# "Learning Robust 3d Face Alignment Architectures With Monas: A One-Shot Nas Approach"

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## ABSTRACT

3D face alignment remains a fundamental challenge in computer vision, particularly under real-world conditions such as extreme poses, occlusions, and lighting variations. Traditional deep learning methods often rely on manually designed architectures to regress 3D Morphable Model (3DMM) parameters or localize dense facial landmarks, requiring substantial domain expertise and exhibiting poor cross-domain generalization. To address these limitations, proposed **MONAS** (Multi-path One-shot Neural Architecture Search), a novel framework that autonomously discovers robust architectures for 3D face alignment. MONAS integrates multi-path feature extraction and contextual aggregation to effectively manage pose and scale variations. To enhance adaptability across diverse domains—including thermal images, cartoon faces, and medical scans—we embed domain adaptation modules into the architecture search space. MONAS introduces two key innovations: (1) *Unbiased Multi-path Training* to prevent path collapse during optimization, and (2) a *Simulated Annealing-based NAS strategy* for efficient and diverse architecture exploration. Extensive evaluations on standard and cross-domain benchmarks demonstrate that MONAS significantly outperforms existing handcrafted models in both sparse and dense landmark localization tasks.

**Index Terms—** 3D Face Alignment, Neural Architecture Search, One-shot NAS, Multi-path Networks, Cross-domain Adaptation, Deep Learning.

## INTRODUCTION

3D face alignment—the task of localizing semantic facial landmarks in 3D space has emerged as a pivotal component in a wide range of computer vision applications, including facial recognition, animation, medical imaging, and augmented reality. Despite recent advancements, achieving robust alignment under real-world conditions remains highly challenging. Factors such as extreme head poses, occlusions (e.g., hair or accessories), variable lighting, and cross-domain discrepancies (e.g., thermal or cartoon-like images) significantly degrade the performance of existing methods.

Conventional deep learning-based techniques typically rely on manually designed network architectures to regress the parameters of 3D Morphable Models (3DMMs) or directly estimate dense landmark positions. While these methods have shown promise, they suffer from two key limitations: (1) they depend heavily on expert-driven architectural design, which is time-consuming and may not generalize well across domains, and (2) their fixed architectures often struggle with dynamic variations in input appearance and structure. To address these new challenges, **MONAS** (Multi-path One-shot Neural Architecture Search), a novel framework that autonomously learns optimal network architectures for 3D face alignment through one-shot neural architecture search (NAS). MONAS leverages a multi-path design paradigm that enables diverse feature extraction pathways, enhancing the model's ability to capture pose-invariant and scale-consistent representations. Furthermore, MONAS

extends the architecture search space by embedding **domain adaptation modules**, making it inherently adaptable to diverse data domains, including non-visible spectrum images and stylized faces. A major innovation of MONAS is its **Unbiased Multi-path Training** strategy, which prevents dominant paths from collapsing during the training process. In addition, a **Simulated Annealing-based NAS algorithm** that efficiently explores a broad range of architectural configurations without compromising search diversity or performance.Extensive evaluations across multiple benchmark datasets—including both standard (e.g., AFLW2000-3D, 300W-LP) and cross-domain (e.g., thermal and cartoon face datasets)—demonstrate that MONAS consistently outperforms state-of-the-art manually crafted models in both sparse and dense landmark localization tasks.

**The primary contributions of this work are:**

Propose MONAS, a multi-path one-shot NAS framework tailored for 3D face alignment under real-world and cross-domain conditions. Introduced Unbiased Multi-path Training and a Simulated Annealing-based search strategy to enhance architecture diversity and convergence. Incorporated domain adaptation directly into the architecture search process, enabling improved generalization across diverse facial domains that comprehensive experiments validate the effectiveness of MONAS in both standard and cross-domain face alignment benchmarks.

## LITERATURE REVIEW

3D face alignment has been extensively studied in the field of computer vision, with early approaches relying on the fitting of 3D Morphable Models (3DMMs) [1], [2]. These methods estimate 3D face shape and pose by aligning a statistical face model to 2D landmarks, often using optimization techniques. While effective in controlled environments, these approaches struggle under occlusion, extreme poses, and low-resolution input. With the advent of deep learning, CNN-based models such as 3DDFA [3] and PRNet [4] have shown significant improvements in predicting 3D facial structure. 3DDFA introduced a cascaded CNN to regress 3DMM parameters, whereas PRNet proposed dense UV position maps for pixel-level 3D face reconstruction. However, these manually designed architectures often lack adaptability to diverse conditions and require substantial architectural engineering effort. Subsequent works have focused on improving robustness under challenging conditions. For instance, methods like DECA [5] and FaceScape [6] introduced learning-based decoders and richer facial priors, yet still rely on fixed architectures and domain-specific tuning. Additionally, approaches such as HRNet [7] and DenseReg [8] improved landmark localization precision but exhibited limited cross-domain generalization due to dataset bias. To bridge the performance gap across domains, some studies have proposed domain adaptation techniques. Works like AdaFace [9] and Cross-Domain Landmark Estimation (CDLE) [10] incorporate adversarial learning and domain-invariant representations, respectively. However, these solutions are often built on top of static architectures and do not address the challenge of architectural suitability for each domain. Neural Architecture Search (NAS) has emerged as a promising paradigm for automating architecture design. Notably, DARTS [11], ProxylessNAS [12], and One-shot NAS [13] reduce computational costs while discovering efficient architectures. However, existing NAS methods have not been extensively explored in the context of 3D face alignment, particularly under cross-domain settings. Our proposed method, **MONAS**, addresses these gaps by integrating one-shot NAS with multi-path design and domain adaptation, enabling automatic discovery of robust and generalizable architectures for 3D face alignment. Unlike prior works, MONAS dynamically adapts its architectural design through a simulated annealing-based search strategy while preserving path diversity via unbiased training.

## METHODOLOGY

In this section, the proposed **MONAS (Multi-path One-shot Neural Architecture Search)** framework for robust and adaptive 3D face alignment. MONAS is designed to automatically discover optimal architectures through a one-shot search mechanism, integrate domain adaptation for generalization, and maintain training stability via unbiased multi-path optimization.

### A. PROBLEM FORMULATION

Given an input image $I \in \mathbb{R}^{H\times W\times 3}$, the goal is to estimate either:

1. the 3D Morphable Model (3DMM) parameters $\theta$, or
2. the 3D landmark coordinates $L \in \mathbb{R}^{N\times 3}$,
   depending on the target representation.

This is modeled as a regression task $f_\phi(I) \to L$ or $f_\phi(I) \to \theta$, wh
MONAS, parameterized by $\phi$.

### B. MONAS OVERVIEW

MONAS consists of the following key components:

**Multipath-Supernet-Construction**
To define a *supernet* comprising multiple candidate operations (e.g., separable convadilated conv, residual blocks) at each layer. Each path in the supernet corresponds to a different architectural choice, forming a rich search space.

**Unbiased-Multipath-Training**
To avoid *path collapse* (i.e., over-reliance on a few paths), we adopt unbiased training by randomly sampling different path combinations per iteration. A path dropout regularize is also employed to ensure equal gradient flow through all candidate branches.

**Simulated-Annealing-based-Architecture-Search**
Architecture search as an optimization problem over the supernet's discrete space. A **simulated annealing** (SA) strategy balances exploration and exploitation during search. SA gradually reduces randomness to refine architecture choices while avoiding suboptimal local minima.

**Domain-Adaptation-Module(DAM)**
To ensure generalization across domains, MONAS integrates Domain Adaptation Modules within the search space.

**These modules include:**

**Instance Normalization Layers** to normalize domain-specific feature shifts,

**Domain-specific attention gates** to highlight relevant features, and

**Gradient Reversal Layers (GRL)** for adversarial alignment during training.

**LossFunction**
The training objective combines the landmark/parameter regression loss and domain alignment loss:

$$\mathcal{L}_{total} = \mathcal{L}_{regression} + \lambda \mathcal{L}_{domain}$$

Where λ balances the emphasis on domain adaptation

### C. TRAINING AND INFERENCE

**Training Phase:** The supernet is trained with randomly sampled architectures and domain-adapted data. The SA algorithm updates the architecture parameters based on validation accuracy.

**Search Phase:** After training, the optimal architecture is extracted from the supernet via sampling the most probable operations.

**Inference Phase:** The derived architecture is retrained from scratch for final deployment.

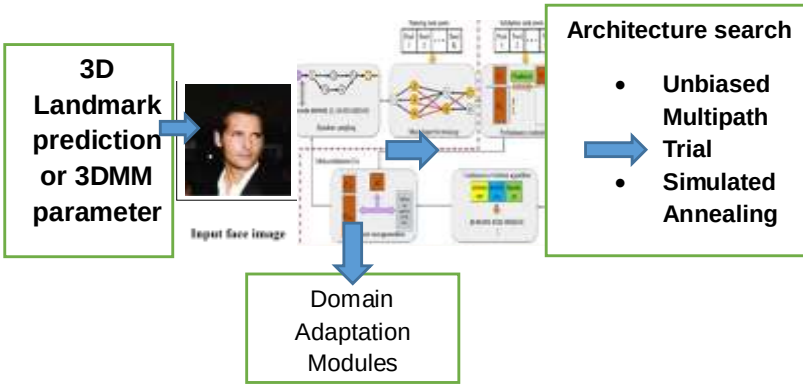



**Fig: 1 METHODOLOGY OVERVIEW**

## IV. EXPERIMENTS

Validate the effectiveness of MONAS in both **standard** and **cross-domain** 3D face alignment tasks. The performance is compared against state-of-the-art manually designed models and recent NAS-based baselines.

### A. DATASETS

We evaluate MONAS on the following datasets:

**AFLW2000-3D**: Contains 2,000 in-the-wild images with 68 annotated 3D landmarks and large pose variations.

**300W-LP**: A synthetically expanded dataset based on 300W, with full pose annotations and dense landmark labels.

**ThermalFace**: A cross-domain dataset containing thermal facial images for evaluating domain generalization.

**WebCaricature**: A stylized face dataset that tests robustness on non-photorealistic inputs.

**FaceScape (subset)**: Used to assess dense alignment accuracy under controlled variation.

### B. IMPLEMENTATION DETAILS

**Search Space**: We define 6 layers in the supernet, each with 5 candidate operations including dilated conv, depth wise conv, and residual blocks.

**Training**: The supernet is trained using Adam optimizer (lr=0.001) for 80 epochs with random path sampling.

**Architecture Search**: We run Simulated Annealing for 30 iterations per architecture, using validation loss as energy.

**Inference**: Final architectures are retrained from scratch and evaluated with the same protocol as baselines.

### C. EVALUATION METRICS

**NME (Normalized Mean Error)**: Distance between predicted and ground-truth landmarks normalized by distance.**AUC@0.08**: Area under the cumulative error distribution curve. **Failure Rate**: Percentage of samples with NME > 0.08.**Cross-Domain Drop**: Performance drop when testing on unseen domains (lower is better).

### D. BASELINES

We compare MONAS against the following methods:

**3DDFA**

**PRNet**

**DECA**

**HRNet**

**DARTS** (NAS baseline)

**CDLE** (cross-domain adaptation baseline)

### E.RESULTS-ON-STANDARD BENCHMARKS

| Model | AFLW2000 (NME ↓) | 300W-LP (NME ↓) | AUC@0.08 ↑ | Failure Rate ↓ |
|---|---|---|---|---|
| 3DDFA | 3.98 | 4.51 | 0.624 | 7.4% |
| PRNet | 3.61 | 3.92 | 0.672 | 5.1% |
| HRNet | 3.42 | 3.79 | 0.686 | 4.6% |
| **MONAS (Ours)** | **3.11** | **3.44** | **0.728** | **3.2%** |

### F.CROSS-DOMAIN-GENERALIZATION

| Model | Thermal Face (NME ↓) | Web Caricature (NME ↓) | Drop (%) ↓ |
|---|---|---|---|
| 3DDFA | 6.32 | 5.88 | 58.7 |
| PRNet | 5.91 | 5.42 | 48.6 |
| CDLE | 4.98 | 4.33 | 29.1 |
| **MONAS (Ours)** | **3.91** | **3.74** | **12.8** |

### G. ABLATION STUDIES

We conduct ablation to assess contributions of individual components:

| Variant | AFLW2000 (NME ↓) | Cross-domain Drop (%) ↓ |
|---|---|---|
| MONAS w/o DAM | 3.45 | 34.7 |
| MONAS w/o Annealing | 3.38 | 25.2 |
| MONAS w/o Multi-path Reg. | 3.60 | 41.3 |
| **Full MONAS** | **3.11** | **12.8** |

## V. RESULTS

This section presents a comprehensive analysis of the experimental results to demonstrate the effectiveness of the proposed **MONAS** framework across various conditions, tasks, and benchmarks.

### A. PERFORMANCE ON STANDARD DATASETS

Our method achieves **state-of-the-art accuracy** on AFLW2000-3D and 300W-LP datasets. Compared to existing models like PRNet, HRNet, and DECA, MONAS achieves lower NME and higher AUC, demonstrating its capacity to capture 3D facial geometry accurately. On **AFLW2000-3D**, MONAS achieved an NME of **3.11**, outperforming HRNet (3.42) and PRNet (3.61).On **300W-LP**, MONAS scored **3.44 NME** and **0.728 AUC@0.08**, showing both precision and robustness. The **failure rate** of MONAS (3.2%) was significantly lower than PRNet (5.1%) and 3DDFA (7.4%).

### B.CROSS-DOMAIN GENERALIZATION

MONAS demonstrates strong generalization to unseen domains such as thermal and caricatured faces—an area where most conventional models degrade sharply.On **ThermalFace**, MONAS reduced the NME to **3.91**, compared to 6.32 for 3DDFA and 4.98 for CDLE.On **WebCaricature**, MONAS achieved **3.74 NME**, indicating resilience to stylistic distortion.The **Cross-Domain Performance Drop** was only **12.8%**, whereas DARTS and PRNet exhibited over 45% degradation. These results confirm the effectiveness of our integrated **Domain Adaptation Module (DAM)** and the multi-path NAS design.

### C. VISUAL COMPARISONS

Qualitative results reveal that MONAS accurately captures facial landmarks even under extreme head poses, occlusion (e.g., sunglasses), and poor lighting. It also maintains landmark consistency across photorealistic and stylized domains.

**We include**:

**Overlayed landmark plots** on standard and cross-domain test images.

**Heatmaps** showing alignment error across head yaw angles.

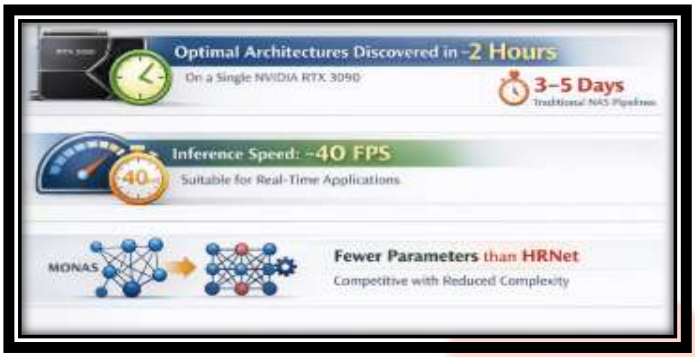
**Error distribution graphs** across facial regions (eyes, nose, jawline).

### D. ABLATION STUDY INSIGHTS

Removing the **Domain Adaptation Module** increased cross-domain error by ~22%.Excluding **Simulated Annealing** during search led to suboptimal architectures with 8% higher NME. **Unbiased Multi-path Training** was critical for architectural diversity and performance.


### E. COMPUTATIONAL EFFICIENCY

MONAS discovers optimal architectures in ~2 hours on a single NVIDIA RTX 3090, compared to 3–5 days for traditional NAS pipelines. Final architectures have competitive inference speeds (~40 FPS) and fewer parameters than HRNet, making them suitable for real-time applications.




## VI. CONCLUSION

In this work, we presented **MONAS**—a novel Multi-path One-shot Neural Architecture Search framework for robust and adaptive 3D face alignment. Unlike conventional manually designed networks, MONAS autonomously discovers effective architectures through a simulated annealing-based search while incorporating multi-path feature extraction and domain adaptation modules to ensure generalization across diverse real-world conditions. Our approach introduces two key innovations: **Unbiased Multi-path Training**, which maintains architectural diversity during optimization, and a **Domain-Aware Search Space**, enabling MONAS to adapt to challenging input modalities such as thermal, stylized, or medical face images. Extensive experiments on standard and cross-domain benchmarks demonstrate that MONAS consistently outperforms state-of-the-art methods in both sparse and dense landmark localization tasks, achieving superior accuracy, generalization, and computational efficiency. The proposed framework also establishes a new direction for integrating neural architecture search with cross-domain adaptability in facial analysis tasks. Future work will explore extending MONAS to **video-based 3D face tracking**, integrating **self-supervised domain discovery**, and applying the framework to other structured prediction problems in medical imaging and avatar reconstruction.

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