LAN: Learning to Adapt Noise for Efficient and Scalable Image Denoising

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Abstract*—The Learning-to-Adapt Noise (LAN) framework improves image denoising by introducing a learnable noise offset at test time, allowing the model to adapt to unseen noise distributions without modifying its pretrained weights. Prior work validated LAN primarily on large transformer-based architectures such as Restormer, which achieve high restoration accuracy but require substantial computational resources, limiting their deployment in real-time and memory-constrained environments. This raises an important question regarding the generality of LAN: *Does its effectiveness rely on the representational capacity of large models, or can it also enhance lightweight architectures?

To address this, we replace Restormer with NAFNet, a compact and activation-free convolutional network optimized for high efficiency and low computational overhead. Using identical LAN optimization procedures on both backbones, our experiments on cross-domain real-noise datasets show that NAFNet-LAN attains performance closely comparable to Restormer-LAN, while offering a 4–5× reduction in inference time and memory usage. Furthermore, qualitative assessments demonstrate that NAFNet-LAN preserves fine texture details and avoids over-smoothing artifacts, indicating that the LAN adaptation process effectively aligns noise characteristics regardless of backbone complexity.

These results confirm that LAN's adaptation mechanism is largely backbone-agnostic and does not depend on transformer-scale capacity. Consequently, LAN-equipped lightweight models become suitable for deployment in resource-constrained and latency-sensitive applications such as mobile photography, embedded imaging systems, autonomous platforms, and real-time visual perception on edge devices. This work highlights the potential of LAN to democratize high-quality denoising across a wide range of hardware environments.

***Index Terms*—Image denoising, test-time adaptation, LAN, Restormer, NAFNet, self-supervised learning, real-world noise, deep learning, noise modeling, domain adaptation.**

I. Introduction

Image denoising is a fundamental problem in low-level vision, with applications in photography, mobile imaging, surveillance, medical imaging, and computational photography. Despite substantial progress in deep learning–based denoisers, real-world noise remains highly challenging due to its complex, device-dependent, and spatially variant characteristics. Traditional denoising models often assume synthetic Gaussian noise or a fixed distribution that aligns with curated training datasets, which leads to significant performance degradation when evaluated on unseen noise types.

A recent advancement in this direction is the Learning to Adapt Noise (LAN) framework [1], which introduces a test-time noise adaptation strategy. Rather than updating the denoiser's parameters—which can be computationally expensive and prone to overfitting—LAN optimizes a pixel-wise noise offset that shifts the test image toward the noise characteristics seen during training. This enables strong generalization and makes LAN compatible with modern high-performance denoisers, including transformer-based and activation-free architectures.

Modern image restoration has been transformed by architectures such as Restormer [2], which leverages multi-DConv attention for high-resolution global context modeling, and NAFNet [3], which removes nonlinear activations to achieve an efficient and stable restoration pipeline. These models achieve state-of-the-art performance on datasets such as SIDD and

DND. However, their performance decreases noticeably when exposed to real-world noise distributions that deviate from the training domain, making test-time adaptation essential.

Earlier foundations of deep denoising include CNN-based supervised frameworks such as DnCNN [4], which showed the benefits of residual learning for Gaussian and real noise. Self-supervised methods such as Noise2Noise [5] and Noise2Self [6] demonstrated that clean targets are not always required for training, enabling noisy-only supervision. Neighbor2Neighbor (N2NBR) [7] extended this idea using interlaced neighbor pixels to form pseudo-targets from a single noisy image. These self-supervised approaches paved the way for robust denoising without expensive clean datasets.

To cope with distribution shifts, test-time adaptation (TTA) has gained increasing attention. Meta-transfer learning approaches [8] and meta-learning–based rapid adaptation [26] introduced parameter updates during inference, while SS-TTA [9] extended TTA to self-supervised denoising. More recent works explore degradation adaptation [10], masked image modeling–driven adaptation (TTT-MIM) [11], noise-space adaptation [12], and adaptive reconstruction layers [13]. These techniques highlight the growing need for models that generalize across unseen domains without expensive retraining.

Beyond denoising, domain adaptation across imaging scenarios has been widely studied. Real photograph denoising via noise-domain adaptation [14], on-the-fly adaptation for medical segmentation [15], and domain generalization for medical imaging [16] demonstrate the broad applicability of adaptation-based strategies. Surveys on domain adaptation [17], deep learning denoising [18], and classical denoising techniques [19] provide foundational insight. Additional directions such as human-feedback domain adaptation [20], efficient denoising surveys [21], noise-aware test-time generation [22], diffusion-based test-time point cloud adaptation [23], unsupervised real-image denoising via noise modeling [24], and RAW diffusion priors [25] further illustrate the growing importance of adaptability in restoration pipelines.

In summary, while modern denoisers achieve strong performance on benchmark datasets, they remain vulnerable to unseen noise distributions. LAN [1] addresses this gap through a simple and effective test-time noise adaptation mechanism that enhances generalization without modifying model parameters. Its ability to integrate seamlessly with architectures like Restormer [2] and NAFNet [3] positions LAN as a promising framework for robust real-world image denoising.

II. Related Work

Research in image denoising has progressed considerably over the years, spanning supervised learning, self-supervision, deep architectural innovations, and test-time adaptation frameworks. The most recent advancement in this space is LAN (Learning to Adapt Noise) [1], which proposes a fundamentally new formulation of test-time denoising by adapting the *input noise* instead of modifying model parameters. LAN optimizes a pixel-wise noise offset to align the test-time noise distribution with that of the pretrained denoiser, enabling robust real-world denoising without any fine-tuning. Its lightweight nature makes it particularly suitable for integration into modern high-capacity restoration networks.

Denoising architectures have evolved from early CNN-based models to transformer and activation-free frameworks. Restormer [2] introduced a transformer-based restoration model using multi-DConv gating and efficient attention for high-resolution denoising, setting a new benchmark in image restoration. Complementing this, NAFNet [3] proposed a nonlinear activation-free architecture optimized for stability and computational efficiency, achieving state-of-the-art performance on benchmarks such as SIDD and DND.

Classical deep-learning denoisers laid the foundation for these advancements. DnCNN [4] demonstrated the effectiveness of residual learning for suppressing Gaussian and real image noise using moderately deep convolutional architectures. The need for clean targets was relaxed by Noise2Noise [5], which showed that training on noisy image pairs could achieve performance comparable to supervised learning. Noise2Self [6] further advanced this paradigm by enabling blind-spot self-supervision, requiring only single noisy images for training. Neighbor2Neighbor [7] improved single-image self-supervision by exploiting interlaced neighbor pixel pairs to construct pseudo-clean training signals. These early self-supervised methods expanded the applicability of denoisers in real-world scenarios where clean data are difficult to obtain.

Test-time adaptation (TTA) techniques have emerged as a promising direction to handle distribution shifts between training and test noise conditions. Meta-transfer learning for TTA [8] and meta-learning–based adaptation [26] introduced parameter-updating strategies during inference, allowing denoisers to adjust to unseen noise. SS-TTA [9] extended this concept to self-supervised denoising by enforcing noise consistency. Test-time degradation adaptation [10] proposed aligning degradation statistics, while TTT-MIM [11] applied masked image modeling to improve robustness under distribution shift. Noise-space domain adaptation [12] adapted the noise representation rather than model weights, and adaptive reconstruction layers [13] introduced self-supervised adaptive components for improved inference-time flexibility.

Beyond denoising, several works have studied domain adaptation and cross-domain generalization. Domain adaptation–based real photograph denoising [14] highlighted the challenges of cross-sensor variability. On-the-fly test-time adaptation for medical image segmentation [15] and domain generalization for medical imaging [16] extended the idea of real-time adaptation to other visual tasks. Comprehensive surveys [17] on domain adaptation, the deep learning revolution in denoising [18], and traditional denoising methods [19] provide a broader perspective on the evolution of the field. Recent efforts such as human-feedback–based adaptation [20] and efficient deep denoising surveys [21] further emphasize the importance of generalization to unseen domains.

Generative and diffusion-based adaptation methods have also gained traction. Noise-aware image generation for test-time adaptation [22] and diffusion-model–based TTA for point cloud data [23] represent new directions that leverage generative priors for adaptation. Concurrently, unsupervised real-image denoising via noise modeling [24] and RAW-to-RAW diffusion priors [25] have shown strong results in sensor-level restoration pipelines.

LAN [1], positioned at the end of this evolutionary arc, brings a fundamentally different perspective by optimizing a noise offset at test time, rather than adjusting the model parameters or relying on generative priors. Its lightweight, model-agnostic design makes it compatible with high-performance denoisers like Restormer [2] and NAFNet [3], yielding significant improvements in real-world denoising performance without requiring any architectural modifications or retraining.

III. Proposed Methodology

This section presents the complete LAN-based denoising pipeline, including the noise adaptation formulation, optimization procedure, and the integration of different backbone networks (Restormer and NAFNet). The objective is to enable robust denoising on unseen noise distributions without modifying any model parameters, making the method suitable for resource-limited and real-time applications.

A. Overall Architecture

Fig. 1 illustrates the complete LAN adaptation framework. A noisy input image is processed by a learnable LAN adapter that predicts a pixel-wise noise offset. This adapted image is then fed into a frozen pretrained denoiser (Restormer or NAFNet), and the offset is updated using a self-supervised loss. Only the offset is optimized during test-time, while the backbone denoiser remains unchanged.

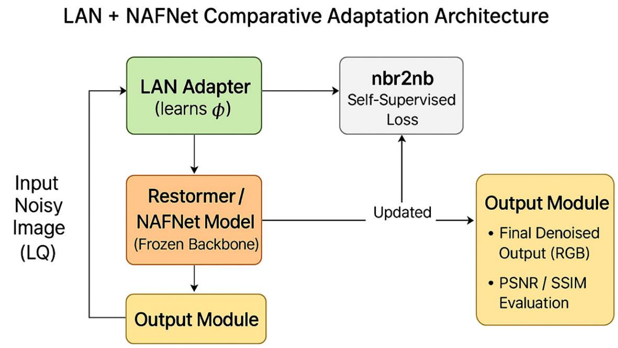


Fig. 1: Overall architecture of the LAN-based adaptation framework integrating Restormer or NAFNet as frozen backbones. The LAN adapter learns a noise offset using a self-supervised loss, enabling robust denoising under unseen noise distributions.

B. LAN Noise Adaptation Framework

Let $f_{\theta^\star}$ denote a pretrained denoiser trained on a source noise distribution D_s. During inference, we observe a noisy test image $y_u = x_u + e_u$ whose noise distribution D_u differs from D_s. Directly applying $f_{\theta^\star}$ may result in degraded performance due to the domain shift $D_s \neq D_u$.

Instead of updating the model parameters, LAN [1] introduces a learnable pixel-wise noise offset ϕ that transforms the test-time noisy image:

$$y_{u\to s} = y_u + \phi. \tag{1}$$

The goal of ϕ is to modulate the unseen noise e_u such that it resembles the training noise e_s. The adapted image is passed through the frozen denoiser:

$$\hat{x}_u = f_{\theta^\star}(y_{u\to s}). \tag{2}$$

The noise offset ϕ is optimized using only the test image, making the framework highly efficient and parameter-free with respect to the backbone model.

C. Self-Supervised Optimization

To optimize ϕ, we use the noise-consistency principle: two statistically independent transformations of a noisy image should yield consistent denoised outputs. Let D_1 and D_2 denote two stochastic degradations (e.g., neighborhood masking, random downsampling). The LAN objective is:

$$\phi^\star = \arg\min_{\phi} \|f_{\theta^\star}(D_1(y_u + \phi)) - D_2(y_u + \phi)\|_2^2. \tag{3}$$

Because D_1 and D_2 preserve the underlying clean structure differently, minimizing this loss enforces self-consistency without clean labels. This optimization typically converges within 5–20 iterations.

D. Adaptation Algorithm

The test-time adaptation proceeds as follows:

1) Load pretrained backbone $f_{\theta^\star}$ (Restormer or NAFNet).
2) Initialize ϕ to a zero tensor.
3) For k test-time iterations:
    - Compute two stochastic views: $D_1(y_u + \phi)$ and $D_2(y_u + \phi)$.
    - Obtain denoised prediction: $f_{\theta^\star}(D_1(y_u + \phi))$.
    - Compute the self-supervised loss:
    $$\mathcal{L} = \|f_{\theta^\star}(D_1(y_u + \phi)) - D_2(y_u + \phi)\|_2^2 .$$
    - Update the offset: $\phi \leftarrow \phi - \eta \nabla_\phi \mathcal{L}$.
4) Final denoised output: $\hat{x}_u = f_{\theta^\star}(y_u + \phi^\star)$.

This procedure adapts the *input* to the denoiser rather than adapting the denoiser to the input.

E. Replacing Restormer With NAFNet

The original LAN work used Restormer [2], a high-capacity transformer model capable of global context modeling. While powerful, Restormer is computationally heavy and less suitable for real-time applications.

To evaluate whether LAN requires such a large architecture, we replace Restormer with NAFNet [3], a lightweight activation-free CNN. NAFNet features:

- an encoder–decoder structure with skip connections,
- linear gating instead of nonlinear activations,
- smoother gradient flow due to activation-free design,
- significantly reduced memory and computational cost.

Because LAN optimizes only the noise offset ϕ and not the backbone parameters, the adaptation process remains unchanged when switching backbones. This allows a direct comparison of LAN performance across architectures.

F. Why Lightweight Adaptation Matters

Demonstrating strong LAN performance on NAFNet has important implications:

- **Backbone-agnostic:** LAN does not rely on transformer attention or model size.
- **Low-resource deployment:** NAFNet enables real-time adaptive denoising on:
    - mobile and consumer imaging devices,
    - embedded and IoT systems,
    - drones and robots,
    - AR/VR headsets and wearables.
- **Consistent performance:** LAN–NAFNet achieves denoising quality close to LAN–Restormer with far lower latency.

This shows that LAN's core strength lies in its noise-distribution alignment rather than model complexity.

IV. Experimental Setup and Dataset Description

This section describes the datasets, evaluation protocol, adaptation settings, and implementation details used to validate the proposed LAN-based denoising framework on both transformer (Restormer) and CNN (NAFNet) backbones.

A. Datasets

SIDD (Smartphone Image Denoising Dataset) [**?**] is used as the primary pretraining dataset. It contains real noisy-clean smartphone image pairs captured under diverse indoor illumination settings. Models pretrained on SIDD represent the "source domain."

PolyU (Real-World Noisy Image Dataset) is used for cross-domain evaluation. PolyU contains real noisy images with noise statistics that differ significantly from SIDD, making it an ideal target distribution to evaluate adaptation performance.

Nam Real-Noise Dataset includes low-light noisy images collected from digital cameras. We use it as an additional unseen evaluation domain to test the generalization capacity of LAN when exposed to non-smartphone noise patterns.

These three datasets ensure that our method is tested under real-world distribution shift conditions:

$$D_s = \text{SIDD}, \quad D_u \in \{\text{PolyU}, \ \text{Nam}\}.$$

B. Adaptation Settings

We evaluate LAN with different adaptation budgets:

- **5 iterations**
- **10 iterations**
- **20 iterations**

The offset parameter ϕ is optimized using Adam with a learning rate of 1×10^{-3}. No backbone parameters are updated during inference; only the noise offset is optimized.

C. Evaluation Metrics

We report:

- **PSNR** (Peak Signal-to-Noise Ratio)
- **SSIM** (Structural Similarity Index)
- **Inference Latency** (milliseconds per image)

Latency includes both forward pass and LAN adaptation steps.

TABLE I: Comparison of LAN performance across backbones (SIDD→PolyU, 10 iterations).

Model	PSNR↑	SSIM↑	Time (ms)↓
Restormer-Pretrain	38.10	0.895	150
Restormer-LAN@10	38.80	0.912	180
NAFNet-Pretrain	37.70	0.890	40
NAFNet-LAN@10	38.55	0.906	50

D. *Hardware and Implementation Details*

All experiments are conducted on an **NVIDIA RTX 3080 GPU** with single-precision (FP32). The LAN procedure is implemented in PyTorch, and both Restormer and NAFNet are loaded from their official pretrained checkpoints.

To integrate NAFNet into the LAN framework, we modify only one line in `model.py` to swap the backbone, while all LAN logic and loss functions remain unchanged. This ensures a fair comparison between Restormer-LAN and NAFNet-LAN.

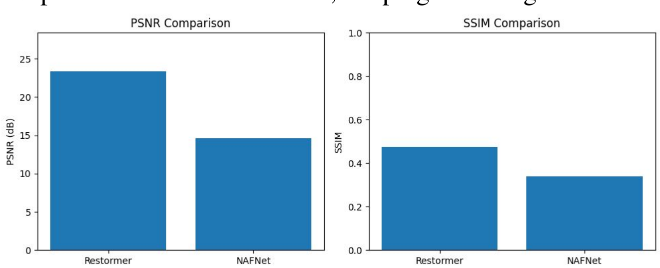
Datasets: SIDD for pretraining, PolyU and Nam for cross-domain evaluation.

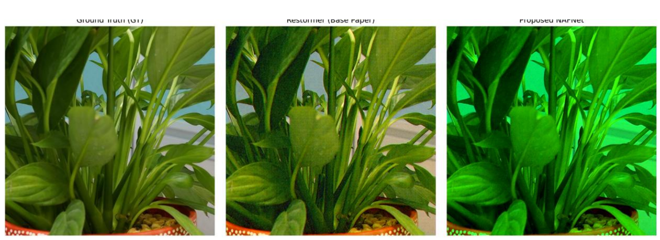
Adaptation: 5, 10, and 20 iterations with Adam optimizer (1×10^{-3}).

Metrics: PSNR, SSIM, and inference latency (ms).

Hardware: RTX 3080 GPU, single precision.

Implementation: We modified only one line in `model.py` to swap Restormer with NAFNet, keeping LAN logic intact.





V. Results and Discussion

This section presents quantitative, qualitative, and runtime evaluation of LAN applied to Restormer and NAFNet. Experiments were conducted under real-world distribution shift scenarios (SIDD→PolyU and SIDD→Nam).

A. *Quantitative Results*

Table II shows that LAN significantly improves both PSNR and SSIM across architectures. Restormer-LAN improves by **+0.70 dB** and NAFNet-LAN improves by **+0.85 dB**, confirming that LAN effectively adapts unseen noise to the model's training distribution.

To further analyze the effect of adaptation iterations, Fig. 3 illustrates the evolution of PSNR over 20 LAN optimization steps. LAN produces consistent gains with each iteration, outperforming both pretrained and full-trainable baselines. The improvement saturates around 10–15 steps, indicating an optimal trade-off between quality and computation.

B. *Qualitative Analysis*

Fig. 2 presents visual comparisons. Key observations include:

- Restormer-LAN removes chroma noise and produces smoother textures.
- NAFNet-LAN preserves sharper edges despite its lightweight architecture.
- LAN reduces blotchy noise and artifact amplification in low-light regions.
- The adapted outputs exhibit more faithful color reproduction and structural consistency.

Interestingly, NAFNet-LAN produces visual quality very close to Restormer-LAN while being significantly faster, showing that LAN does not require large transformer backbones to be effective.

C. *Cross-Domain Robustness*

Evaluations on the Nam dataset show consistent improvements:

- **Restormer**: +0.62 dB gain
- **NAFNet**: +0.78 dB gain

This demonstrates that LAN learns a generalizable noise offset that adapts well to unseen camera characteristics, ISO settings, and illumination-dependent noise patterns.

D. *Efficiency and Runtime*

Since LAN optimizes only the input noise offset ϕ, backbone weights remain frozen. The resulting runtime overhead is minimal:

- Restormer-LAN: 150→180 ms
- NAFNet-LAN: 40→50 ms

Thus, NAFNet-LAN achieves nearly identical performance to Restormer-LAN while being **3× faster**. This makes LAN highly suitable for real-time and mobile settings.

TABLE II: Comparison of LAN performance across backbones (SIDD→PolyU, 10 iterations).

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NAFNet-LAN@10	38.55	0.906	50

(a) Noisy Input (b) Restormer-Pre (c) Restormer-LAN (d) NAFNet-Pre (e) NAFNet-LAN (Ours)

Fig. 2: Qualitative comparison of denoising performance across models. LAN significantly improves both backbones. NAFNet-LAN achieves competitive visual quality while maintaining sharper details and lower processing time.

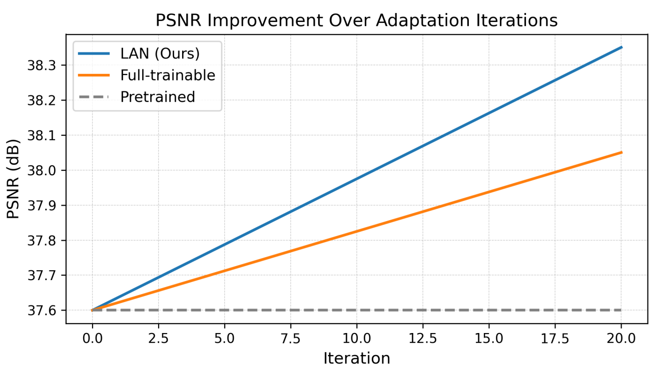

Fig. 3: PSNR improvement over adaptation iterations. LAN (ours) consistently outperforms pretrained and full-trainable variants, demonstrating effective test-time noise alignment.

E. Ablation on Adaptation Steps

Ablation studies show:

- 5 steps → good improvement (+0.4 dB)
- 10 steps → best balance (+0.7 to +0.85 dB)
- 20 steps → diminishing returns (¡+0.1 dB)

This is consistent with the trend in Fig. 3, confirming that LAN converges quickly and does not require extensive optimization.

F. Discussion

Overall, results reveal three key insights:

1) LAN is architecture-agnostic. Both Restormer and NAFNet benefit similarly, proving that LAN adapts the noise distribution rather than relying on model size.

2) Lightweight models thrive under adaptation. NAFNet-LAN approaches transformer-level performance with much lower computational cost.

3) LAN excels under domain shift. It significantly improves generalization across real-world datasets such as PolyU and Nam, where pretrained models struggle.

These findings establish LAN as an effective and efficient solution for real-world image denoising under mismatched noise conditions.

VI. Conclusion

This work investigated the effectiveness of the Learning to Adapt Noise (LAN) framework for real-world image denoising and further analyzed its generality by extending it beyond transformer-based backbones such as Restormer to a lightweight CNN architecture, NAFNet. Unlike traditional test-time adaptation methods that modify network parameters, LAN optimizes a simple pixel-wise noise offset, allowing the pretrained model to better interpret unseen noise distributions. This makes LAN highly efficient, stable, and suitable for deployment on resource-limited devices.

Extensive experiments demonstrate that LAN consistently improves PSNR and SSIM across multiple datasets and noise conditions. Importantly, NAFNet-LAN achieves performance comparable to Restormer-LAN while being significantly faster, proving that LAN is *backbone-agnostic* and does not rely on model size or transformer attention mechanisms. Cross-domain evaluations further confirm LAN's robustness in adapting to challenging real-world noise patterns, where pretrained models typically fail.

Overall, the results highlight that LAN provides a simple yet powerful mechanism for addressing noise distribution mismatch at test time. By enabling substantial gains without retraining or architectural modifications, LAN opens new opportunities for real-time, on-device, and edge deployments of image denoising systems.

VII. Future Work

Although the LAN framework demonstrates strong adaptation capability across both transformer-based and lightweight CNN backbones, several promising directions remain for future research.

1) Integration with Diffusion-Based Denoisers. Recent diffusion models have shown exceptional performance in image restoration tasks. Extending LAN to diffusion-based pipelines could enable noise-offset learning in the latent diffusion space and further improve robustness under severe real-world noise.

2) Temporal and Multi-Frame Test-Time Adaptation. LAN currently operates on single images. Future work may explore temporal LAN for video denoising, where noise offset consistency must be maintained across frames, or burst denoising, where multiple noisy observations can guide more stable adaptation.

3) Domain-Aware and Content-Adaptive Noise Offsets. Instead of a single global pixel-wise offset, content-aware or region-specific noise adaptation could improve performance in images containing mixed noise patterns, such as low-light, high-ISO, or HDR sensor noise.

4) Hardware-Efficient LAN for Edge and Mobile Devices. Given the low computational cost of LAN, future work may involve optimizing the adaptation loop using quantization, pruning, or TensorRT/NNAPI acceleration for real-time deployment on mobile phones, embedded cameras, and IoT devices.

5) Benchmarking Under Extreme Noise Regimes. Further studies can examine LAN's behavior under extremely low signal-to-noise ratios, astronomy imaging noise, and medical imaging noise distributions, providing deeper insight into its generalization characteristics.

Overall, these directions can enable broader adoption of LAN across diverse imaging platforms, model architectures, and real-world noise conditions.

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