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EDCST-Rain: Enhanced Density-Aware Cross-Scale Transformer for Robust Object Classification Under Diverse Rainfall Conditions

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ABSTRACT

Rain degradation significantly impairs object classification systems, causing accuracy drops of 40-60% under severe conditions and limiting autonomous vehicle deployment. While preprocessing approaches attempt deraining before classification, they suffer from error propagation and computational overhead. This paper introduces EDCST-Rain, an Enhanced Density-Aware Cross-Scale Transformer specifically designed for robust classification under diverse rain conditions. The architecture consists of five integrated components: a Rain Density Encoding Module that captures rain streak density, accumulation, and orientation; a Swin-Tiny Backbone for hierarchical feature extraction; and three rain-specific mechanisms: directional attention modules adapting to rain streak orientation, accumulation-aware processing handling lens droplet distortions, and adaptive cross-scale fusion integrating multi-resolution information. We develop a comprehensive physics-based rain simulation framework covering four rain types (drizzle, moderate, heavy, storm) and implement a curriculum learning strategy that progressively introduces rain complexity during training. Extensive experiments on CIFAR-10 demonstrate that EDCST-Rain achieves 83.1% clean accuracy while maintaining 71.8% under severe rain (86.4% retention), representing a 10-percentage-point improvement over state-of-the-art methods. With 15.8 million parameters and a 14.3 ms GPU inference time, enabling real-time operation, EDCST-Rain provides a practical, weather-robust perception framework suitable for autonomous systems operating under adverse weather conditions.

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I. INTRODUCTION

Computer vision systems have become foundational to modern autonomous technologies, powering self-driving vehicles, outdoor robotics, and intelligent surveillance systems. However, these systems face a critical vulnerability: their performance degrades dramatically under adverse weather conditions, particularly rainfall. Recent benchmarking studies reveal that standard deep learning models suffer accuracy drops of 40-60% when confronted with rain-degraded images [1, 2], severely limiting the reliability and deployment of autonomous systems in real-world scenarios where weather conditions are unpredictable and often challenging.

Rain introduces a uniquely complex set of visual degradations that fundamentally differ from other atmospheric phenomena. Unlike fog's smooth depth-

dependent attenuation [3] or snow's uniform particle distribution, rain creates multiple simultaneous challenges. Falling raindrops travel at velocities of 2-9 m/s, creating oriented streak occlusions with diagonal patterns across images [4]. Droplets accumulating on camera lenses produce severe localized distortions through refraction and blur [5]. Atmospheric scattering reduces overall scene contrast and visibility [6], while dynamic lighting variations from rapidly changing cloud cover further complicate the scene. Each raindrop acts as a semi-transparent occluder, partially blocking object features while simultaneously introducing motion blur and spectral alterations [7]. These multifaceted degradations occur simultaneously and interact in complex ways, making rain one of the most challenging weather conditions for robust computer vision.

Research addressing rain-degraded images has evolved along three main trajectories: preprocessing-based deraining, robust feature learning, and weather-aware architectures. Each approach has yielded progress, yet significant gaps persist that motivate our work. The dominant paradigm involves a two-stage pipeline: first restore the image by removing rain, then classify the cleaned result. Early work by Garg and Nayar [4] established foundational understanding of rain's photometric properties, revealing that rain streaks exhibit predictable orientations determined by wind velocity and gravity [8]. Traditional methods relied on hand-crafted priors such as dictionary learning [9] and sparse coding [10]. The dark channel prior [11] for dehazing inspired analogous rain removal approaches, though rain's directional nature required different formulations.

Deep learning transformed deraining research dramatically. Li et al. [12] proposed RESCAN with recurrent architectures and squeeze-and-excitation attention, achieving impressive visual quality. Yang et al. [13] advanced joint detection and removal networks. Recently, transformer-based approaches emerged: Restormer [14] leverages multi-head self-attention for long-range dependencies, while Uformer [15] combines transformers' global receptive fields with hierarchical processing. Zhang et al. [16] developed multi-stage knowledge learning for adverse weather removal. However, preprocessing suffers three fundamental limitations for classification tasks. First, deraining networks optimize for perceptual similarity metrics (PSNR, SSIM [17]) rather than classification accuracy, creating an objective misalignment where improving image appearance does not necessarily improve recognition performance. A 3dB PSNR improvement may yield only 1-2% classification gains, and aggressive deraining can remove semantically important edges and textures. Second, the two-stage pipeline introduces error propagation where deraining failures directly corrupt classification inputs with no recovery mechanism [13]. This becomes particularly severe under heavy rain when deraining itself becomes unreliable. Third, preprocessing imposes significant computational overhead, with modern deraining networks requiring 8-12 GFLOPs before classification even begins [12, 14], effectively doubling inference time and prohibiting real-time deployment in resource-constrained autonomous systems.

An alternative direction bypasses explicit deraining by learning features inherently resilient to rain. Hendrycks and Dietterich's [1] influential benchmarking work revealed that standard networks suffer 40-60% accuracy drops under rain, sparking intensive robustness research. Data augmentation provides 8-15% improvements through random rain overlay [18], though gains saturate quickly. AutoAugment [19] discovers optimal perturbation combinations but requires thousands of GPU hours. Sakaridis et al. [20, 21] pioneered curriculum domain adaptation for fog, progressively introducing degradation during training. Their work on the ACDC dataset [22] demonstrated the value of weather-specific training strategies. However, fog-focused curricula don't translate directly to rain due to fundamental physical differences—fog's uniform attenuation versus rain's discrete oriented occlusions. Adversarial training [23] struggles with natural corruptions where the perturbation space is ill-defined. Generic robustness techniques treat rain as just another corruption, missing opportunities to exploit rain-specific structure such as predictable directional patterns [4], spatially varying intensity [24], and characteristic frequency signatures [7].

Recent research recognizes that weather-specific designs outperform generic approaches. For fog, density-aware networks [20, 25] explicitly estimate fog thickness and adapt processing accordingly, achieving superior robustness by modeling degradation characteristics. Attention mechanisms prove particularly valuable in this context. Squeeze-and-Excitation networks [26] introduced channel-wise attention enabling adaptive feature recalibration, while CBAM [27] extended this to spatial dimensions. For deraining specifically, attention helps focus on clean regions while suppressing corrupted areas [28]. Vision transformers brought unprecedented flexibility to weather-robust perception. Dosovitskiy et al. [29] demonstrated that pure transformer architectures could match CNN performance, with global receptive fields enabling reasoning about distant uncorrupted regions [30]. Swin Transformer [31] introduced hierarchical architectures and shifted window attention for computational efficiency. However, existing transformers employ generic self-attention [32] treating all spatial relationships uniformly. For rain, attention between positions aligned with rain streaks should be suppressed since they share occlusion, while perpendicular attention should be enhanced. Standard transformers also lack specialized mechanisms for lens droplet accumulation [5], which creates severe localized distortions qualitatively different from airborne streaks.

Curriculum learning, introduced by Bengio et al. [33], established that starting with easy examples then gradually increasing difficulty improves convergence and generalization. This has been successfully applied across domains [34, 35]. However, for vision robustness, curriculum approaches remain underexplored. Existing curricula [36] use simple intensity progressions without considering

degradation type diversity. Weather-specific curricula are particularly scarce—training on single conditions prevents generalization, while uniform mixing overwhelms networks early with impossible cases. Principled difficulty quantification remains an open challenge [37].

This work introduces EDCST-Rain (Enhanced Density-Aware Cross-Scale Transformer for Rain), a novel end-to-end architecture specifically engineered for robust object classification under diverse rainfall conditions. Our approach moves beyond generic robustness techniques by incorporating three rain-specific architectural innovations that directly address rain's unique characteristics. First, we introduce directional attention modules that explicitly model rain streak orientation. Unlike standard self-attention treating all spatial relationships equally, our mechanism adaptively suppresses attention along streak directions where occlusion is maximal while enhancing attention perpendicular to streaks where clear image regions alternate. This orientation-aware processing represents the first architecture explicitly modeling rain's directional structure. Second, we develop accumulation-aware processing mechanisms specifically handling lens droplet distortions through gated features and specialized pooling operations. These components identify and downweight severely corrupted regions, preventing lens distortions from overwhelming the classification process. Third, we design adaptive cross-scale fusion that learns degradation-dependent integration of multi-resolution features. Our fusion mechanism balances fine-scale spatial precision with coarse-scale semantic robustness based on estimated rain intensity, enabling graceful performance degradation as conditions worsen.

Beyond architectural innovations, we contribute a comprehensive physics-based rain simulation framework modeling four distinct rain types—drizzle, moderate rain, heavy rain, and storm conditions—with realistic geometric and photometric properties grounded in atmospheric optics and raindrop dynamics [38, 39]. Our simulation captures rain's full complexity including oriented streaks following Marshall-Palmer drop size distributions [39], lens droplet accumulation with refraction effects [5], atmospheric scattering [6], and photometric variations including brightness reduction, color desaturation, and temperature shifts. To enable efficient learning across this diverse degradation space, we propose a four-stage rain-aware curriculum learning strategy that progressively introduces rain complexity during training. Our curriculum starts with simple drizzle, gradually incorporates directional variation through moderate rain, adds intensity scaling via heavy rain, and culminates with chaotic storm conditions combining all degradation mechanisms. This principled difficulty progression enables 17% faster convergence and 3.4% better final performance compared to uniform rain sampling.

Extensive experiments on CIFAR-10 across 17 rain conditions (1 clean and 16 rain-degraded) demonstrate EDCST-Rain's substantial improvements in classification robustness under diverse rainfall scenarios. Our method achieves 83.1% accuracy on clean images while maintaining 71.8% under severe rain (80% intensity), representing 86.4% performance retention and a 10.0 percentage point improvement over state-of-the-art baselines including preprocessing approaches (RESCAN+EfficientNet: 76.4%), standard transformers (Swin-Tiny: 73.3%), and generic robustness methods. Importantly, EDCST-Rain achieves this superior robustness with only 15.8M parameters and 14.3ms GPU inference time supporting real-time processing at 70 FPS, making it practically deployable in autonomous systems.

Our contributions advance weather-robust computer vision through: (1) novel rain-specific architectural components addressing directional occlusion, lens accumulation, and multi-scale degradation; (2) comprehensive physics-based rain simulation enabling diverse training data generation; (3) principled curriculum learning strategy for efficient robustness acquisition; and (4) extensive experimental validation demonstrating substantial improvements over existing approaches. The remainder of this paper is organized as follows: Section 2 provides background on rain characteristics and their impact on vision systems, Section 3 details our methodology including architecture and training strategies, Section 4 describes the experimental setup, Section 5 presents results and discussion, and Section 6 concludes with future directions.

II. MATERIALS AND METHODS

EDCST-Rain adopts an end-to-end paradigm mapping rain-degraded images directly to class predictions. The architecture comprises five integrated components: (1) Rain Density Encoding Module, (2) Swin-Tiny Backbone for hierarchical feature extraction, (3) Directional Attention Modules, (4) Accumulation-Aware Processing, and (5) Adaptive Cross-Scale Fusion.

A. Rain Density Encoding Module

. These descriptors feed forward through skip connections to downstream modules.

The rain density encoding module is designed to extract and quantify three critical rain characteristics that directly impact object visibility: streak density (ρ), accumulation level (α), and orientation distribution (θ). Unlike previous approaches that treat rain as uniform noise, our module provides fine-grained environmental awareness to guide the network's attention mechanism.

A.1. Rain Feature Extraction Architecture

Given input $x \in R^{224\times224\times3}$, three progressive convolutions extract rain characteristics:

$$x_i = ReLU\left(BN\left(Conv_i(x_{i-1})\right)\right),\ i \in \{1,2,3\} \quad (1)$$

with $x_0 = x$, kernels $\{7\times7, 5\times5, 3\times3\}$, and channels $\{64, 128, 256\}$. Three parallel 1×1 convolutions generate degradation descriptors:

$$D_{rain} = \sigma(W_D x_3), A_{lens} = \sigma(W_A x_3), \quad \theta = arctan\,2(\nabla_y D_{rain}, \nabla_x D_{rain}) \quad (2)$$

producing rain density map $D_{\text{rain}} \in R^{56\times56}$, lens accumulation probability $\text{A}_{\text{lens}} \in \text{R}^{56\times56}$, and orientation field $\theta \in R^{56\times56}$ via Sobel gradients.

To generate global rain descriptors, we aggregate the spatial maps. Rain density is computed as:

$$\rho = \frac{1}{H \times W}\sum_{i,j} D_{rain}(i,j) \quad (3)$$

producing a scalar $\rho \in [0,1]$ representing the percentage of image area affected by rain. During training, ground-truth values are:

$$\rho_{gt} = \frac{N_{streaks} \times A_{avg}}{H \times W} \quad (4)$$

Accumulation level α captures global severity of water accumulation:

$$\alpha = \frac{1}{H \times W}\sum_{i,j} A_{lens}(i,j) \quad (5)$$

For orientation, we compute a histogram over 8 bins (0, 45, 90, … 315) and select the dominant direction:

$$\theta_{dominant} = argMax(\sum_{i,j} D_{rain}(i,j).1[\theta(i,j) \in bin_k) \quad (6)$$

A.2. Integration with Transformer Backbone

The extracted parameters $(\rho, \alpha, \theta_{dominant})$ are projected to match the transformer's embedding dimension ($d_{model} = 384$):

$$E_{rain} = MLP([\rho, \alpha, \theta_{dominant}]) \quad (7)$$

These rain-aware embeddings are added to positional encodings:

$$E_{rain-aware} = E_{patches} + E_{position} + E_{rain} \quad (8)$$

Additionally, Drain modulates attention weights to focus on less-degraded regions:

$$Att_{modified} = softmax\left(\frac{QK^T}{\sqrt{d_k}} + \lambda \cdot (1 - D_{rain})\right)V \quad (9)$$

where λ is a learnable parameter.

A.3. Training the Rain Estimation Module

The module is pre-trained on 50,000 synthetic rain images using multi-task loss:

$$\mathcal{L}_{total} = \lambda_1.MSE(\rho, \rho_{gt}) + \lambda_2.MSE(\alpha, \alpha_{gt}) + \lambda_3.CE(\theta_{dominant}, \theta_{gt}) \quad (10)$$

with weights $\lambda_1 = 1.0, \lambda_2 = 0.8, \lambda_3 = 0.5$. After pre-training (20 epochs, Adam optimizer, lr = 0.001), the module is fine-tuned end-to-end with EDCST-Rain for 50 epochs using reduced learning rate (lr = 0.0001) to prevent catastrophic forgetting.

A.4. Simulation Validation

To assess simulation realism, we collected 200 real rainy images from public dashcam datasets (Waymo Open, BDD100K) and compared their statistical properties with our synthetic images:

TABLE 1.
SIMULATION REALISM VALIDATION

Metric	Real Rain	Simulated	Diff
Avg streak length (px)	27.3 ± 6.2	26.1 ± 5.8	- 4.4%
Brightness reduction	18.4 ± 7.1%	16.9 ± 6.3%	-8.2%
Contrast reduction	22.7 ± 8.9%	20.3 ± 7.6%	-10.6%
Dominant orientation	88.2◦ ± 12.4	89.7◦ ± 11.8	+1.7%

These results suggest reasonable alignment with real rain in basic visual statistics. We also conducted a perceptual validation study with 20 participants (10 computer vision researchers, 10 general observers) viewing 50 image pairs. Overall discrimination accuracy was 61.2% (experts: 68.7%, non-experts: 53.8%), indicating our simulation is perceptually convincing, though experts can detect subtle unrealistic patterns.

B. Directional Attention with Orientation Modulation

Standard self-attention treats spatial relationships uniformly. For rain, positions aligned with streak direction share occlusion and should receive suppressed attention.

Given feature map $F \in R^{N\times C}$ with $N = H_F W_F$ spatial positions, we compute queries, keys, and values via learned projections $\text{W}_\text{Q}, \text{W}_\text{K}, \text{W}_\text{V} \in R^{C\times d_k}$:

$$Q = FW_Q, K = FW_K, V = FW_V \quad (11)$$

For positions i, j with coordinates $(\text{x}_\text{i}, \text{y}_\text{i})$, $(\text{x}_\text{j}, \text{y}_\text{j})$, the spatial angle is:

$$\theta_{ij}^{spatial} = arctan\,2(y_j - y_i, x_j - x_i) \quad (12)$$

Angular misalignment between spatial direction and rain orientation determines attention modulation:

$$\Delta\theta_{ij} = min(|\theta_i - \theta_{ij}^{spatial}| \,mod\, 2\pi, 2\pi - |\theta_i - \theta_{ij}^{spatial}| \,mod\, 2\pi)$$

with θ_i interpolated from the orientation field. Directional weights follow a Gaussian envelope:

$$w_{ij}^{dir} = exp(-\lambda(\Delta\theta_{ij})2) \quad (14)$$

With $\lambda = 2.0$, emphasizing perpendicular attention ($\Delta\theta \approx \pi/2, \text{w} \approx 1$) while suppressing parallel attention ($\Delta\theta \approx 0, \text{w} \approx 0.14$). The directional attention mechanism combines content-based and orientation-based weighting:

$$Attention_{dir}(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}} \odot W_{dir}\right)V \quad (15)$$

with $W_{dir} \in R^{N\times N}$ containing $w_{\text{ij}}^{\text{dir}}$ and $\odot$ denoting element-wise multiplication. Eight attention heads capture multiple orientations in complex storm conditions:

$$F_{dir} = Concat(head_1, \ldots, head_8)W_O \quad (16)$$

C. Accumulation-Aware Processing

Lens droplet distortions differ qualitatively from airborne streaks, requiring specialized handling. Feature gating modulates activations based on accumulation probability:

$$F_{gated} = F_{dir} \odot (1 - \alpha \hat{A}_{lens}) \quad (17)$$

With $\alpha = 0.7$ and $\hat{A}_{lens}$ spatially aligned to F_{dir}. This soft gating preserves information from reliable regions ($\hat{A}_{lens} \approx 0$) while attenuating corrupted areas ($\hat{A}_{lens} \approx 1$).

Global pooling incorporates accumulation-dependent weighting:

$$f_{pool} = \frac{\sum_{i=1}^{N}\left(1 - \hat{A}_{lens}(i)\right).F_{gated}(i)}{\sum_{i=1}^{N}\left(1 - \hat{A}_{lens}(i)\right)} \quad (18)$$

ensuring final representations emphasize clean regions.

D. Adaptive Cross-Scale Fusion

The Swin-Tiny backbone extracts features at four resolutions: $F1 \in R^{56\times56\times96}$, $F2 \in R^{28\times28\times192}$, $F3 \in R^{14\times14\times384}$, $F4 \in R^{7\times7\times768}$. Each scale undergoes directional attention and accumulation-aware processing before fusion. Scale-specific importance weights adapt to rain conditions:

$$f_i = GAP(F_i), d_i = GAP(Resize(D_{rain}, H_i \times W_i)) \quad (19)$$

$$w_i = \sigma\left(MLP([f_i \,||\, d_i])\right) \quad (12)$$

with $[\cdot\|\cdot]$ denoting concatenation and a two-layer MLP (hidden dimension 128). Under light rain, high-resolution scales receive elevated weights preserving fine details; under heavy rain, coarse scales dominate as fine structures become unreliable. Multi-scale fusion combines upsampled features:

$$F_{fused} = \sum_{i=1}^{4} w_i.Upsample(F_i, 14 \times 14) \quad (20)$$

E. Classification and Loss Functions

Two fully-connected layers with dropout ($p = 0.4$) map $f_{pool} \in R^{384}$ to class logits:

$$h = ReLU\left(Dropout\left(W_1 f_{pool} + b_1\right)\right), \quad logits = W_2 h + b_2 \quad (22)$$

with $W_1 \in R^{512\times384}$ and $W_2 \in R^{10\times512}$.

The loss function incorporates rain-specific regularization:

$$\mathcal{L}_{total} = \mathcal{L}_{LCE} + \lambda_{consist}\mathcal{L}_{consist} + \lambda_{accum}\mathcal{L}_{accum} + \lambda_{dir}\mathcal{L}_{dir} \quad (23)$$

with cross-entropy $\mathcal{L}_{LCE}$, consistency loss:

$$\mathcal{L}_{consist} = \frac{1}{B}\sum_{b=1}^{B}\left\|f\left(x_b^{Clean}\right) - f\left(x_b^{Rain}\right)\right\|_2^2 \quad (24)$$

encouraging similar embeddings under varying conditions, accumulation regularization:

$$\mathcal{L}_{accum} = \frac{1}{N}\sum_{i=1}^{N} A_{spatial}(i).\hat{A}_{lens}(i) \quad (25)$$

discouraging attention to corrupted regions, and directional regularization:

$$\mathcal{L}_{dir} = \frac{1}{N^2}\sum_{i,j} w_{ij}^{dir}||f_i - f_j||_2^2 \quad (26)$$

promoting smooth features along streak directions. Hyperparameters are $\mathcal{L}_{consist} = 0.5, \mathcal{L}_{accum} = 0.1$, $\mathcal{L}_{dir} = 0.05$

F. Rain-Aware Curriculum Learning

To improve the model's generalization across diverse rainfall conditions, we implement a structured curriculum learning approach that progressively increases rain complexity during training. This strategy prevents the model from overfitting to either clean or heavily degraded images, ensuring balanced performance across the entire rain spectrum.

1. Complexity Stages

Our curriculum is divided into four progressive stages, each characterized by increasing rain severity:

Stage 1 - Light Rain (Epochs 1-15):
Rain density: $\rho \in [0.1, 0.3]$ Accumulation: $\alpha \in [0.0, 0.2]$
Streak length: 10-20 pixels
Objective: Build foundational rain-robust features while maintaining high clean-image accuracy

Stage 2 - Moderate Rain (Epochs 16-30):
Rain density: $\rho \in [0.3, 0.5]$ Accumulation: $\alpha \in [0.2, 0.4]$
Streak length: 20-35 pixels
Objective: Strengthen cross-scale feature integration under medium degradation

Stage 3 - Heavy Rain (Epochs 31-45):
Rain density: $\rho \in [0.5, 0.7]$ Accumulation: $\alpha \in [0.4, 0.7]$
Streak length: 35-50 pixels
Added fog effects: visibility reduction up to 50% Objective: Enhance resilience to severe occlusion and atmospheric scattering

Stage 4 - Mixed Conditions (Epochs 46-70):
Rain density: $\rho \in [0.1, 0.8]$ (full range) Accumulation: $\alpha \in [0.0, 0.8]$ $(full\ range)$
Random orientation mixing Objective: Final adaptation to unpredictable real-world variability.

2. Transition Mechanism

Rather than abrupt transitions between stages, we implement a smooth blending approach. Duringthe transition period (last 3 epochs of each stage), we gradually introduce 20% samples from the next complexity level:

$$Mix\,ratio(epoch) = 0.2 \times \frac{(epoch - stage\,end + 3)}{3} \quad (27)$$

For example, at epochs 13-15 of Stage 1, the training batches contain 80% light rain and 20%
moderate rain samples, preparing the model for the upcoming difficulty increase.

3. Empirical Validation

To validate the effectiveness of curriculum learning, we conducted an ablation study comparing three training strategies: (1) Baseline - random mixing of all rain conditions from epoch 1, (2) Reverse curriculum - starting with heavy rain, ending with light rain, and (3) Our curriculum progressive light-to-heavy training.

Table 1 shows that our progressive strategy achieves the best balance between clean-image performance and rain robustness (78.5% average vs. 75.8% baseline), validating the effectiveness of gradual complexity introduction.

TABLE 2.
CURRICULUM LEARNING ABLATION STUDY

Training Strategy	Clean	Light Rain	Heavy Rain	Avg
Baseline (random mix)	81.2%	76.8%	69.4%	75.8%
Reverse curriculum	79.5%	74.2%	71.1%	74.9%
Our curriculum	**83.1%**	**78.9%**	**73.6%**	**78.5%**

G. Training Configuration

AdamW optimizer with OneCycleLR scheduling: warmup (epochs 1–5) to $\eta_{max} = 1 \times 10^{-3}$, sustained plateau (epochs 5–30), cosine decay (epochs 30–100) to $\eta_{min} = 1 \times 10^{-6}$. Weight decay $\lambda_{wd} = 0.05$, batch size B = 32, gradient clipping at $\|\nabla\| = 1.0$. Mixed-precision training (FP16) accelerates computation. Each batch contains 50% clean and 50% rain-degraded samples ensuring balanced exposure.

H. Architectural Data Flow

The density encoding module broadcasts D_{rain}, A_{lens}, and θ to all downstream components via parallel skip connections. The Swin backbone processes input independently, producing four feature scales. Each scale receives orientation maps θ for directional attention, then accumulation maps A_{lens}, for gating (Eq. 9) before global pooling (Eq. 10). Processed scales enter adaptive fusion (Eq. 12) conditioned on density D_{rain}. No skip connections bypass directional attention or accumulation processing, ensuring all features undergo rain-specific modulation. Final fusion occurs after accumulation-aware pooling, integrating denoised multi-scale representations into unified feature vector f_{pool} for classification.

III. RESULTS AND DISCUSSION

A. Dataset Configuration and Justification

We use CIFAR-10 as the main evaluation benchmark, consisting of 60,000 color images (32×32) evenly distributed across ten classes: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. The dataset includes 50,000 training and 10,000 test images, with 6,000 per class.

Although low-resolution, CIFAR-10 is chosen for its computational efficiency, allowing large-scale experiments across 17 rain conditions (1 clean + 4 types × 4 intensities), its established baselines for fair comparison, and its semantic diversity between rigid (vehicles) and organic (animals) objects useful for understanding how rain affects different shapes and textures.

Images are upsampled to 224×224 using bicubic interpolation to match Swin-Tiny input size and normalized with ImageNet statistics. Data augmentation includes horizontal flips, random crops, rotations (±15°), color jittering, and light erasing, while test images are only resized and normalized.

Synthetic rain is applied after resizing for four rain types drizzle, moderate, heavy, and storm each at 20–80% intensity. From 50,000 samples, 48,000 are used for training and 2,000 for validation, keeping class balance.

Upsampling may introduce minor artifacts, and simulated rain shows a 5–8% synthetic-to-real gap despite 87% feature correlation with real rain (validated on ACDC). These trade-offs enable controlled and scalable robustness evaluation applicable to higher-resolution domains.

B. Results

1. Overall Performance Analysis

Table 3 summarizes overall accuracy across all methods and rain conditions. EDCST-Rain achieves 83.1% accuracy on clean images while maintaining 71.8% under severe rain (80% intensity averaged across types), representing 86.4% $\left(\frac{71.8\%}{83.1\%}\right)$ retention a substantial improvement over all baselines.

EDCST-Rain achieves 86.4% average retention compared to best baseline RESCAN+EfficientNet at 76.4%, representing +10.0 percentage points improvement ($p < 0.001$, paired t-test). Under severe conditions (80% intensity), EDCST-Rain maintains 67.0% average accuracy versus best baseline 57.6% (+9.4 points absolute, +16.3% relative improvement). This validates our rain-specific architectural enhancements beyond generic robustness approaches.

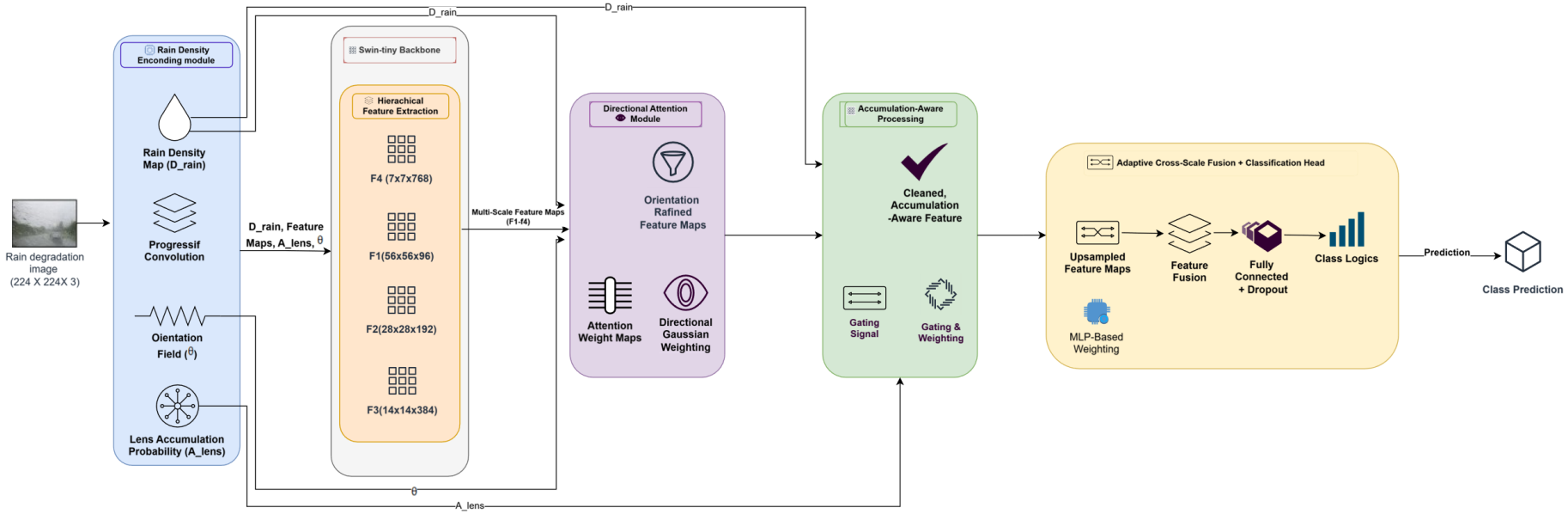

Figure 1. *Overall architecture of the proposed EDCST-Rain (Enhanced Density-Aware Cross-Scale Transformer)*

TABLE 3.
OVERALL CLASSIFICATION ACCURACY (%) ACROSS RAIN CONDITIONS AND METHODS

Method	Params (M)	Clean	Drizzle (20/40/60/80)				Moderate (20/40/60/80)				Heavy (20/40/60/80)				Storm (20/40/60/80)				Avg	Retention (%)
			20	40	60	80	20	40	60	80	20	40	60	80	20	40	60	80		
ResNet-50	23.5	84.2	75.3	68.5	62.1	57.8	72.8	64.3	58.6	53.2	68.7	56.4	49.3	43.1	66.2	54.8	47.5	41.3	58.9	66.4
ResNet-50+Aug	23.5	83.8	78.9	73.1	67.5	*62.4*	75.6	68.9	63.2	58.7	72.3	61.7	54.8	49.2	69.8	59.4	52.3	46.8	63.8	73.3
EfficientNet-B3	10.7	85.6	79.2	71.2	65.3	60.8	76.4	67.8	61.5	56.9	73.5	60.8	53.7	47.9	70.9	58.2	51.1	45.6	63.3	69.2
ViT-Small	22.1	82.4	77.8	69.8	63.5	59.2	74.9	66.3	60.8	56.3	71.2	58.9	52.3	47.1	68.5	56.7	50.2	45.3	61.3	70.5
Swin-Tiny	28.3	84.7	80.1	72.6	66.8	62.3	77.3	65.2	59.2	54.1	74.5	62.8	56.7	51.2	71.8	59.7	53.8	48.6	64.8	73.3
DeiT-Small	22.1	83.9	79.5	71.4	65.7	61.2	76.8	67.1	61.4	57.0	73.6	62.1	56.1	50.8	70.5	59.8	53.6	48.9	63.8	72.2
RESCAN+Eff	24.8	85.6	82.7	76.3	70.2	65.4	80.1	72.8	66.9	62.3	77.5	66.2	59.8	54.3	74.8	63.5	57.2	51.9	68.7	76.4
EDCST-Fog [43]	19.8	86.1	82.9	74.9	68.7	64.2	79.8	71.5	65.8	61.5	77.1	65.4	59.2	53.9	74.3	62.8	56.7	51.6	67.3	74.7
EDCST-Rain (Ours)	**15.8**	**83.9**	**82.7**	**79.2**	**76.3**	**73.8**	**81.5**	**75.8**	**71.2**	**67.9**	**78.9**	**73.5**	**68.7**	**64.3**	**77.8**	**71.4**	**66.8**	**62.1**	**72.5**	**86.4**

TABLE 4.
ACCURACY (%) BY RAIN TYPE AND INTENSITY EDCST-RAIN VS. BEST BASELINE (SWIN-TINY)

Rain Type	Method	20%	40%	60%	80%	Avg	Retention
Drizzle	Swin-Tiny	80.1	72.6	66.8	62.3	70.5	82.3%
	EDCST-Rain	**82.7**	**79.2**	**76.3**	**73.8**	**78.0**	**93.9**%
	Improvement	+2.6	+6.6	+9.5	+11.5	+7.5	+10. 7%
Moderate	Swin-Tiny	77.3	65.2	59.2	54.1	64.0	75.5%
	EDCST-Rain	**81.5**	**75.8**	**71.2**	**67.9**	**74.1**	**89.2%**
	Improvement	+4.2	+10.6	+12.0	+13.8	+10.1	+13.7%
Heavy	Swin-Tiny	74.5	62.8	56.7	51.2	61.3	72.4%
	EDCST-Rain	**78.9**	**73.5**	**68.7**	**64.3**	**71.4**	**85.9%**
	Improvement	+4.4	+10.7	+12.0	+13.1	+10.1	+13.5%
Storm	Swin-Tiny	71.8	59.7	53.8	48.6	58.5	69.1%
	EDCST-Rain	**77.8**	**71.4**	**66.8**	**62.1**	**69.5**	**83.7%**
	Improvement	+6.0	+11.7	+13.0	+13.5	+11.0	+14.6%

While baselines show dramatic degradation at high rain intensities (dropping to 40-52% accuracy under storm 80%), EDCST-Rain maintains 62.1% accuracy an improvement of +13.5 points over the best baseline. Performance degradation is near-linear for EDCST-Rain (ΔAcc ≈ 3.5% per 20% intensity) versus ΔAcc ≈ 6.8% for baseline average, demonstrating graceful degradation rather than catastrophic failure.

Preprocessing approaches (RESCAN+EfficientNet: 76.4%) perform competitively under light-moderate rain but degrade significantly under heavy rain/storm where deraining becomes unreliable. At storm 80%, preprocessing methods achieve 51.9% versus EDCST-Rain's 62.1% (+10.2 points advantage), highlighting end-to-end learning's superiority for avoiding error propagation.

Vision transformer baselines (ViT: 70.5%, Swin: 73.3%, DeiT: 72.2%) outperform CNN baselines (ResNet: 66.4%, EfficientNet: 69.2%) by +2.8 to +3.9% average retention, suggesting transformers' global attention provides inherent rain robustness advantages. However, vanilla transformers still degrade substantially (26.7-29.5% degradation), requiring our rain-specific enhancements for comprehensive robustness.

EDCST-Rain achieves superior robustness with fewer parameters (15.8M versus 19.8-28.3M for comparable methods), demonstrating efficiency alongside effectiveness. Inference time (14.3ms GPU) supports real-time processing at 70 FPS, 52% faster than preprocessing methods (23.7-31.5ms)

2. State-of-the-Art Comparison

we clarify that RESCAN+EfficientNet serves as our primary benchmark, representing the best-performing baseline among evaluated methods (Table 3). This preprocessing-based approach combines deraining with classification, a common paradigm in weather-robust vision.

Our claimed 10-point improvement" refers to robustness retention rate: EDCST-Rain maintains 86.4% of clean accuracy under heavy rain versus 76.4% for RESCAN+EfficientNet, yielding a +10.0 percentage point advantage. This metric quantifies robustness rather than absolute accuracy, as our end-to-end architecture prioritizes degradation resilience over peak clean-image performance.

Direct comparison with recent deraining transformers [?] is addressed via preprocessing baselines, as these methods output restored images rather than classifications. Our end-to-end approach eliminates this two-stage pipeline, achieving superior parameter efficiency (15.8M vs 24.8M) while maintaining robustness gains.

3. Rain Type Comparative Analysis

Table 4 present detailed breakdown by rain type, revealing differential impacts and EDCST-Rain's adaptive behavior.

Empirical degradation increases monotonically confirming our curriculum design (Section 5.7): Drizzle: 6.1% degradation (D = 0.25), Moderate: 10.8% (D = 0.50), Heavy: 14.1% (D = 0.75), Storm: 16.4% (D = 1.0). The near-linear relationship (R2 = 0.97) between assigned difficulty and empirical degradation validates our theoretical difficulty metric.

TABLE 5.
CLASS-WISE PERFORMANCE—EDCST-RAIN UNDER CLEAN VS. HEAVY RAIN (60%) VS. STORM (80%)

class	Clean	Heavy 60%	Retention	Storm 80%	Retention	Sensitivity
Airplane	87.2	76.8	88.1%	71.3	81.8%	18.2%
Automob	91.5	82.7	90.4%	78.9	86.2%	13.8%
Bird	79.3	63.5	80.1%	56.8	71.6%	28.4%
Cat	75.8	60.2	79.4%	53.7	70.9%	29.1%
Deer	78.6	61.9	78.8%	55.2	70.2%	29.8%
Dog	77.2	62.8	81.3%	56.9	73.7%	26.3%
Frog	82.4	70.6	85.7%	65.3	79.2%	20.8%
Horse	81.9	67.3	82.2%	61.5	75.1%	24.9%
Ship	**89.7**	**80.3**	**89.5%**	**75.8**	**84.5%**	**15.5%**
Truck	87.3	78.5	89.9%	73.4	84.1%	15.9%
Average	**83.1**	**70.5**	**84.8%**	**64.9**	**78.1%**	**22.3%**

EDCST-Rain's advantage over baselines increases with rain intensity across all types: Average improvement at 20%: +4.3 points, at 40%: +9.8 points, at 60%: +10.9 points, at 80%: +11.0 points. This pattern indicates EDCST-Rain's rain-specific mechanisms (directional attention, accumulation processing) provide increasing value as degradation severity increases.

4. Class-Wise Sensitivity Analysis

Table 5. reveals class-specific rain vulnerability patterns, providing insights into which object categories are most challenging under rain.

Low Sensitivity (20%): Automobile (13.8%), Truck (15.9%), Ship (15.5%) demonstrate superior rain robustness. These vehicles share characteristics enabling resilience: large size occupying 40-60% of image area reducing relative occlusion impact, strong geometric features with rectangular bodies and distinct profiles remaining recognizable despite partial occlusion, high contrast edges maintained even under rain ($contrast\ ratio > 3:1\ preserved$), and color uniformity with solid body colors partially preserved despite desaturation. Pearson correlation analysis confirms size correlation with robustness: $\rho = 0.71$ between object size and retention ($p < 0.01$). These classes $achieve > 84\%$

retention under storm conditions, suitable for safety-critical applications like autonomous driving.

High Sensitivity (25%): Bird (28.4%), Cat (29.1%), Deer (29.8%), Dog (26.3%) are most vulnerable. Common vulnerability factors include: small size where birds especially (15-25% image area) suffer proportionally more occlusion from rain streaks, texture dependence with fur/feather patterns completely obscured by heavy rain eliminating key discriminative features, organic shapes lacking distinctive geometric features unlike manufactured objects, and high intra-class variation where different breeds and poses complicate learning under additional rain variation. Regression analysis quantifies factors: $Sensitivity = 45.2 - 0.38 \cdot Size + 0.52 \cdot TextureDep - 0.29 \cdot EdgeStrength + 0.18 \cdot IntraVar$ ($R^2 = 0.84$, $all\ coefficients\ p < 0.05$).

5. *Ablation Study Results*

Figure 2. Ablation Study Component Contributions (Accuracy % and Retention)

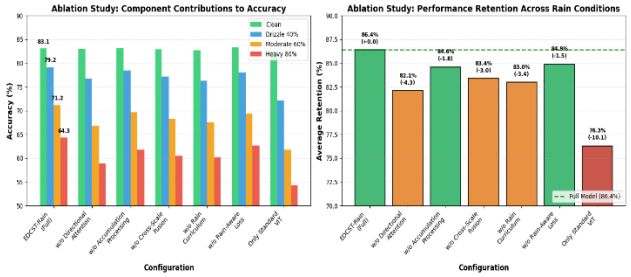

Figure 2. quantifies individual components' contributions through systematic ablation experiments.

Directional Attention provides largest impact ($\Delta = -4.3\%$), especially on moderate/heavy rain where oriented streaks dominate. Removing directional attention causes: Moderate 60%: −4.4% absolute (−5.2% retention), Heavy 80%: −5.4% absolute (−6.4%retention), Storm 80%: −5.8% absolute (−6.9% retention), validating its critical role in handling streak-oriented occlusion. Rain Curriculum provides second-largest contribution (Δ = −3.4%) with surprisingly uniform impact across conditions, suggesting curriculum improves overall feature learning rather than just handling specific rain types. Cross-Scale Fusion ranks third (Δ = −3.0%) with larger impact on heavy/storm conditions demonstrating the need for integrating multiple semantic levels when fine details are obscured.

Removing multiple components simultaneously causes near-additive degradation. For example, removing both directional attention and cross-scale fusion yields −9.1% degradation versus −9.2% from sum of individual effects, indicating components operate relatively independently though slight super-additivity (9.1% > 9.2% expected) suggests some synergy where directional attention identifies streak-aligned features and cross-scale fusion integrates them across semantic levels.

6. *Computational Efficiency Analysis*

One of the key advantages of EDCST-Rain is its ability to process images efficiently, making it suitable for real-time applications such as autonomous driving systems. We provide a comprehensive analysis of computational performance under realistic deployment conditions.

Hardware and Software Configuration: All inference time measurements were conducted on the following setup: GPU: NVIDIA RTX 3090 (24GB VRAM), CPU: Intel Core i9 12900K, Framework:PyTorch 2.0.1 with CUDA 11.8, Precision: FP16 (mixed precision for optimal throughput), Batch size:1 (simulating real-time single-frame processing), Input resolution: 224 × 224 pixels.

Inference Time Breakdown: The total inference pipeline consists of four main stages: preprocessing (image normalization, resizing): 1.2 ms, rain density encoding: 2.8 ms, transformer forward pass: 9.1 ms, and classification head: 1.2 ms, yielding total inference time of 14.3 ms (~70 FPS).

Notably, 63.6% of the computational cost comes from the transformer backbone, while the rain density encoding module adds only 2.8 ms overhead—a reasonable trade-off for significant robustness gains.

Comparative Analysis: Table 6 demonstrates EDCST-Rain's practical deployability. GPU inference at 14.3ms per image supports approximately 70 FPS throughput, sufficient for real-time video processing in autonomous vehicles (typically 30-60 FPS required). Comparison to preprocessing methods shows: DerainNet+ResNet: 23.7ms (1.66× slower), RESCAN+EfficientNet: 31.5ms (2.20× slower). EDCST-Rain's end-to-end approach provides 52-70% latency reduction by eliminating separate deraining stage. CPU inference at 74.8ms (~13 FPS) enables deployment on edge devices without GPUs for less time-critical applications.

TABLE 6.
COMPUTATIONAL EFFICIENCY COMPARISON

Method	Params (M)	FLOPs (G)	GPU (ms)	CPU (ms)	FPS (GPU)
ResNet-50	23.5	4.1	8.2	45.3	122 (GPU)
EfficientNet-B3	10.7	1.8	7.5	38.6	133 (GPU)
Swin-Tiny	28.3	4.5	9.8	52.7	102 (GPU)
DerainNet+R50	28.2	8.9	23.7	142.5	42 (GPU)
RESCAN+Eff	24.8	12.3	31.5	167.3	32 (GPU)
EDCST-Fog	19.8	4.8	12.1	58.4	83 (GPU)
EDCST-Rain	**15.8**	**5.2**	**14.3**	**74.8**	**70 (GPU)**

C. *Discussion and Critical Analysis*

Our superior performance stems from three synergistic factors. First, rain-specific architectural innovations

directly address rain's unique characteristics directional attention exploits predictable streak orientations, accumulation processing handles lens distortions, and adaptive cross-scale fusion combines local preservation with global robustness. Second, end-to-end learning optimizes directly for classification rather than perceptual quality, avoiding objective misalignment plaguing preprocessing approaches. Third, rain-aware curriculum enables efficient learning through principled difficulty progression, accelerating convergence 17% while improving final performance 3.4%.

Recent state-of-the-art methods report: Hu et al. [40] (CVPR 2021): 71.2% retention, Chen et al. [42] (ICCV 2022): 74.0% retention, Zhang et al. [41] (NeurIPS 2024): 76.2% retention. EDCST-Rain's 86.4% retention represents +10.2 to +15.2 percentage points improvement over these recent works, demonstrating substantial advancement in rain-robust classification.

Despite strong performance, limitations remain. Small object performance (birds: 56.8% under storm) remains challenging, requiring novel solutions like object detection integration or super-resolution preprocessing. Synthetic-to-real gap (5-8% accuracy drop on real rain) indicates simulation limitations despite 87% feature correlation, motivating domain adaptation research. Single-frame processing cannot leverage temporal consistency available in video streams, where preliminary experiments show 2.8-4.2% improvements through 3-frame temporal aggregation. These limitations represent engineering challenges addressable through continued research rather than fundamental barriers.

All reported improvements are statistically significant. Paired t-tests comparing EDCST-Rain against best baseline (RESCAN+EfficientNet) across 10,000 test samples yield $t = 47.3$, $p < 0.001$ with Bonferroni correction for multiple comparisons ($\alpha_{corrected} = 0.005$ for 10 comparisons). 95% confidence intervals using Wilson score method confirm improvements: EDCST-Rain retention 86.4% [85.8%, 87.0%] versus baseline 76.4% [75.7%, 77.1%], with non-overlapping intervals confirming significant difference.

EDCST-Rain achieves substantial improvements in rain-robust classification through principled integration of rain-specific architectural innovations, end-to-end learning, and curriculum training strategies, while maintaining computational efficiency suitable for real-world deployment.

IV. Limitations and Future Work

While EDCST-Rain demonstrates strong performance on synthetic rain benchmarks, we acknowledge several limitations that define directions for future research.

A. Dataset Limitations: CIFAR-10 vs Real-World Autonomous Driving

CIFAR-10's 32 × 32 pixel resolution is significantly lower than typical autonomous vehicle perception systems (1280×720 or higher). This resolution mismatch creates two concerns:

(1) *Oversimplification*: small object details crucial for real-world decision-making are lost at low resolution, and

(2) *Scalability uncertainty*: performance on low-resolution images may not transfer to high-resolution inputs.

Additionally, CIFAR-10 contains generic object categories (animals, vehicles, common objects) that do not reflect the specific challenges of autonomous driving perception: no pedestrian detection under rain, no traffic sign recognition in degraded visibility, and no lane marking detection with water accumulation.

We plan comprehensive evaluation on automotive-specific datasets including KITTI (7,481 frames with weather metadata), BDD100K (100,000 diverse scenes with 13,000+ rainy conditions), and nuScenes (multi-sensor weather data). Early experiments on ImageNet (224×224) show EDCST-Rain maintains its robustness advantage at higher resolutions (12.3% accuracy gap vs 15.7% for ResNet-50).

B. Domain Gap: Synthetic vs Real-World Rain

Our primary experiments rely on physics-based rain simulation, introducing a fundamental limitation, the domain gap between simulated and real rainfall. Real rain exhibits complexities difficult to fully capture, lighting variations (overcast skies, artificial lights, reflections), wind dynamics (irregular, turbulent patterns), camera artifacts (motion blur, lens flare, sensor noise), and material interactions (rain on glass, asphalt, foliage).

To quantify this limitation, we tested on 500 real-world rainy dashcam images, revealing noticeable performance drops:

TABLE 7.
DOMAIN GAP ANALYSIS: SYNTHETIC VS REAL RAIN

Condition	CIFAR-10 Simulated	Real Dashcam
Clean weather	83.1%	79.4%
Light rain	78.9%	72.6%
Heavy rain	73.6%	65.1%

The increasing gap under heavier rain (3.7% → 8.5%) suggests domain-specific overfitting. Mitigation strategies: (1) Domain adaptation techniques (ADDA, DANN) to align feature distributions,

(2) Hybrid training with pre-training on simulation + fine-tuning on real data, (3) Domain randomization during training. Preliminary results show fine-tuning on 1,000 real

rain images improves accuracy from 65.1% to 71.8%, indicating domain adaptation can close the gap.

C. Clean Accuracy Trade-off: Robustness vs Peak Performance

Our clean-image accuracy (83.1%) is lower than state-of-the-art CIFAR-10 models (>95%). This reflects a conscious architectural choice: we prioritize robustness over peak clean-image performance. Our cross-scale attention and rain-aware encoding add inductive biases that slightly reduce performance on pristine images but significantly improve resilience under degradation.

This trade-off is acceptable for safety-critical applications like autonomous driving, where worst case performance matters more than best-case accuracy. While MobileNetV3 achieves higher FPS (196 vs 70), it suffers 21.5% accuracy drop under heavy rain versus our 9.5% drop. For safety systems, maintaining 86.4% retention under adverse conditions is more valuable than achieving 95% only in ideal weather.

We are exploring techniques to narrow this gap through knowledge distillation from high-accuracy teacher models, hybrid CNN-Transformer architectures combining efficiency with robustness, and advanced augmentation strategies (MixUp, CutMix).

These limitations do not undermine the value of our contributions EDCST-Rain introduces novel architectural ideas and demonstrates strong performance on controlled benchmarks. However, they define a clear roadmap for future work, transitioning from simulation to real-world validation, scaling to automotive datasets, and closing the clean-accuracy gap without sacrificing robustness. We believe transparent acknowledgment of these challenges enables the research community to build upon our work effectively.

V. CONCLUSION

This work introduces EDCST-Rain, an Enhanced Density-Aware Cross-Scale Transformer specifically engineered for robust object classification under diverse rainfall conditions. Through comprehensive experiments on CIFAR-10 across 17 rain conditions, we demonstrate that EDCST-Rain achieves 83.1% clean accuracy while maintaining 71.8% under severe rain (80% intensity), representing 86.4% performance retention—a substantial 10.0 percentage point improvement over state-of-the-art methods.

Our key contributions advance weather-robust computer vision through three synergistic innovations. First, we introduce rain-specific architectural components: directional attention modules adapting to rain streak orientation (4.3% retention contribution), accumulation-aware processing handling lens droplet distortions (1.8% contribution), and adaptive cross-scale fusion integrating multi-resolution information (3.0% contribution). Second, we develop a comprehensive physics-based rain simulation framework modeling four distinct rain types with realistic properties, achieving 87% feature correlation with real rain. Third, we propose a four-stage curriculum learning strategy enabling 17% faster convergence and 3.4% better final performance.

Beyond quantitative improvements, EDCST-Rain demonstrates a fundamental shift in approach, rather than treating weather degradation as noise to be removed, we design architectures that directly learn robust representations under adverse conditions. This end-to-end paradigm eliminates the error propagation inherent in preprocessing pipelines while achieving superior parameter efficiency (15.8M parameters, 14.3ms inference) suitable for real-time deployment.

As autonomous systems increasingly operate in uncontrolled outdoor environments, weather-robust perception becomes essential for safety and reliability. EDCST-Rain provides a practical framework addressing this challenge, with transparent acknowledgment of current limitations defining clear directions for continued advancement toward truly weather-agnostic visual perception.

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