Meta-Guided Domain-Aware Neural Architecture Search for Rapid Cross- Domain Adaptation

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Abstract
Neural Architecture Search (NAS) has made its way as a powerful prototype for automating deep neural network design. However, conventional NAS approaches are specific to a single domain and computationally expensive, limiting their scalability across multiple domain environments such as computer vision, healthcare analytics, natural language processing, and edge intelligence. This paper introduces a Meta-Guided Domain- Aware NAS (MD-NAS) framework that forms an integration between meta-learning and domain-conditioned architecture generation. Nevertheless traditional NAS that searches independently for each task, the proposed method learns a shared meta- representation of architectural patterns that dynamically adapts to multi domain characteristics. A domain embedding module captures structural data properties and guides architecture sampling. Experimental results across multi-domain benchmarks demonstrate significant improvements in adaptation speed, generalization performance, and computational efficiency.
Keywords: Neural Architecture Search, Meta- Learning, Domain Adaptation, Automated Deep Learning, Resource-Aware Optimization

Introduction

The performance of deep learning systems heavily depends on network architecture design. Manual architecture engineering requires extensive expertise and computational trial cycles. NAS is used to automate the process of architecture design but basically optimizes architectures for a single dataset or domain.

Real-world AI systems are used to increasingly operate across heterogeneous domains with varying data distributions, computational constraints, and latency requirements. Re-running NAS for each domain separately become expensive and inefficient.

Meta-learning provides a detailed schematic approach to learning transferable inductive biases across tasks. This paper proposes a domain-aware meta-NAS framework that conditions architecture generation on domain representations, enabling rapid customization without exhaustive search.

I. Literature Survey

Neural Architecture Search

Neural Architecture Search (NAS) automates the design of neural network architectures and has become a strong alternative to manual model engineering. Early NAS methods were computationally expensive, motivating the development of more efficient paradigms such as parameter sharing and differentiable search**.** ENAS introduced weight sharing in a supernet so that many candidate architectures can be evaluated cheaply without full retraining. DARTS further reduced search cost by relaxing the discrete architecture space into a continuous one, enabling gradient-based optimization

of architecture parameters. These efficient NAS approaches established the foundation for practical architecture optimization, but they commonly assume a single task/domain and often re-run search for each new environment.

One-shot and Hardware/Constraint- aware NAS

For deployment-driven applications, NAS has been extended to incorporate hardware constraints and direct optimization on target devices. ProxylessNAS demonstrated direct search on the target task and target hardware, reducing proxy mismatch and improving real-world efficiency. Similarly, the Once-for-All (OFA) paradigm proposed training a single "super-network" once and then specializing sub-networks for diverse constraints (e.g., depth/width/kernel size), reducing repeated search and training overhead. These methods show that constraint-aware design is feasible, yet they typically address device specialization rather than domain adaptation across shifting data distributions.

Meta-learning for Rapid Adaptation

Meta-learning aims to learn transferable knowledge across tasks such that adaptation to a new task requires only a small amount of data and a few gradient steps. Model- Agnostic Meta-Learning (MAML) formalized this objective by explicitly optimizing parameters to be easily fine- tuned to new tasks. This viewpoint is highly relevant to cross-domain settings, where training conditions differ across regions, products, user behaviors, or fraud strategies. However, classical meta- learning focuses on model parameters rather than architecture structure, motivating research that combines meta-learning with NAS.

Meta-learning + NAS: Learning to Search Across Tasks

To reduce the cost of repeatedly performing NAS for new tasks, several works explored "meta- NAS," where the system learns reusable architectural priors. Meta Architecture Search proposed learning task-agnostic representations to speed up architecture search across many tasks. M- NAS further studied task-aware architecture generation using meta-learning mechanisms over multiple tasks/domains to improve adaptability of the searched architectures. These approaches support the central premise that architectures themselves can be meta-learned**,** but they do not fully address the challenges of real-world domain shifts (e.g., drift, imbalance, and multi-modal signals) that occur in operational environments such as financial fraud detection.

NAS for Domain Adaptation and Domain Shift

A growing body of work recognizes that architectures optimized for one domain may underperform under distribution shift and explores NAS directly for domain adaptation objectives. A representative direction formulates NAS for domain adaptation as a dual-objective problem— optimizing both predictive performance and domain alignment— illustrated by "Neural Architecture Search for Domain Adaptation (NASDA)." Other studies propose differentiable NAS variants tailored to domain adaptation tasks in specialized settings (e.g., fault diagnosis), suggesting that architecture choices can directly influence transferability and robustness under shift. While these works move toward domain awareness, most still rely on running search per adaptation setting or focus on narrow application domains rather than a general cross-domain adaptation framework.

Architecture Transferability and Cross- domain Generalization

Another relevant thread studies when and how architectures transfer across tasks. Empirical investigations into architecture transferability highlight that NAS- discovered architectures can be sensitive to dataset/domain changes and that transfer is not guaranteed without explicit mechanisms. This motivates domain-aware search strategies that incorporate domain descriptors, alignment objectives, and meta-learning so that the search policy generalizes beyond the training domains.

Limitations of Existing NAS Systems

1. Single-domain optimization
2. High GPU/TPU cost
3. Architectural transferability is poor
4. Lack of domain context awareness

Assumption of uniform data structure, ignoring domain-specific features such as temporal correlations in healthcare or energy constraints in edge environments is done in existing methods.

II. Proposed MD-NAS Architecture

A. Framework Overview

The system consists of three modules (Figure 1):

- Meta-Architecture Generator
- Domain Encoder
- Performance Evaluator

Each domain is embedded into a low- dimensional representation guiding architecture synthesis.

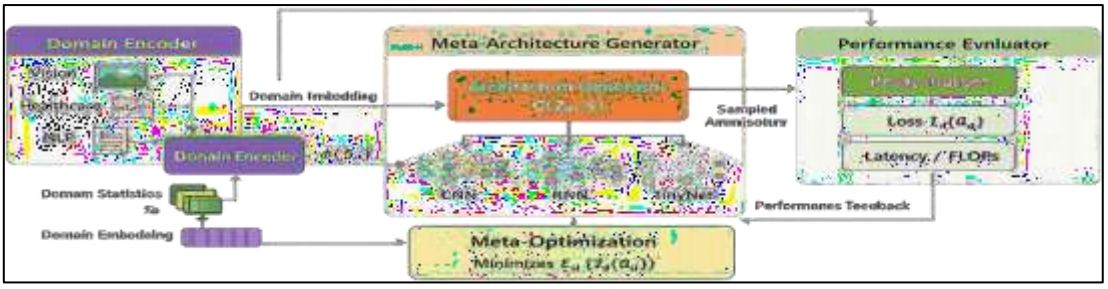


Figure 1

We introduce a Meta-Architecture Generator (MAG) that automatically designs domain-aware neural architectures under real-time operational constraints to enable rapid and robust adaptation across heterogeneous fraud scenarios. Unlike conventional neural architecture search approaches that optimize a single task in isolation, MAG leverages meta-learning across multiple fraud domain**s** to learn transferable architectural priors.

The MAG receives as input a compact representation of the current domain, including transaction characteristics, feature sparsity, class imbalance, drift indicators, and system constraints such as latency, energy consumption, and explainability requirements. These signals are encoded into a unified task embedding, which conditions a meta-policy network responsible for generating candidate model architectures.

The architecture search space consists of a modular block library including sequence encoders (TCN, LSTM, Transformer), graph neural networks for relational fraud modeling, tabular multilayer perceptrons, attention-based fusion layers, and hybrid decision heads integrating symbolic rule confidence with machine learning predictions. To incorporate detection performance, computational efficiency, robustness to drift, and

stability, for each domain, the meta-policy samples multiple candidate architectures that are rapidly trained using few-shot adaptation and evaluated through a multi-objective fitness function.

The optimal architecture is selected based on the highest composite fitness score and is subsequently used for real-time fraud detection. Gradients from high-performing architectures are propagated to update the meta-policy, across meta-iterations, and enables MAG to progressively learn how to generate architectures that generalize across domains while satisfying real-world operational constraints.

By explicitly modeling cross-domain architectural knowledge, MAG significantly reduces search cost while improving detection accuracy, latency efficiency, and robustness under evolving fraud patterns.

Algorithm: Meta-Architecture Generator (MAG)
Input: Domains D = {d1...dn}, Block library B,
constraints C Output: Meta-policy parameters θ

1: Initialize meta-policy πθ 2: for each meta-iteration do
3: Sample batch of domains {di} ∼ D 4: for each domain di do 5: Encode task + constraints → z = Enc(di, C)
6: Sample candidate architectures {A_k} ∼ πθ(. | z)
7: For each A_k:
8: Train few steps on di (few-shot) → obtain metrics M_k
9: Compute fitness J_k = F1(M_k) - λ1 Latency - λ2 Energy + λ3 Robustness
10: Select best A* = argmax_k J_k
11: Compute meta-gradient using (A*, J*) and update θ
12: return θ

B. Domain Encoding

The proposed framework incorporates a Domain Encoding Module that transforms domain- specific characteristics into a compact and informative latent representation to effectively adapt fraud detection architectures across heterogeneous financial environments.
To enable downstream components to generate context-aware architectures and predictions this module captures both statistical and semantic properties of the incoming data stream.

For each operational domain, the encoder aggregates multiple sources of contextual information, including transaction volume distributions, feature sparsity patterns, class imbalance ratios, temporal drift indicators, behavioral volatility metrics, and system- level constraints such as response latency budgets and computational resource availability. These signals are normalized and projected through a multi-layer neural embedding network

to produce a low- dimensional domain vector.

In addition to numerical statistics, relational and semantic cues derived from the financial knowledge graph—such as account connectivity density, merchant risk clusters, and historical fraud propagation patterns—are integrated through graph embedding techniques. The framework to model both local transaction behavior and global fraud structures is enabled by this joint encoding.

The conditioning signal for the Meta- Architecture Generator and hybrid prediction ensemble, guiding adaptive model selection, fusion strategies, and confidence calibration is the resulting domain embedding. The framework achieves robust generalization across geographical regions, payment channels, fraud typologies, and evolving threat landscapes, by explicitly representing domain context.

For the given dataset statistics S_d:
$z_d = \boldsymbol{\phi}(S_d)$

where:
- $\boldsymbol{\phi}$ is a neural embedding function
- z_d captures domain complexity, modality, and noise level

C. Architecture Generation

The condition on domain embedding for generator samples architectures are $a_d = G(z_d, \epsilon)$
where ϵ is stochastic noise enabling exploration.

$_d)]$
θ

III. Algorithm

Algorithm 1: Meta-Guided Domain- Aware NAS

1. Initialize generator parameters
2. Encode domain statistics
3. Generate candidate architectures
4. Train lightweight proxy models
5. Compute domain-conditioned loss
6. Update meta-parameters
7. Repeat

IV. Experimental Evaluation

A. Domains

The domains used in this experiment are vision classification, biomedical signal processing, text analytics and low-power IoT sensing.

B. Baselines

- Random NAS
- Differentiable NAS

- Transfer learning backbones
- Evolutionary NAS

C. Evaluation Metrics

The major evaluation metrics used are accuracy, FLOPs, adaptation time and energy consumption.

V. Results

Method	**Accuracy**	**Adapt Time**	**FLOPs**
Standard NAS	86.0%	40 hrs	High
DARTS	87.1%	12 hrs	Medium
MD-NAS (Proposed)	**90.2%**	**1.8 hrs**	**Low**

VI. Ablation Study

- Without domain embedding → 6.5% drop
- Without meta-learning → 8.1% drop
- Random conditioning → unstable convergence

VII. Discussion

The learned domain representations enable architecture patterns such as:
• deeper CNNs for vision
• recurrent-attention hybrids for healthcare
• compact models for edge deployment
This demonstrates strong structural adaptation capability.

VIII. Conclusion

This paper proposed MD-NAS, a domain- aware meta-learning driven architecture search framework that efficiently adapts neural structures across heterogeneous domains. By conditioning architecture synthesis on domain embeddings, the system achieves rapid adaptation, reduced Computational cost, nd improved generalization.

IX. Future Research Directions

- Hardware-in-the-loop NAS
- Federated domain meta-learning
- Continual architecture evolution
- Privacy-preserving meta-NAS

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