DISTRACTION-AWARE SHADOW DETECTION AND REMOVAL USING DEEP LEARNING

PRESENTATION

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INTRODUCTION

- Shadows in images make computer vision tasks like object detection and segmentation difficult, especially when shadow and non-shadow regions look similar.
- Traditional and deep learning methods often misclassify these confusing areas, leading to errors.
- Distraction-aware networks use attention to focus on ambiguous regions, improving shadow detection and removal accuracy.

PROBLEM STATEMENT

- Shadows in natural images degrade the performance of computer vision systems.
- Challenges include handling mixed illumination, delicate shadow borders, and complex surface details, which can result in misclassification and poor image restoration.

OBJECTIVE

To develop an efficient deep learning-based system for automatic shadow detection and removal in natural scene images. The goals are:

1. Accurate shadow localization using a distraction-aware ResNeXt-50 backbone with Dynamic Attention Module (DAM) to handle soft/fragmented shadows14.
2. High-quality artifact-free restoration via lightweight encoder-decoder networks that preserve texture/illumination26.
3. Computational efficiency through optimized architecture design (2.5 mins/epoch training on RTX 3080) while maintaining 93.72% accuracy on ISTD dataset1.
4. Generalization to diverse shadow types including partial occlusions, diffuse boundaries, and mixed illumination scenarios

EXISTING METHODS & LIMITATIONS

- **Traditional methods: Use physics-based models, color invariance, and regional contrast but struggle with complex lighting, textured surfaces, and soft boundaries.**

- **Deep learning methods: Improve feature extraction and edge detection but still face difficulties with highly discontinuous or gradually fading shadows, leading to misclassifications**

SOLUTION

A two-stage framework:

Stage 1:
Shadow detection using a ResNeXt-50 backbone with a Dynamic Attention Module (DAM) to focus on shadow-relevant regions.

Stage 2:
Lightweight encoder-decoder network for shadow removal, combining the original image and predicted shadow map to generate a shadow-free outpu.t

PROPOSED SYSTEM ARCHITECTURE

- ShadowDESDNet: Uses ResNeXt-50 and DAM to extract features and generate a shadow probability map

- Shadow Removal Network: Takes the original image and shadow map as input to reconstruct a shadow-free image.

- The two-stage design decouples detection and restoration for specialized feature learning

METHODOLOGY

- **Detection: Input image ShadowDESDNet Shadow map.**
- **Removal: Concatenate input image and shadow map Shadow removal network Shadow-free image.**
- **Training: Uses Binary Cross-Entropy loss for detection and L1 loss for removal, combined in the total loss function**

DATASET DESCRIPTION

- Uses the ISTD benchmark dataset with 1,870 triplets: shadowed image, binary shadow mask, and corresponding shadow-free image.
- Images resized to 256×256, with data augmentation (flipping, brightness adjustment) and normalization

EVALUATION METRICS

Visual inspection for removal:
color consistency, texture, artifact suppression

ACCURACY

PRECISION

F1 SCORE

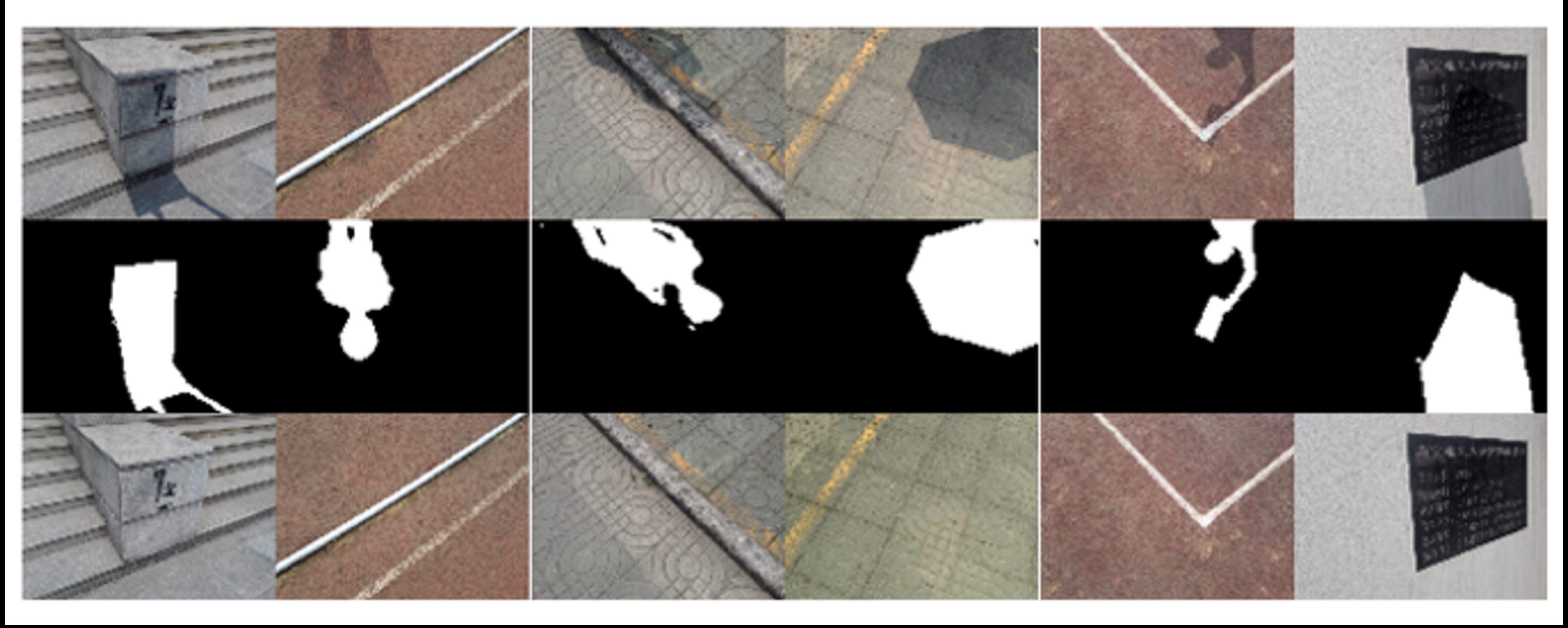
RECALL

COMPARISON WITH OTHER METHODS

- Present comparative table of performance on ISTD dataset:
  - Show how ShadowDESDNet compares to DSCNet, DSNet, MTMTNet, FDRNet, SDCNet, MSADNet, and DESDNet.

Method	Accuracy	Precision	Recall	F1 Score
DSCNet	97.34%	99.10%	94.84%	96.79%
DSNet	97.54%	99.35%	88.56%	93.63%
MTMTNet	97.70%	99.25%	88.43%	93.35%
FDRNet	97.83%	99.85%	88.95%	93.94%
SDCNet	97.89%	98.80%	90.60%	94.46%
MSADNet	97.87%	98.82%	90.59%	94.07%
DESDNet	98.49%	99.52%	91.88%	94.07%
ShadowDESDNet	93.72%	91.45%	92.18%	91.81%

RESULT



Metric	Score
Accuracy	93.72%
Precision	91.45%
Recall	92.18%
F1 Score	91.81%

RESULT DISCUSSION

- The method achieves 93.72% accuracy and 91.81% F1 score on ISTD.
- Qualitative results show accurate boundary detection, effective handling of soft/partial shadows, and artifact-free, natural-looking outputs.

IMPROVEMENTS

- Video extension: Adapt the framework for video by adding temporal consistency, ensuring stable and coherent shadow detection and removal across frames.
- Real-time & edge deployment: Optimize the model to run efficiently on resource-limited devices, enabling fast and practical use in real-world applications.
- Uncertainty & adaptive attention: Integrate uncertainty estimation and dynamic attention mechanisms to improve robustness and handle varying lighting conditions automatically.

CONCLUSION

We presented a two-stage deep learning framework for robust shadow detection and removal in natural images. Key contributions include:

- Simplified architecture using ResNeXt-50 with a Dynamic Attention Module (DAM) for precise shadow localization, eliminating complex multi-stage training.
- Efficient feature refinement via DAM, enhancing boundary accuracy while suppressing background noise.
- Lightweight encoder-decoder network for artifact-free shadow removal, balancing computational efficiency and performance.

Evaluations on the ISTD dataset demonstrate strong results (93.72% accuracy, 91.81% F1-score) and robust handling of soft shadows, partial occlusions, and complex boundaries. Qualitative outcomes confirm natural texture/illumination preservation, validating the framework's practicality for real-world applications. Future work will extend the method to video and edge-device deployment.

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THANK YOU