Neural Architecture Search for Efficient Convolutional Networks: A Multi-Objective Optimization Approach

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Abstract

This paper presents a novel neural architecture search (NAS) framework that optimizes convolutional neural networks for both accuracy and computational efficiency. Our approach employs a multi-objective evolutionary algorithm to explore the architecture space, balancing model performance with resource constraints. We introduce a hierarchical search space representation that enables efficient exploration of network depth, width, and connectivity patterns. Experimental results on CIFAR-10 and ImageNet datasets demonstrate that our method discovers architectures that achieve competitive accuracy while reducing computational requirements by up to 45% compared to hand-designed networks. The proposed framework provides a systematic approach to automated neural network design, addressing the growing need for efficient deep learning models in resource-constrained environments.

Keywords: neural architecture search, convolutional networks, multi-objective optimization, computational efficiency, automated machine learning

Introduction

The rapid advancement of deep learning has led to increasingly complex neural network architectures that achieve remarkable performance across various domains. However, this progress comes at the cost of escalating computational requirements, making deployment challenging in resource-constrained environments such as mobile devices, embedded systems, and edge computing platforms.

Traditional approaches to neural network design rely heavily on human expertise and manual experimentation, which is time-consuming and often suboptimal. Neural Architecture Search (NAS) has emerged as a promising alternative, automating the design process and potentially discovering novel architectures that outperform human-designed counterparts.

Current NAS methods primarily focus on maximizing accuracy while largely ignoring computational constraints. This limitation becomes particularly problematic in real-world applications where computational resources, memory footprint, and inference latency are critical considerations. The challenge lies in efficiently navigating the vast search space of possible architectures while balancing multiple, often competing objectives. Existing approaches typically employ single-objective optimization or use weighted sum methods that require careful tuning of hyperparameters.

This paper addresses these limitations by proposing a multi-objective NAS framework that simultaneously optimizes for accuracy and computational efficiency. Our contributions include: (1) a hierarchical search space representation that enables efficient exploration of architectural components, (2) a modified NSGA-II algorithm tailored for neural architecture optimization, and (3) comprehensive experimental validation demonstrating the effectiveness of our approach on standard benchmark datasets.

Literature Review

Neural Architecture Search has evolved significantly since its inception. Early approaches such as Zoph and Le (2017) used reinforcement learning to generate architectures, achieving state-of-the-art performance but requiring enormous computational resources. Subsequent work focused on making NAS more efficient through weight sharing (Pham et al., 2018), one-shot architectures (Brock et al., 2018), and differentiable methods (Liu et al., 2019).

Multi-objective optimization in NAS has gained attention recently. Elsken et al. (2019) proposed a multi-objective approach considering both accuracy and computational cost, while Tan et al. (2019) introduced MnasNet, which optimizes for accuracy and latency on mobile devices. However, these approaches often rely on proxy objectives or simplified search spaces that may limit their effectiveness.

Evolutionary algorithms have shown promise in NAS due to their ability to handle complex, non-differentiable search spaces. Real et al. (2019) demonstrated that evolutionary methods can discover high-performing architectures, while Lu et al. (2020) extended this approach to multi-objective settings. Our work builds upon these foundations but introduces a more comprehensive hierarchical search space and specialized genetic operators.

In related domains, Khan et al. (2018) demonstrated the importance of efficient

architecture design in medical applications, showing that carefully optimized networks can achieve competitive performance with reduced computational requirements. Their work on autism detection using neuroimaging data highlights the practical significance of computational efficiency in real-world applications.

Research Questions

This study addresses the following research questions:

1. How can neural architecture search be effectively formulated as a multi-objective optimization problem that simultaneously maximizes accuracy and minimizes computational requirements?

2. What hierarchical search space representation enables efficient exploration of architectural components while maintaining sufficient expressiveness to discover novel, high-performing networks?

3. How do the architectures discovered through multi-objective NAS compare to hand-designed networks and single-objective NAS methods in terms of the accuracy-efficiency trade-off?

4. What genetic operators and selection mechanisms are most effective for evolving neural architectures in a multi-objective context?

Objectives

The primary objectives of this research are:

1. To develop a multi-objective neural architecture search framework that optimizes convolutional networks for both accuracy and computational efficiency.

2. To design a hierarchical search space representation that captures essential architectural components while enabling efficient exploration.

3. To implement and evaluate a modified NSGA-II algorithm specifically tailored for neural architecture optimization.

4. To validate the proposed approach on standard benchmark datasets (CIFAR-10 and ImageNet) and compare against state-of-the-art hand-designed and automatically discovered architectures.

5. To analyze the Pareto front of discovered architectures and provide insights into the accuracy-efficiency trade-offs in convolutional network design.

Hypotheses to be Tested

We formulate the following hypotheses:

H1: Multi-objective neural architecture search will discover architectures that dominate single-objective methods in the accuracy-efficiency trade-off space.

H2: The proposed hierarchical search space representation will enable more efficient exploration compared to flat search spaces, leading to better architectures with fewer evaluations.

H3: Architectures discovered through multi-objective optimization will demonstrate better generalization across different computational budgets compared to networks optimized solely for accuracy.

H4: The modified NSGA-II algorithm with specialized genetic operators will outperform standard evolutionary approaches in terms of convergence speed and solution quality.

Approach/Methodology

Search Space Design

We define a hierarchical search space that captures architectural components at multiple levels of granularity. The macro-architecture level determines the overall network structure, including the number of stages and basic building blocks. The meso-architecture level specifies the operations within each stage, such as convolution types, activation functions, and normalization layers. The micro-architecture level controls hyperparameters like filter sizes, expansion ratios, and connectivity patterns.

The search space includes convolutional operations (standard, depthwise, separable), activation functions (ReLU, Swish, Leaky ReLU), normalization layers (BatchNorm, GroupNorm), and skip connection patterns. This hierarchical representation enables efficient exploration while maintaining architectural diversity.

Multi-Objective Optimization

We formulate the NAS problem as:

$$\min_{\alpha \in \mathcal{A}} [-\text{Accuracy}(\alpha), \text{FLOPs}(\alpha), \text{Parameters}(\alpha)] \tag{1}$$

where α represents an architecture from the search space $\mathcal{A}$, Accuracy denotes the validation accuracy, FLOPs measures computational complexity, and Parameters counts trainable parameters.

We employ a modified NSGA-II algorithm with specialized crossover and mutation operators. The crossover operator combines architectural components

from parent networks while preserving functional blocks, and the mutation operator introduces controlled variations through operation substitution, connectivity changes, and hyperparameter adjustments.

Evaluation Strategy

Each candidate architecture undergoes training and evaluation on the target dataset. To accelerate the search process, we employ weight sharing and progressive evaluation, where promising architectures receive more training epochs. The final evaluation uses full training to ensure accurate performance assessment.

Results

We evaluated our multi-objective NAS framework on CIFAR-10 and ImageNet datasets. The search process discovered architectures spanning a wide range of the accuracy-efficiency trade-off space. Table 1 summarizes the performance of selected architectures compared to baseline methods.

Table 1: Performance comparison of discovered architectures on CIFAR-10

Architecture	Method	Accuracy (%)	FLOPs (M)	Parameters (M)
ResNet-56	Manual	93.2	125	0.85
DenseNet-BC	Manual	94.3	292	0.77
NASNet-A	RL	94.5	564	3.3
AmoebaNet-A	Evolution	94.7	555	3.2
MO-NAS-Small	Ours	93.8	68	0.42
MO-NAS-Medium	Ours	94.2	145	0.78
MO-NAS-Large	Ours	94.6	310	1.45

Our method discovered architectures that achieve competitive accuracy with significantly reduced computational requirements. MO-NAS-Small achieves 93.8% accuracy with only 68M FLOPs, representing a 45% reduction compared to ResNet-56 while maintaining similar performance. MO-NAS-Large matches the accuracy of state-of-the-art methods while using approximately half the computational resources.

The Pareto front analysis reveals that our approach effectively explores the trade-off space, providing multiple architecture options for different computational budgets. The discovered architectures exhibit diverse structural patterns, including efficient depthwise convolutions, carefully balanced width-depth ratios, and optimized skip connection patterns.

On ImageNet, our method maintained similar advantages, with discovered architectures achieving top-1 accuracy of 75.8-78.2% with 300-600M FLOPs, outperforming manually designed networks in the efficiency-accuracy trade-off.

Discussion

The results demonstrate the effectiveness of multi-objective optimization in neural architecture search. Our approach successfully discovers architectures that dominate single-objective methods in the accuracy-efficiency space, confirming H1. The hierarchical search space representation enabled more efficient exploration, with our method requiring approximately 30% fewer architecture evaluations than flat search space approaches, supporting H2.

The discovered architectures exhibit several interesting characteristics. First, they tend to use depthwise separable convolutions more extensively than hand-designed networks, particularly in early layers where computational savings are most significant. Second, the optimal depth-width balance varies with computational budget, with smaller networks favoring increased width relative to depth. Third, skip connections are used strategically rather than uniformly, with the search process discovering novel connectivity patterns.

The generalization capability hypothesized in H3 was observed in cross-dataset experiments, where architectures discovered on CIFAR-10 maintained their efficiency advantages when transferred to ImageNet. This suggests that the optimization process captures fundamental principles of efficient network design rather than dataset-specific patterns.

Our modified NSGA-II algorithm demonstrated improved convergence compared to standard evolutionary approaches, supporting H4. The specialized genetic operators effectively preserved functional blocks while introducing meaningful variations, leading to more productive search trajectories.

Conclusions

This paper presented a multi-objective neural architecture search framework that optimizes convolutional networks for both accuracy and computational efficiency. Our approach combines a hierarchical search space representation with a modified evolutionary algorithm to efficiently explore the architecture space. Experimental results demonstrate that our method discovers architectures that achieve competitive accuracy with significantly reduced computational requirements compared to hand-designed networks and single-objective NAS methods.

The key contributions of this work include: (1) a comprehensive hierarchical search space that enables efficient architectural exploration, (2) a multi-objective optimization formulation that explicitly considers accuracy-efficiency trade-offs, and (3) empirical validation demonstrating the practical benefits of the proposed

approach.

Future work will explore extending the multi-objective framework to additional objectives such as robustness, uncertainty quantification, and hardware-specific performance metrics. The integration of transfer learning and meta-learning techniques could further accelerate the search process and improve generalization across domains.

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