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

Wei Zhang
Tsinghua University

Maria Rodriguez
Universidad Politécnica de Madrid

Kenji Tanaka
University of Tokyo

Fatima Al-Mansoori
King Abdullah University of Science and Technology

Abstract

This paper presents a novel neural architecture search (NAS) framework that optimizes convolutional neural networks for both accuracy and computational efficiency. Traditional NAS methods often prioritize accuracy at the expense of computational requirements, making them impractical for resource-constrained environments. Our approach employs a multi-objective optimization strategy that simultaneously maximizes classification accuracy while minimizing computational complexity. We introduce a hierarchical search space that incorporates depth-wise separable convolutions, bottleneck structures, and attention mechanisms. Experimental results on CIFAR-10 and ImageNet datasets demonstrate that our method discovers architectures that achieve competitive accuracy with state-of-the-art models while requiring 3.2× fewer floating-point operations and 2.8× less memory usage. The proposed framework provides a systematic approach to designing efficient deep learning models suitable for deployment on edge devices and mobile platforms.

Keywords: neural architecture search, convolutional networks, multi-objective optimization, computational efficiency, deep 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 often comes at the cost of substantial computational requirements, limiting the deployment of state-of-the-art models in

resource-constrained environments such as mobile devices, embedded systems, and edge computing platforms. The challenge lies in designing architectures that maintain high accuracy while being computationally efficient.

Neural Architecture Search (NAS) has emerged as a promising approach to automate the design of neural networks. Early NAS methods primarily focused on maximizing accuracy, often resulting in architectures with billions of parameters and excessive computational demands. This limitation has prompted research into efficient NAS techniques that consider multiple objectives beyond mere accuracy. Our work addresses this gap by proposing a comprehensive multi-objective optimization framework that balances accuracy with computational efficiency.

The contributions of this paper are threefold. First, we introduce a novel hierarchical search space that enables efficient exploration of architectural components. Second, we develop a multi-objective optimization algorithm that simultaneously optimizes for accuracy and computational efficiency. Third, we validate our approach through extensive experiments on benchmark datasets, demonstrating significant improvements in efficiency without compromising accuracy.

Literature Review

The field of Neural Architecture Search has evolved significantly since its inception. Early approaches such as reinforcement learning-based methods and evolutionary algorithms demonstrated the potential of automated architecture design but suffered from excessive computational costs. Zoph and Le (2017) pioneered the use of reinforcement learning for NAS, achieving impressive results but requiring thousands of GPU hours.

Subsequent research focused on improving the efficiency of NAS through weight sharing and one-shot approaches. Pham et al. (2018) introduced ENAS, which enabled parameter sharing across architectures, significantly reducing search time. However, these methods still prioritized accuracy over efficiency considerations.

Recent work has begun addressing the multi-objective nature of NAS. Tan et al. (2019) proposed MnasNet, which incorporates latency as an optimization objective. Similarly, Cai et al. (2019) developed ProxylessNAS, which directly optimizes for hardware-specific metrics. Our work builds upon these foundations but introduces a more comprehensive optimization framework that considers multiple computational constraints simultaneously.

In the broader context of efficient deep learning, techniques such as pruning, quantization, and knowledge distillation have been employed to reduce model complexity. However, these are typically applied post-hoc to existing architectures rather than being integrated into the architecture design process itself.

Research Questions

This research addresses the following fundamental questions:

1. How can neural architecture search be formulated as a multi-objective optimization problem that simultaneously considers accuracy and computational efficiency?

2. What search space design enables efficient exploration of architectures that balance performance and resource constraints?

3. To what extent can multi-objective NAS discover architectures that outperform hand-designed efficient networks across different computational budgets?

4. How does the proposed framework scale to large-scale datasets and complex tasks while maintaining search efficiency?

Objectives

The primary objectives of this research are:

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

2. To design a hierarchical search space that incorporates modern architectural components known to improve efficiency, such as depth-wise separable convolutions and attention mechanisms.

3. To implement an efficient search algorithm that can explore the architecture space while considering multiple constraints.

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

5. To analyze the trade-offs between accuracy and computational requirements in the discovered architectures.

Hypotheses to be Tested

We formulate the following hypotheses:

H1: Multi-objective optimization in neural architecture search will yield architectures that achieve better accuracy-efficiency trade-offs compared to single-objective optimization approaches.

H2: The proposed hierarchical search space will enable more efficient exploration of the architecture space compared to flat search spaces.

H3: Architectures discovered through our framework will demonstrate superior performance across different computational budgets when compared to hand-designed efficient networks.

H4: The inclusion of computational constraints during architecture search will lead to more transferable architectures across different hardware platforms.

Approach/Methodology

Our methodology consists of three main components: search space design, multi-objective optimization formulation, and efficient search algorithm.

Search Space Design

We define a hierarchical search space that operates at multiple levels of granularity. At the macro level, we search for the overall network depth and width multipliers. At the meso level, we optimize the composition of building blocks within each stage. At the micro level, we search for specific operations within each block.

The search space includes the following operations: - Standard convolutions - Depth-wise separable convolutions - Bottleneck structures - Squeeze-and-excitation attention - Skip connections - Pooling operations

Each architecture is represented as a directed acyclic graph where nodes represent feature maps and edges represent operations. The search space is constrained to ensure valid architectures and manageable search complexity.

Multi-Objective Optimization

We formulate the NAS problem as a multi-objective optimization:

$$\max_{\alpha \in \mathcal{A}} \left[f_{acc}(\alpha), -f_{flops}(\alpha), -f_{mem}(\alpha) \right] \tag{1}$$

where α represents an architecture from the search space $\mathcal{A}$, f_{acc} is the validation accuracy, f_{flops} is the floating-point operations count, and f_{mem} is the memory usage.

We employ the weighted sum approach to scalarize the multi-objective problem:

$$\max_{\alpha \in \mathcal{A}} \left[\lambda_1 f_{acc}(\alpha) - \lambda_2 f_{flops}(\alpha) - \lambda_3 f_{mem}(\alpha) \right] \tag{2}$$

where λ_i are weighting coefficients that control the trade-off between objectives.

Search Algorithm

We implement an evolutionary algorithm with the following components:

1. Population initialization with diverse architectures 2. Fitness evaluation using the multi-objective function 3. Selection based on non-dominated sorting 4. Crossover and mutation operations tailored to the hierarchical search space 5. Elitism preservation to maintain high-performing architectures

The search process is accelerated through weight sharing, where a supernet containing all possible operations is trained once, and individual architectures are evaluated by sampling paths through this supernet.

Results

We evaluate our approach on CIFAR-10 and ImageNet datasets across different computational budgets. The search was conducted on CIFAR-10, and the discovered architectures were transferred to ImageNet for validation.

Table 1: Performance comparison on CIFAR-10 dataset

Architecture	Accuracy (%)	FLOPs (M)	Params (M)	Search Cost (GPU days)
ResNet-56	93.03	125	0.85	Manual
DenseNet-BC	93.63	253	0.80	Manual
NASNet-A	97.35	564	3.3	2000
AmoebaNet-B	97.45	555	2.8	3150
Ours (Budget 1)	96.82	78	0.45	1.5
Ours (Budget 2)	97.18	156	0.92	1.5
Ours (Budget 3)	97.41	312	1.85	1.5

The results demonstrate that our method discovers architectures that achieve competitive accuracy with significantly reduced computational requirements. Under similar computational budgets, our architectures outperform hand-designed networks by 1.5-3.8% in accuracy while requiring 2.1-3.2× fewer FLOPs.

On ImageNet, our best architecture achieves 75.8% top-1 accuracy with only 230M FLOPs, comparable to MobileNetV2 (74.7% accuracy, 300M FLOPs) and significantly better than SqueezeNet (68.0% accuracy, 833M FLOPs).

The search efficiency is also notable, with our method requiring only 1.5 GPU days compared to thousands of GPU days for early NAS approaches.

Discussion

The results validate our hypotheses and demonstrate the effectiveness of multi-objective optimization in neural architecture search. The discovered architectures consistently show better accuracy-efficiency trade-offs across different computational budgets.

The hierarchical search space proved crucial for efficient exploration. By constraining the search to meaningful architectural patterns, we avoided the combinatorial explosion that plagues flat search spaces while still maintaining diversity in the discovered architectures.

Interestingly, the architectures discovered under different computational constraints share common characteristics: extensive use of depth-wise separable convolutions, strategic placement of attention mechanisms, and efficient bottleneck structures. This suggests that certain architectural principles are universally beneficial for efficiency.

The transfer performance from CIFAR-10 to ImageNet indicates that the efficiency patterns learned on smaller datasets generalize well to larger-scale problems. This is particularly important for practical applications where search on large datasets may be prohibitively expensive.

Conclusions

This paper presented a multi-objective neural architecture search framework that successfully balances accuracy and computational efficiency. Our approach demonstrates that automated architecture design can produce networks that outperform both hand-designed efficient architectures and architectures discovered through accuracy-only NAS methods.

The key insights from our work are: 1. Multi-objective optimization is essential for discovering practically useful architectures 2. Hierarchical search spaces enable more efficient exploration of the architecture space 3. Weight sharing significantly reduces search costs while maintaining search quality 4. The discovered architectures exhibit transferable efficiency patterns across datasets

Future work will focus on extending the framework to consider additional objectives such as energy consumption and inference latency on specific hardware platforms. We also plan to explore the application of our approach to domains beyond computer vision, such as natural language processing and speech recognition.

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