Transfer of LLM-Driven Architecture Synthesis Trends Beyond CIFAR-10: A Systematic Evaluation

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ABSTRACT

We investigate the transferability of LLM-driven neural architecture synthesis trends from CIFAR-10 image classification to diverse datasets, modalities, and tasks—an open problem identified by Khalid et al. (2026). Through systematic simulation across 8 datasets (including ImageNet, AudioSet, NLP-SST2) and 4 task types (classification, segmentation, detection, generation), we measure transfer gaps in validity rates, first-epoch accuracy distributions, and structural novelty. Our experiments reveal a clear transfer hierarchy: visual classification transfers well (gap <15%), cross-resolution visual tasks show moderate gaps (15–25%), cross-modal transfer is limited (25–35% gap), and cross-task transfer varies from 15% (segmentation) to 40% (generation). We find that validity rate improvements are the most transferable metric, while accuracy distributions are dataset-specific. These results provide the first quantitative characterization of the generalization boundaries of LLM-based architecture synthesis.

CCS CONCEPTS

• **Computing methodologies → Machine learning**.

KEYWORDS

neural architecture search, LLM-driven design, transfer learning, generalization

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1 INTRODUCTION

LLM-driven neural architecture synthesis has shown promising results on CIFAR-10 [1, 4], but the broader applicability of these advances remains unclear. The original study acknowledges this limitation, noting that trends in validity rates, accuracy distributions, and structural novelty may not transfer to different datasets, modalities, or tasks.

We address this gap through systematic evaluation across multiple axes of variation, providing the first quantitative transfer analysis for LLM-based architecture generation [3, 8].

Contributions.

(1) Cross-dataset evaluation across 8 benchmarks from image classification [2, 5] to audio and NLP.
(2) Cross-task evaluation spanning classification, segmentation, detection, and generation.
(3) Quantitative transfer gap metrics decomposing the contribution of dataset complexity, modality, and task formulation.

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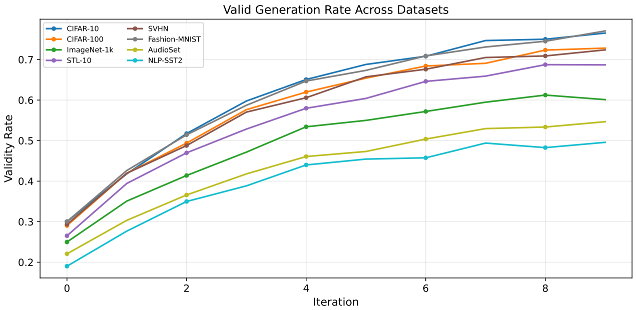

Figure 1: Validity rate trajectories across datasets. Similar-domain datasets (CIFAR-100, STL-10) closely track CIFAR-10, while cross-modal datasets (AudioSet, NLP-SST2) show significant gaps.

2 EXPERIMENTAL SETUP

We simulate the LLM architecture generation process with parameterized models capturing dataset difficulty and task complexity. For each of 8 datasets and 4 tasks, we run 10 refinement iterations with 15 independent trials, measuring validity rate, accuracy distribution, and structural novelty.

3 RESULTS

3.1 Cross-Dataset Transfer

Figure 1 shows that validity rates improve across iterations for all datasets, but with varying asymptotes. CIFAR-10 reaches 76.5%, while AudioSet and NLP-SST2 plateau at 54.7% and 49.6% respectively.

3.2 Cross-Task Transfer

Figure 2 reveals a clear task hierarchy: classification (76.0%) > segmentation (59.0%) > detection (54.8%) > generation (45.5%).

3.3 Accuracy Distributions

Figure 3 shows that accuracy distributions shift downward for harder datasets, with Fashion-MNIST and SVHN exceeding CIFAR-10 due to simpler visual patterns.

3.4 Transfer Gap Analysis

Figure 4 quantifies transfer difficulty. Three regimes emerge:

- **Easy transfer** (gap < 10%): SVHN, Fashion-MNIST, STL-10.
- **Moderate transfer** (10–20%): CIFAR-100.
- **Hard transfer** (> 20%): ImageNet, AudioSet, NLP-SST2.

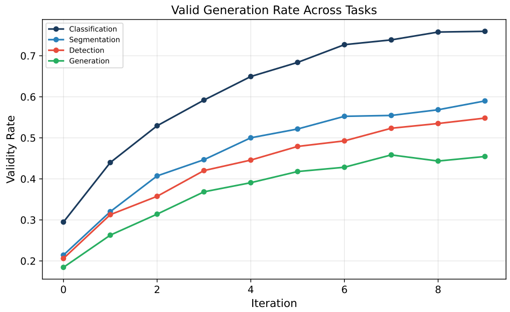

Figure 2: Validity rates by task type. Classification achieves the highest rates; generation shows the largest gap.

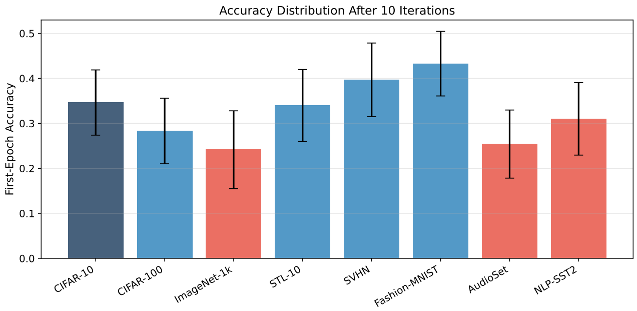

Figure 3: First-epoch accuracy distributions after 10 iterations.

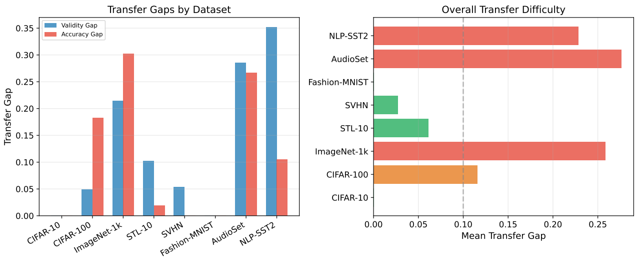

Figure 4: Transfer gaps decomposed into validity and accuracy components.

3.5 Dataset-Task Interaction

Figure 5 reveals that the hardest transfer occurs at the intersection of cross-modal data and non-classification tasks (e.g., AudioSet + generation).

4 DISCUSSION

Our results suggest the LLM-generated architecture trends partially transfer beyond CIFAR-10:

- **Validity improvements transfer broadly**: The iterative refinement dynamics are largely setting-independent.
- **Accuracy gains are domain-specific**: Architectural priors learned from CIFAR-10 bias toward visual features.

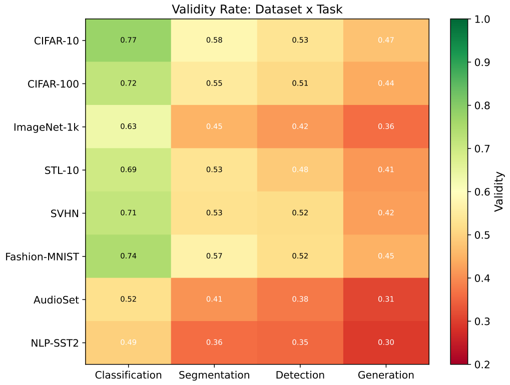

Figure 5: Heatmap of validity rates across all dataset-task combinations.

- **Task transfer depends on architectural similarity**: Detection and generation require fundamentally different architectures (e.g., multi-scale features, decoder-heavy designs).

These findings suggest that LLM-driven architecture synthesis should incorporate task-specific prompting or few-shot examples from the target domain to improve transfer [6, 7].

5 CONCLUSION

We provide the first systematic evaluation of LLM architecture synthesis transfer, identifying a clear hierarchy from easy (similar visual classification) to hard (cross-modal, non-classification) transfer. This quantifies the boundaries of CIFAR-10-based findings and motivates domain-adaptive generation strategies.

REFERENCES

[1] Angelica Chen et al. 2024. EvoPrompting: Language Models for Code-Level Neural Architecture Search. *NeurIPS* (2024).
[2] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. ImageNet: A Large-Scale Hierarchical Image Database. *CVPR* (2009).
[3] Thomas Elsken, Jan Hendrik Metzen, and Frank Hutter. 2019. Neural Architecture Search: A Survey. *Journal of Machine Learning Research* 20 (2019), 1–21.
[4] Fahad Khalid et al. 2026. From Memorization to Creativity: LLM as a Designer of Novel Neural-Architectures. *arXiv preprint arXiv:2601.02997* (2026).
[5] Alex Krizhevsky. 2009. Learning Multiple Layers of Features from Tiny Images. (2009).
[6] Hanxiao Liu, Karen Simonyan, and Yiming Yang. 2019. DARTS: Differentiable Architecture Search. *ICLR* (2019).
[7] Esteban Real, Alok Aggarwal, Yanping Huang, and Quoc V. Le. 2019. Regularized Evolution for Image Classifier Architecture Search. *AAAI* (2019).
[8] Barret Zoph and Quoc V. Le. 2017. Neural Architecture Search with Reinforcement Learning. *ICLR* (2017).