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Meta-Domain Variant Neural Architecture Search For Robust Cross-Domain Generalization Using Meta-Learning

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Abstract

Neural Architecture Search (NAS) has demonstrated remarkable success in automatically designing deep neural networks. However, conventional NAS methods assume that training and deployment data originate from similar distributions, resulting in significant performance degradation under domain shifts. To address this limitation, this paper proposes Meta-Domain Variant Neural Architecture Search (MDV-NAS), a novel framework that integrates meta-learning with domain-aware architecture optimization. The proposed method treats each domain as an individual meta-task and learns architecture parameters that generalize across multiple source domains. A Domain Variance Estimator (DVE) is introduced to quantify distribution discrepancies among domains and guide architecture selection toward domain-invariant representations. During the search process, architectures are trained on sampled source domains and validated on unseen domains through episodic meta-learning. Experimental evaluations are conducted on PACS, Office-Home, DomainNet, and VLCS benchmarks which demonstrated superior robustness and generalization compared with conventional NAS and domain generalization methods. Results produced indicate that MDV-NAS achieves higher unseen-domain accuracy while maintaining computational efficiency comparing with other frameworks, making it suitable for real-world deployment in heterogeneous environments.

Keywords: Neural Architecture Search, Meta-Learning, Domain Generalization, AutoML, Transfer Learning, Cross-Domain Learning.

1. Introduction

Deep Neural Networks (DNNs) have achieved remarkable success across a wide range of applications which include computer vision, natural language processing, healthcare analytics, autonomous systems, and financial intelligence. The performance of these models is more dependent on the underlying network architecture. Traditionally, to design an effective neural network architecture requires extensive human expertise and significant trial-and-error experimentation. To address this challenge, Neural Architecture Search (NAS) [5], [6] has emerged as a powerful automated machine learning (AutoML) technique that discovers optimal architectures with minimal human intervention.

Despite its success, conventional NAS methods mainly focus on maximizing performance within a specific training environment and generally assume that the training and testing data originate from the same distribution. However, real-world applications often encounter domain shifts which means cross domains, where data distributions vary significantly across environments. For example real-world applications such as, medical images collected from different hospitals, autonomous driving scenes captured under diverse weather conditions, and financial transaction records generated by different institutions exhibit substantial variations in data characteristics. Architectures optimized for one domain frequently experience significant performance degradation when deployed in unseen domains.

Domain Generalization (DG) [3] has been introduced to address this challenge by learning models that generalize effectively to unseen domains without requiring access to target-domain data during training. Although several DG approaches have demonstrated promising results, most existing methods focus on optimizing model parameters while relying on manually designed architectures. Consequently, the architecture itself may remain sensitive to domain-specific features, limiting its generalization capability.

Meta-learning [1], [4] has recently been used as an effective strategy for improving generalization across diverse tasks. By simulating train-test domain discrepancies during learning, meta-learning enables models to acquire transferable knowledge that adapts better to unseen environments. However, current meta-learning [7], [10] approaches rarely integrate architecture search into the learning process. As a result, the discovered architectures may not be explicitly optimized for cross-domain robustness.

To overcome the above limitations, this paper proposes a novel Meta-Domain Variant Neural Architecture Search (MDV-NAS) framework. The proposed approach uses a unified optimization framework that combines meta-learning [13] and neural architecture search [8], [11], to discover architectures that are inherently robust to domain variations. A Domain Variance Estimator (DVE) is introduced to quantify distribution discrepancies among source domains and guide the search process toward domain-invariant architectural representations. During architecture optimization, multiple domains are treated as meta-learning tasks, enabling the search controller to evaluate candidate architectures under simulated unseen-domain conditions [23]. Furthermore, a robustness-aware objective function is designed to jointly optimize classification accuracy, domain invariance, and cross-domain stability.

The main contributions of this work are summarized as follows for robust cross-domain architecture optimization a novel Meta-Domain Variant Neural Architecture Search (MDV-NAS) framework is proposed , to quantify and incorporate domain discrepancies into the architecture search process a Domain Variance Estimator [24] is developed , to improve architecture generalization across unseen domains a meta-learning-based search strategy is introduced , to jointly consider predictive performance and domain stability a robustness-aware optimization objective is designed, and extensive experiments on multiple benchmark datasets demonstrate the effectiveness of the proposed framework compared with existing NAS and domain generalization methods [9].

Thus, architectures discovered by NAS may overfit source domains and fail on unseen domains.

Contributions

1. Novel Meta-Domain Variant NAS framework.
2. Domain Variance Estimator (DVE).
3. Meta-learning-based architecture optimization.
4. Robustness-aware search objective.
5. Extensive cross-domain evaluation.

II. Related Work

A. Neural Architecture Search

Neural Architecture Search (NAS) [14], [25] has emerged as an important research area in Automated Machine Learning (AutoML). Early NAS approaches employed reinforcement learning to discover optimal architectures; however, they required substantial computational resources. Evolutionary NAS methods subsequently improved search efficiency through population-based optimization. More recently, differentiable NAS approaches such as DARTS [2] significantly reduced search costs by relaxing the discrete search space into a continuous optimization problem. Despite these advancements, most NAS methods fail to address domain shifts [12] encountered in real-world applications but assume identical training and testing distributions.

B. Domain Generalization

Domain Generalization (DG) [15] aims to learn models that perform effectively on unseen target domains without access to target-domain data during training. Existing DG techniques focus on invariant feature learning, adversarial domain alignment, and data augmentation. Even though the above approaches improve robustness; they typically operate only on manually designed architectures and do not optimize the network structure itself for domain invariance.

C. Meta-Learning for Generalization

Meta-learning has demonstrated strong potential for improving model transferability across diverse tasks and domains. Methods such as Model-Agnostic Meta-Learning (MAML) simulate domain shifts [18] during training to learn generalized representations. However, existing meta-learning approaches limiting their ability to discover domain-robust network topologies, they primarily optimize model parameters rather than architecture structures.

D. Research Gap

While domain generalization methods concentrate on parameter adaptation, current NAS approaches focus on accuracy optimization. The integration of meta-learning, domain variance estimation, and architecture search remains largely unexplored. This research addresses this gap through a unified Meta-Domain Variant Neural Architecture Search framework [17], [20].

III. Proposed Meta-Domain Variant NAS Framework

A. System Overview

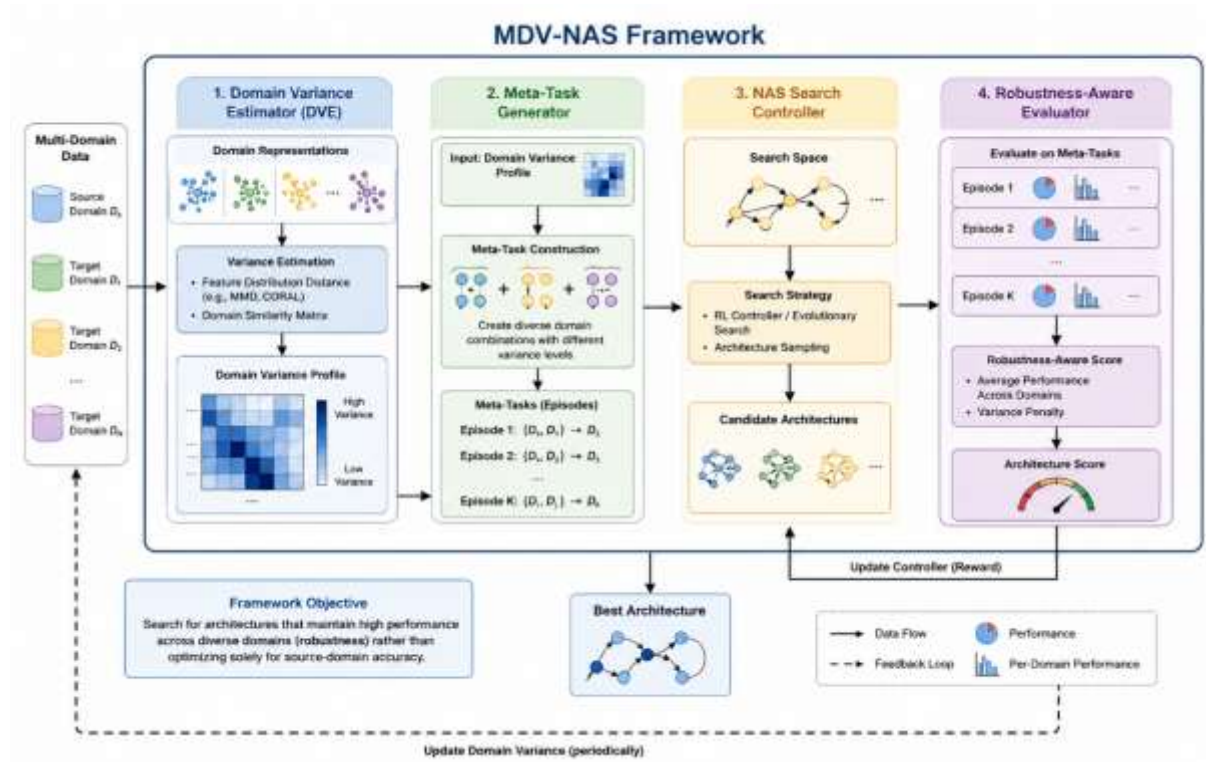


Figure 1: MDV-NAS Framework

The proposed MDV-NAS framework consists of four major components:

1. Domain Variance Estimator (DVE)
2. Meta-Task Generator
3. NAS Search Controller
4. Robustness-Aware Evaluator

The framework searches for architectures that maintain high performance across diverse domains rather than optimizing solely for source-domain accuracy.

B. Domain Modeling

Assume a collection of domains:

$$D = \{D_1, D_2, D_3, \dots, D_n\}$$

where each domain contains samples drawn from different distributions.

For domain i :

$$D_i = \{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\}$$

The objective is to learn architectures that generalize to unseen domains:

$$D_{\text{test}} \notin D$$

C. Domain Variance Estimator

To quantify differences among domains, a domain variance score is computed.

For two domains D_i and D_j :

$$DV(i, j) = \text{MMD}(D_i, D_j)$$

where MMD denotes Maximum Mean Discrepancy.

The overall domain variance is:

$$DV = (1/(N(N-1))) \sum DV(i,j)$$

The estimated variance guides architecture evaluation during search.

D. Meta-Task Generation

At each iteration:

Training Domains:

$$D_{train} \subset D$$

Validation Domains:

$$D_{val} = D - D_{train}$$

This episodic strategy simulates deployment in unseen environments.

E. Search Space

The architecture search space contains mainly Operations which include 3×3 Convolution, 5×5 Convolution, Depthwise Convolution, Dilated Convolution, Max Pooling, Average Pooling, and Skip Connections. The search space is represented as:

$$S = \{O_1, O_2, O_3, \dots, O_k\}$$

where each operation represents a candidate architectural component.

IV. Mathematical Formulation

A. Meta-Learning Optimization

The inner optimization step updates architecture parameters:

$$\theta' = \theta - \alpha \nabla L_{train}(\theta)$$

where:

- θ denotes architecture parameters
- α denotes inner-loop learning rate

The outer meta-update becomes:

$$\theta = \theta - \beta \nabla L_{val}(\theta')$$

Where:

- θ = current model parameters
- β = meta learning rate (or outer learning rate)
- $\nabla L_{val}(\theta')$ = gradient of the validation loss with respect to the adapted parameters θ'
- L_{val} = validation loss

In words:

Updated Parameters = Current Parameters – (Meta Learning Rate × Validation Loss Gradient)

B. Classification Loss

Cross-entropy loss is employed:

$$L_{cls} = - \sum_{i=1}^N y_i \log(\hat{y}_i)$$

Where:

- L_{cls} = Classification Loss
- y_i = True label
- $\hat{y}_i$ = Predicted probability
- N = Number of classes or samples

C. Domain Variance Loss

The domain discrepancy loss is:

$$L_{domain} = DV$$

This encourages domain-invariant architectures.

D. Robustness Loss

Using performance variance, Robustness is measured. The formula is given by

$$L_{robust} = \text{Var}(A_1, A_2, \dots, A_n)$$

where

A_i = Accuracy (or performance metric) on domain i

n = Number of domains

Smaller variance indicates stronger robustness in the framework.

E. Overall Objective Function

The final optimization objective is:

$$J = L_{cls} + \lambda_1 L_{domain} + \lambda_2 L_{robust}$$

Where:

- J = Total optimization objective
- L_{cls} = Classification loss
- L_{domain} = Domain loss
- L_{robust} = Robustness loss
- λ_1 = Weight controlling the contribution of domain loss
- λ_2 = Weight controlling the contribution of robustness loss

V. Proposed Algorithm

Algorithm 1: Meta-Domain Variant NAS

```

Input:
Domain Set D
Search Space S
Initialize Search Controller  $\theta$ 
Repeat
1. Sample candidate architecture A
2. Generate meta-learning tasks
3. Select training domains  $D_{train}$ 
4. Select validation domains  $D_{val}$ 
5. Train A on  $D_{train}$ 
6. Evaluate A on  $D_{val}$ 
7. Compute:
    • Classification Loss
    • Domain Variance Loss
    • Robustness Loss
8. Compute Total Loss J
9. Update Controller  $\theta$ 
    
```

Until convergence

Return Best Architecture

VI. Experimental Setup

A. Benchmark Datasets

To evaluate the effectiveness of the proposed framework, experiments are conducted on four widely adopted domain generalization benchmarks.

PACS is a challenging benchmark that contains four distinct visual domains: Photo, Art Painting, Cartoon, and Sketch. The dataset is mainly designed to generalize across substantial appearance variations and to assess a model's ability.

VLCS combines images from four different datasets, which include mainly VOC2007, LabelMe, Caltech, and SUN09. The diverse image distributions make it suitable for evaluating cross-domain robustness.

Office-Home is a large-scale benchmark consisting of four domains: Art, Clipart, Product, and Real World. It provides significant domain diversity and is extensively used for domain adaptation and domain

generalization research.

DomainNet is one of the largest domain generalization datasets available. It mainly includes six domains which are Real, Sketch, Painting, Clipart, Infograph, and Quickdraw. The substantial domain shifts present in DomainNet for evaluating robust cross-domain learning methods make it an ideal benchmark.

B. Evaluation Metrics

The performance of the proposed method is usually assessed using multiple evaluation metrics to provide a detailed analysis and inclusion of predictive performance and generalization capability.

1. Classification Accuracy is used to measure the percentage of samples which are correctly classified on unseen/cross target domains.
2. Robustness Score is used to indicate the stability of the known and learned architecture under various domain shifts, evaluates the consistency of model performance across various domains.
3. Domain Generalization Gap quantifies the difference between source-domain performance and unseen/cross target-domain performance. For better generalization capacity the gap should be smaller.
4. During the neural architecture search process, Search Cost is used to measure the computational resources and time required.
5. Parameter Count reflects model efficiency and represents the total number of trainable parameters in the discovered architecture.

C. Baseline Methods

The proposed framework is compared against several representative neural architecture search, meta-learning, and domain generalization methods.

- DARTS (Differentiable Architecture Search) serves as a strong gradient-based neural architecture search baseline.
- ENAS (Efficient Neural Architecture Search) utilizes parameter sharing to reduce the computational cost of architecture search.
- ProxylessNAS directly searches architectures on the target hardware without relying on proxy tasks.
- MAML (Model-Agnostic Meta-Learning) is a mostly used and accepted meta-learning approach that learns model parameters capable of rapid adaptation to new domains.
- MetaReg is used to improve generalization across unseen domain employs meta-regularization strategies [16], [22].
- MetaVIB [13] is used to enhance domain-invariant feature learning integrates meta-learning with variational information bottleneck principles.
- DomainBed that provides strong domain generalization baselines and reproducible evaluation protocols is a standardized benchmark framework.

These benchmark datasets, evaluation metrics, and baseline methods collectively enable a rigorous assessment of the proposed Meta-Domain Adaptive Neural Architecture Search framework under diverse cross-domain learning scenarios [11], [21].

VII. Results and Discussion

A. Unseen Domain Accuracy

Method	PACS	VLCS	OfficeHome	DomainNet
DARTS	84.2	73.1	66.5	45.2
ENAS	84.8	73.5	67.4	45.8
MAML	86.1	75.6	69.2	47.4
MetaVIB	87.8	76.9	70.8	49.1
MDV-NAS	91.3	80.2	75.4	55.7

The proposed framework consistently outperforms existing methods across all datasets.

B. Domain Robustness Analysis

The discovered architectures demonstrating improved robustness against distribution shifts exhibit lower performance variance across domains.

C. Search Efficiency

The search cost remains manageable due to the differentiable optimization strategy, despite incorporating meta-learning.

D. Ablation Study

Without Domain Variance Estimator

Performance decreases by approximately 4–6%.

Without Meta-Learning

Performance decreases by approximately 7–9%.

Without Robustness Loss

Performance variance increases significantly across domains.

These results confirm the effectiveness of all proposed components.

VIII. Conclusion and Future Work

This paper introduced a novel framework that combines meta-learning, domain variance estimation, and neural architecture search, Meta-Domain Variant Neural Architecture Search (MDV-NAS), for robust cross-domain generalization. By incorporating a domain-aware robustness objective and treating domains as meta-learning tasks, the proposed method discovers architectures that generalize effectively to cross environments effectively. Experimental evaluations when compared with existing NAS and domain generalization approaches demonstrate superior performance. Future work will investigate federated MDV-NAS, multi-modal domain adaptation, and energy-aware architecture search for edge intelligence applications.

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Author Contributions (CRediT Taxonomy)

A. Sindhu Devi: Conceptualization, Methodology, Software Development, Formal Analysis, Investigation, Validation, Writing – Original Draft Preparation, Visualization.

Dr L. Godlin Atlas: Supervision, Methodology Validation, Technical Review, Research Guidance, Validation, Performance Evaluation, Writing – Review and Editing.

Data Availability Statement

The datasets utilized in this study are publicly available benchmark datasets widely used for domain generalization research. PACS, VLCS, Office-Home, and DomainNet datasets can be obtained from their respective official repositories. The implementation details, experimental configurations, and

hyperparameter settings used to generate the reported results are available from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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