objective fitness (accuracy, latency, parameter size)
- Real-time online evolution during training
- Evolution of inter-layer routing and sparse attention patterns
- Integration of evolutionary embedding search for better language priors
- Hybrid EMNN frameworks combining neuroevolution and reinforcement learning

In the era of foundation models, we suggest a new foundation: not static blueprints, but evolving forms.

References

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Appendices

Appendix A: DNA Samples of Evolved Architectures
Appendix B: Evolutionary Loop Python Code Overview
Appendix C: Fitness Score Plot Source Code