How does the diversity of neural architecture search spaces in AutoML systems affect cross-domain generalizati

Assignee Research

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Abstract

The integration of Large Language Models (LLMs) with Neural Architecture Search (NAS) has introduced new possibilities for automating the design of neural architectures. However, most existing methods face critical limitations, including architectural invalidity, computational inefficiency, and inferior performance compared to traditional NAS. In this work, we present Collaborative LLM-based NAS (CoLLM-NAS), a two-stage NAS framework with knowledge-guided search driven by two complementary LLMs. Specifically, we propose a stateful Navigator LLM to guide search direction, a stateless Generator

1 Introduction

This paper examines: CoLLM-NAS: Collaborative Large Language Models for Efficient Knowledge-Guided Neural Architecture Search. Research question: How does the diversity of neural architecture search spaces in AutoML systems affect cross-domain generalization on language model benchmarks compared to fixed transformer architectures?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 5.0/10.

3 Results

13 papers retrieved. 15 claims extracted; 3 independently verified. Quality review score: 5.0/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
CoLLM-NAS consistently outperforms baselines under different resource constraints while significantly reducing search co	×	0.14
Architectures discovered by CoLLM-NAS achieve superior FLOPs-accuracy trade-off compared to those from state-of-the-art	×	0.10
CoLLM-NAS presents a novel collaborative LLM-based NAS framework to enhance two-stage NAS with knowledge-guided search.	✓	0.23
CoLLM-NAS proposes three key components: a stateful Navigator LLM, a stateless Generator LLM, and a Coordinator module.	✓	0.19
CoLLM-NAS surpasses existing NAS methods across diverse search spaces both in performance and efficiency, achieving new	✓	0.26
Two-stage NAS addresses the computational inefficiency of traditional NAS by employing weight-sharing mechanisms.	×	0.09
Two-stage NAS decomposes the NAS problem into two sequential phases: training a weight-sharing supernet and searching fo	×	0.04
SPOS pioneers uniform single-path sampling in the first stage of two-stage NAS.	×	0.04
OFA enables multi-scale subnet extraction via progressive shrinking in the first stage of two-stage NAS.	×	0.05
AutoFormer adapts the weight-sharing mechanism for vision transformers in the first stage of two-stage NAS.	×	0.06
Most two-stage NAS methods employ random search during the second stage for efficient performance estimation without ret	×	0.08
CoLLM-NAS achieves higher accuracy and lower FLOPs compared to baselines like MobileNetV2, MobileNetV3, FairNAS, OFA, Mi	×	0.03
CoLLM-NAS achieves higher accuracy and lower FLOPs compared to SPOS and MAS-NAS.	×	0.06
CoLLM-NAS achieves higher accuracy and lower FLOPs compared to OFA-T, OFA-S, OFA-B, and OFA-L.	×	0.06
CoLLM-NAS reduces search costs by 4.7$\times$ and 4$\times$ compared to OFA-B and OFA-L, respectively.	×	0.09

References

- http://arxiv.org/abs/2509.26037v2
- http://arxiv.org/abs/2601.03290v1
- http://arxiv.org/abs/1906.02869v2