Document Image Shadow Removal Guided by Color-Aware Background

Poster ID:TUE-AM-173

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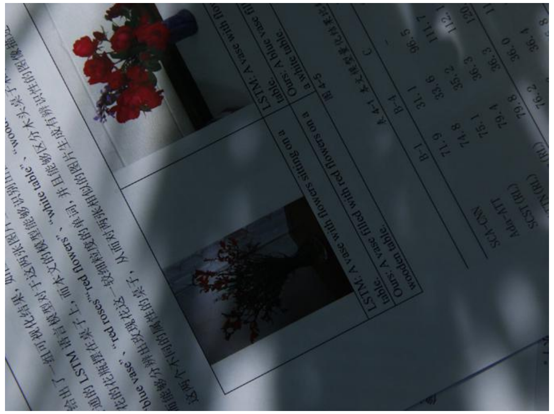
Document image shadow removal

Shadows

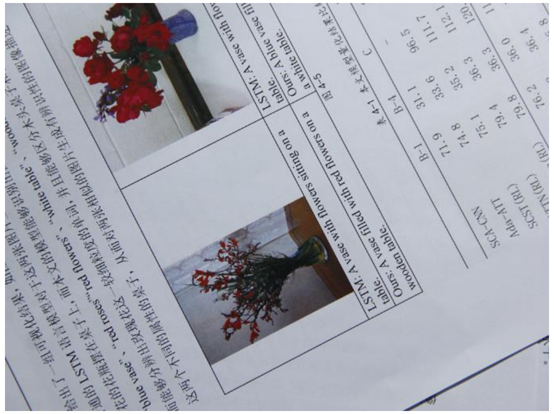
- Low brightness
- Reduce the readability of the image

Domcument image shadow removal

- Remove shadows in the image
- Restore a clear image without changing the original content of the image



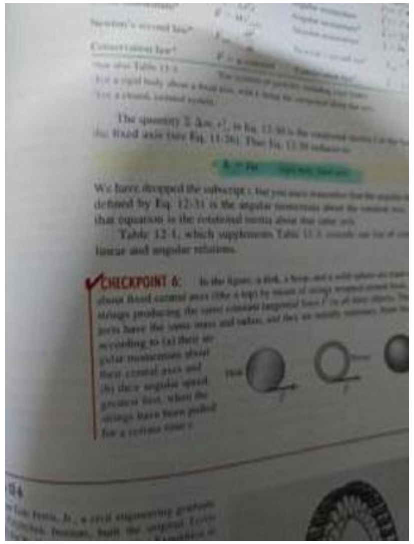
Shadow image



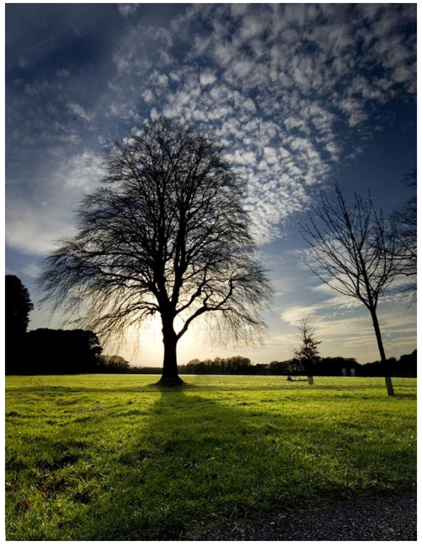
Shadow-removal result

Background

- Natural image shadow removal methods
    - ➢ Generally **perform poorly** on document images



Document image



Natural image

Problem 1:

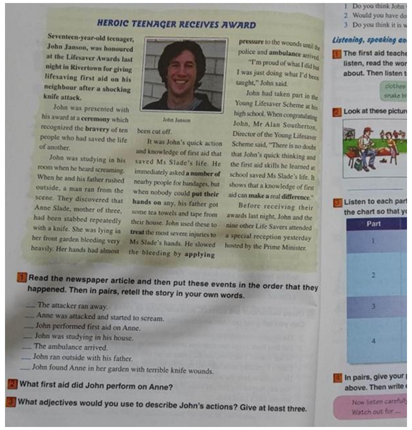
- ☐ Documnet images have drastically **different features** from natural images
- ☐ Without considering **the particular properties** of the document images

Background

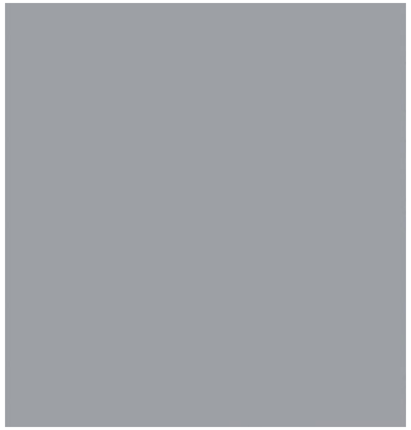
- Document image shadow removal methods
  - ➢ Remove shadows using a **constant background**

Problem 2:

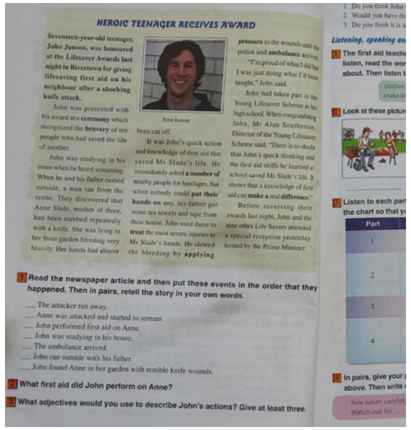
- ☐ Constant background is the color of the paper
- ☐ Provide inaccurate information



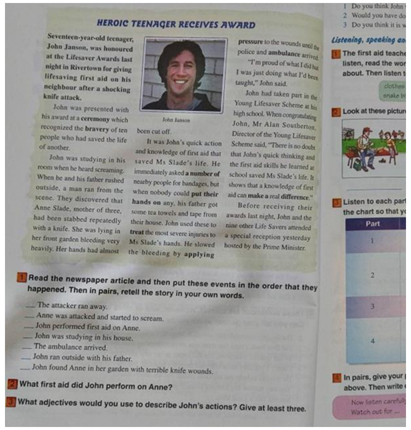
Document image



Constant Background



Result of [1]



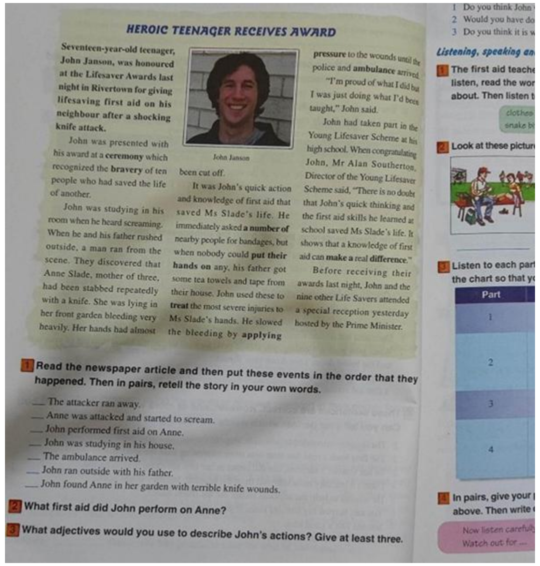
Result of [2]

[1] Removing shadows from images of documents. ACCV2016.

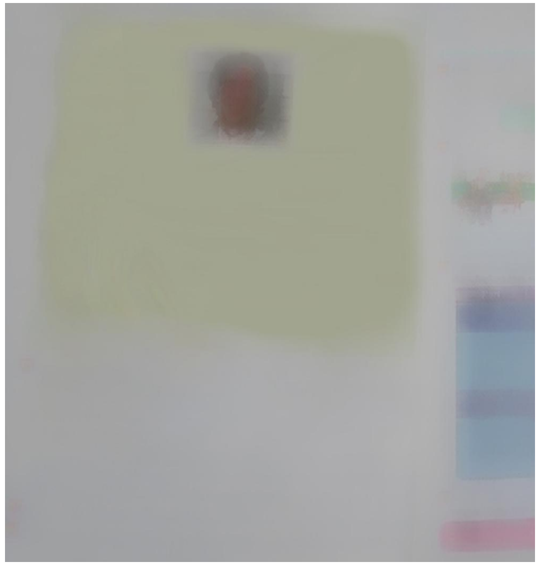
[2] BEDSR-Net: A deep shadow removal network from a single document image. CVPR2020.

Proposed Approach-CBENet

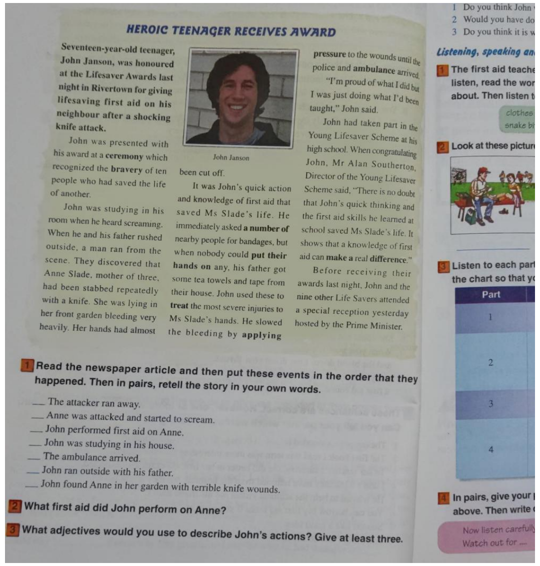
- Color-aware background extraction network (**CBENet**)
  - Spatially varying background
  - Preserve various background colors of the original image



Document image

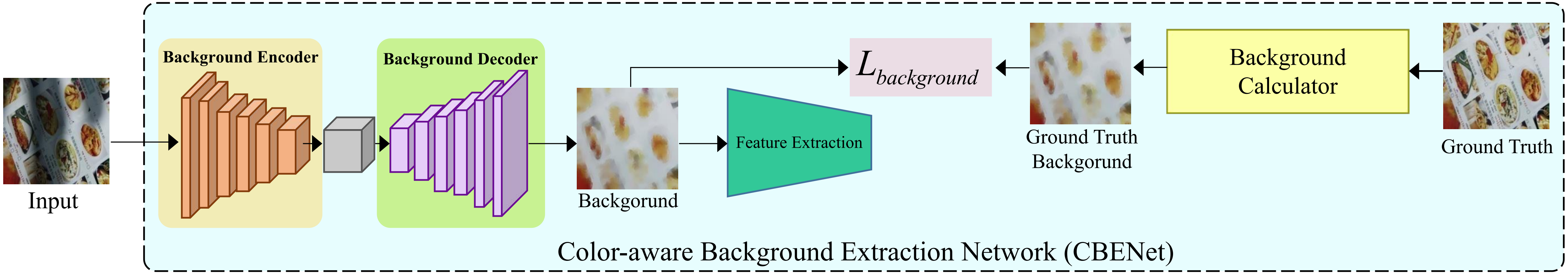


Our background



Our result

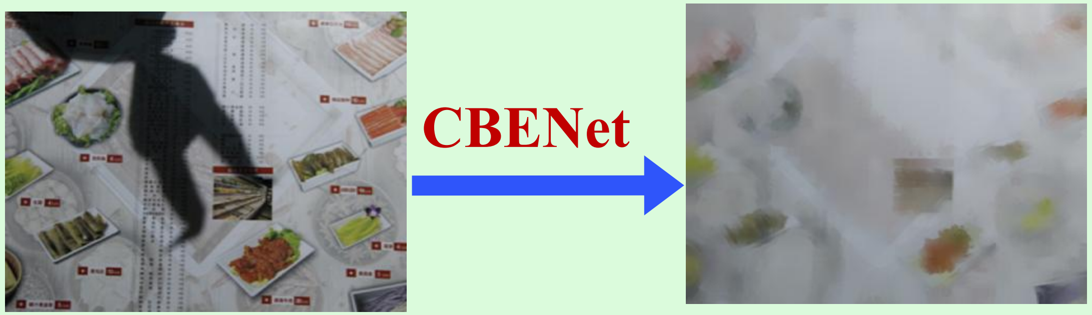
Proposed Approach-CBENet



- Background calculator

Ground truth Local background Our background

- Spatially varying color bakground

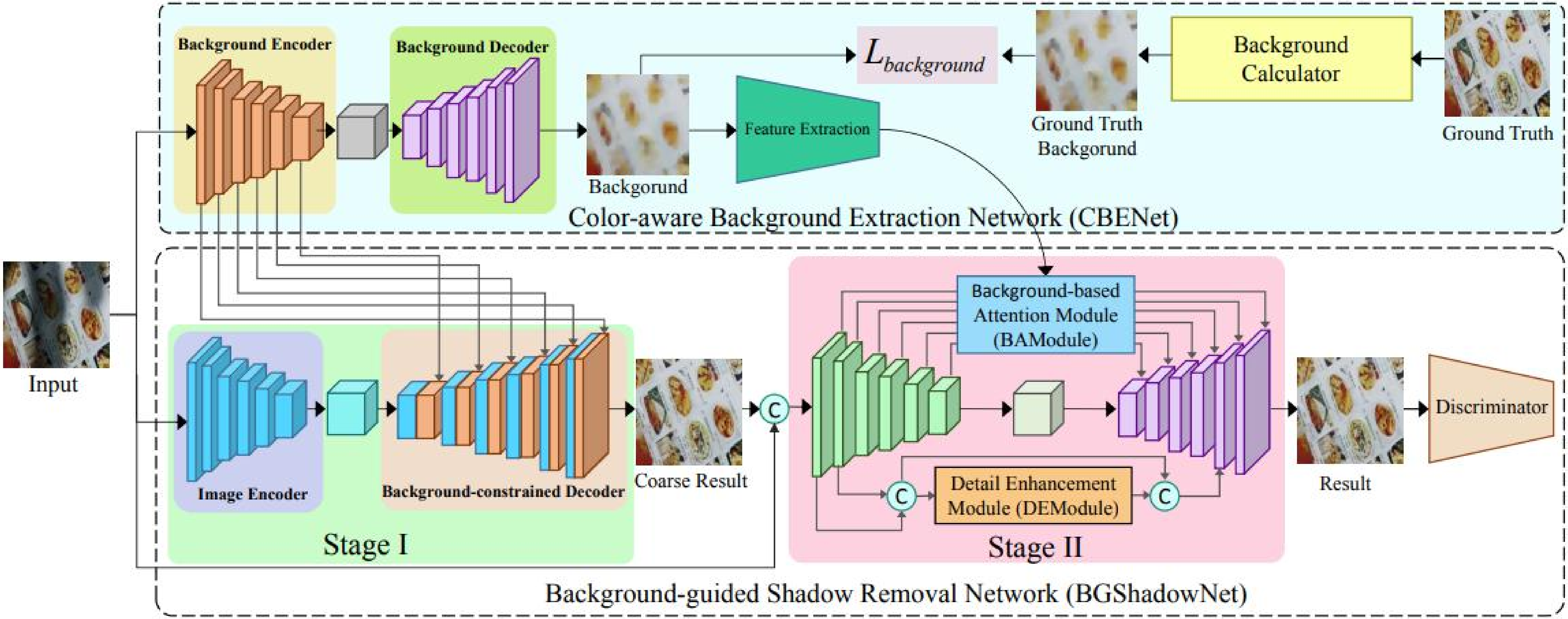


Input image

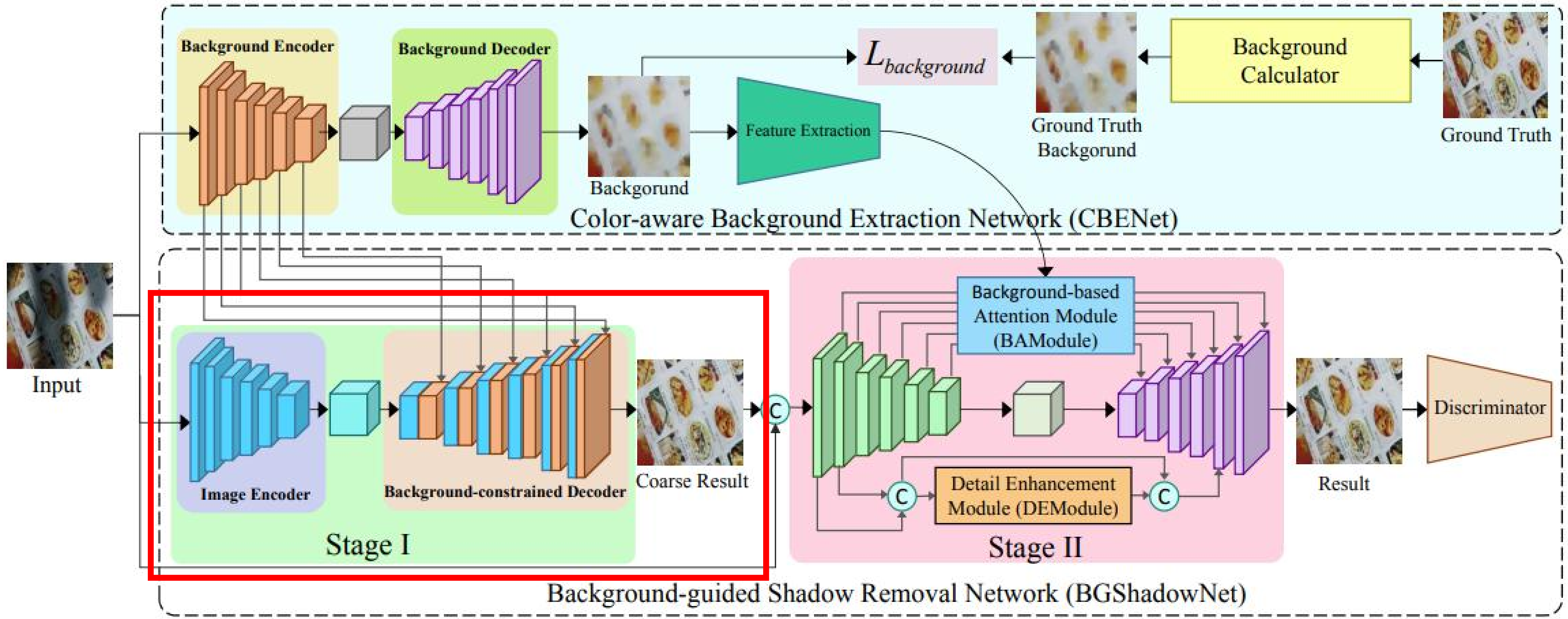
Extracted background

Proposed Approach-BGShadowNet

- Background-guided shadow removal network (**BGShadowNet**)

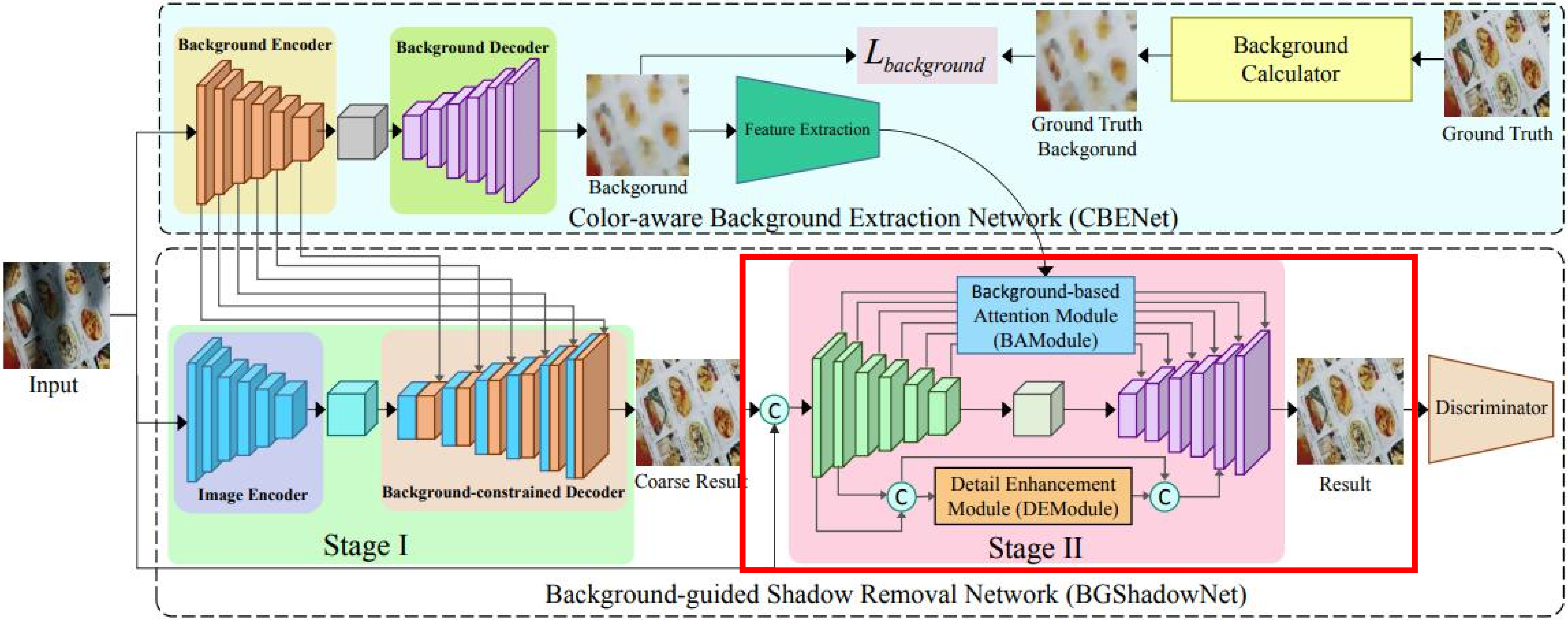


Proposed Approach-BGShadowNet



Stage I:
- Coarse shadow-removal result
- Background-constrained decoder

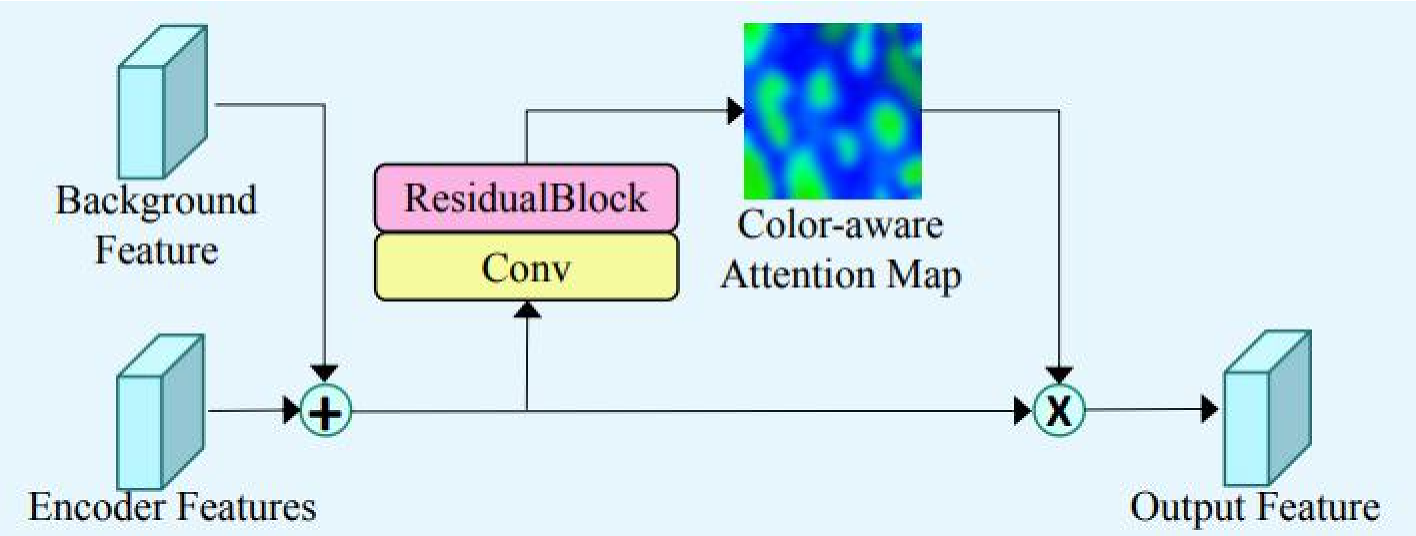
Proposed Approach-BGShadowNet



Stage II:
- Background-based attention module
- Detail enhancement module

Proposed Approach-BGShadowNet

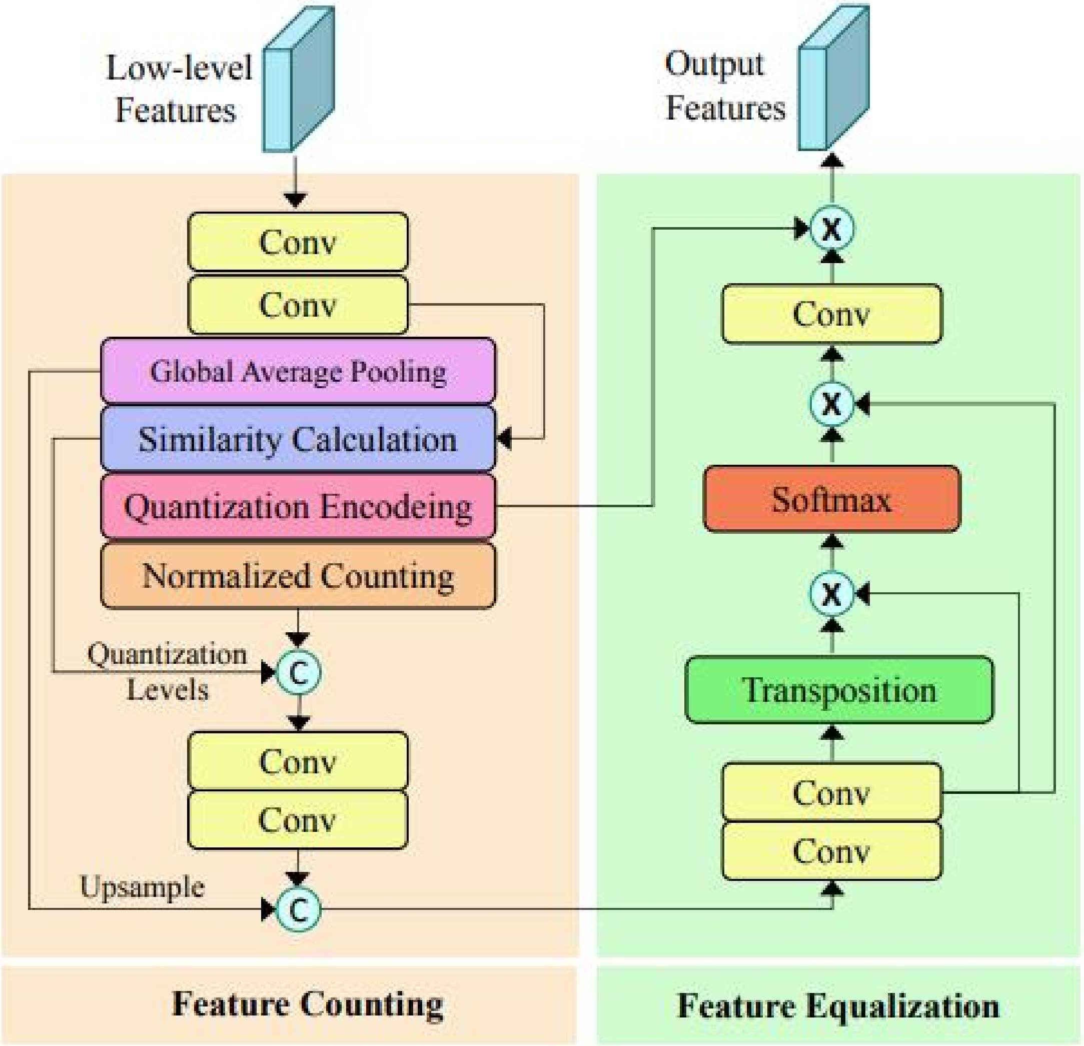
- **Background-based attention module**
  - ➢ Help to eliminate the appearance inconsistency in the image



The network of our background-based attention module (BAModule)

Proposed Approach-BGShadowNet

- **Detail enhancement module**
  - **Enhance the texture details** of the coarse result
  - **Feature counting**: get the quantization encoding map and statistical feature
  - **Feature equalization**: enhance the texture details of low-level layers



Proposed Approach-Loss function

- Loss function for optimizing **CBENet**
  - ➢ Background reconstruction loss $\mathcal{L}_{background} = ||B - \hat{B}||_1$

- Loss function for optimizing **BGShadowNet**
  - ➢ Appearance consistency loss $$\begin{aligned}\mathcal{L}_{appearance} &= \lambda_1 \mathcal{L}_{coarse} + \lambda_2 \mathcal{L}_{final} \\ &= \lambda_1 ||I_{gt} - I_{coarse}||_1 + \lambda_2 ||I_{gt} - I_{free}||_1\end{aligned}$$
  - ➢ Structure consistency loss $\mathcal{L}_{stucture} = \lambda_3 ||\mathrm{VGG}(I_{gt}) - \mathrm{VGG}(I_{free})||_2^2$
  - ➢ Adverarial loss $\mathcal{L}_{adv} = \lambda_4 \mathbb{E}_{(I, I_{free}, I_{gt})}[log(D(I_{gt})) + log(1 - D(I))]$

Dataset-RDD

- Available document shadow dataset
  - ➢ Bako, Kligler, Jung, RDSRD: **small-scale evaluation datasets**
  - ➢ SDSRD: large-scale dataset, **synthetic dataset**
- Our new document shadow dataset: **RDD**
  - ➢ The **first large-scale real** document dataset for shadow removal

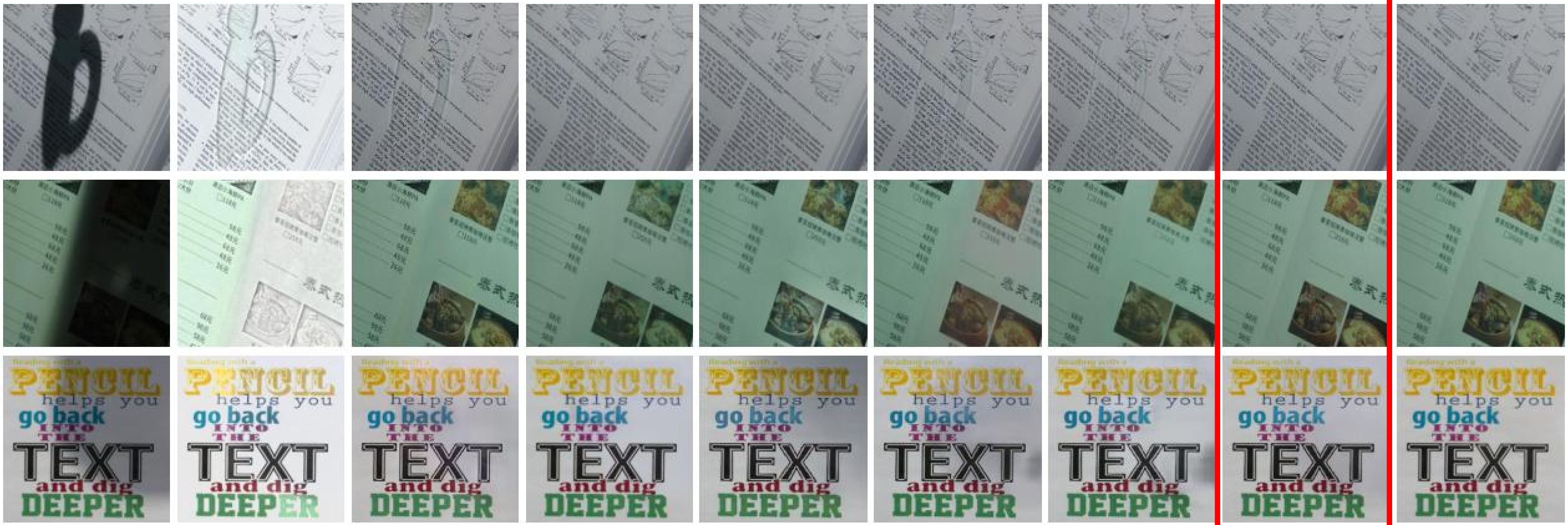
shadow images

corresponding shadow-free images

shadow and shadow-free image pairs in RDD.

Experiments

Comparison with State-of-the-arts

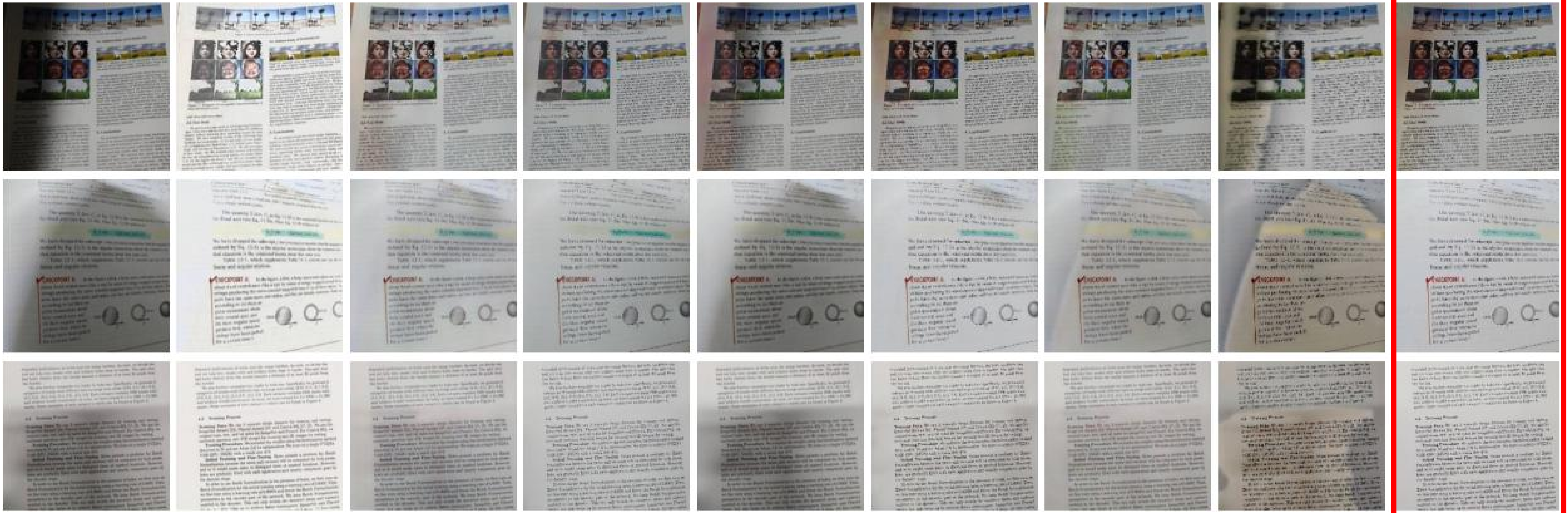


Input | Jung | DSC | Fu | DHAN | CANet | BEDSR-Net | Our result | Ground-truth

Jung: Water-filling: An efficient algorithm for digitized document shadow removal. ACCV2018. DSC: Direction-aware spatial context features for shadow detection and removal. PAMI,2020.
Fu: Autoexposure fusion for single-image shadow removal. CVPR,2021. DHAN: Towards ghost-free shadow removal via dual hierarchical aggregation network and shadow matting gan. AAAI, 2020.
CANet: Canet: A context-aware network for shadow removal. ICCV,2021. BEDSR-Net: A deep shadow removal network from a single document image. CVPR2020.

Experiments

Comparison with State-of-the-arts



Input | Jung | DSC | DHAN | Fu | BEDSR-Net | CANet | BMNet | Our result

Jung: Water-filling: An efficient algorithm for digitized document shadow removal. ACCV2018. *DSC: Direction-aware spatial context features for shadow detection and removal. PAMI,2020.*
Fu: Autoexposure fusion for single-image shadow removal. CVPR,2021. *DHAN: Towards ghost-free shadow removal via dual hierarchical aggregation network and shadow matting gan. AAAI, 2020.*
CANet: Canet: A context-aware network for shadow removal. ICCV,2021. *BEDSR-Net: A deep shadow removal network from a single document image. CVPR2020.*
BMNet: Bijective mapping network for shadow removal. CVPR,2022.

Experiments

Comparison with State-of-the-arts-Quantitative comparisons

Methods	Venue/Year	RDD			Kligler		
		RMSE ↓	PSNR ↑	SSIM ↑	RMSE↓	PSNR ↑	SSIM ↑
ST-CGAN [39]	CVPR/2018	3.143	34.328	0.974	6.826	27.433	0.931
DSC [15]	PAMI/2020	6.357	28.151	0.914	7.705	25.615	0.898
DHAN [6]	AAAI/2020	2.467	36.337	0.978	6.610	27.707	0.937
Fu [11]	CVPR/2021	4.328	31.387	0.946	7.101	27.362	0.914
CANet [5]	ICCV/2021	5.561	28.951	0.918	7.855	25.625	0.899
SG-ShadowNet [36]	ECCV/2022	2.974	34.727	0.972	6.829	27.141	0.920
BMNet [51]	CVPR/2022	9.409	24.289	0.915	16.459	19.031	0.874
Bako [2]	ACCV/2016	14.648	20.741	0.894	9.058	24.777	0.895
Jung [19]	ACCV/2018	30.190	14.364	0.861	28.247	13.726	0.852
BEDSR-Net [24]	CVPR/2020	2.937	34.928	0.973	6.533	28.124	0.932
BGShadowNet	CVPR/2023	**2.219**	**37.585**	**0.983**	**5.377**	**29.176**	**0.948**

ST-CGAN: Stacked conditional generative adversarial networks for jointly learning shadow detection and shadow removal. CVPR,2018. *SG-ShadowNet: Style-guided shadow removal. ECCV,2022.*
DSC: Direction-aware spatial context features for shadow detection and removal. PAMI,2020. *CANet: Canet: A context-aware network for shadow removal. ICCV,2021.*
DHAN: Towards ghost-free shadow removal via dual hierarchical aggregation network and shadow matting gan. AAAI, 2020. *Fu: Autoexposure fusion for single-image shadow removal. CVPR,2021.*
BEDSR-Net: A deep shadow removal network from a single document image. CVPR2020. *Jung: Water-filling: An efficient algorithm for digitized document shadow removal. ACCV2018.*
BMNet: Bijective mapping network for shadow removal. CVPR,2022. *Bako: Removing shadows from images of documents. ACCV,2016.*

Experiments

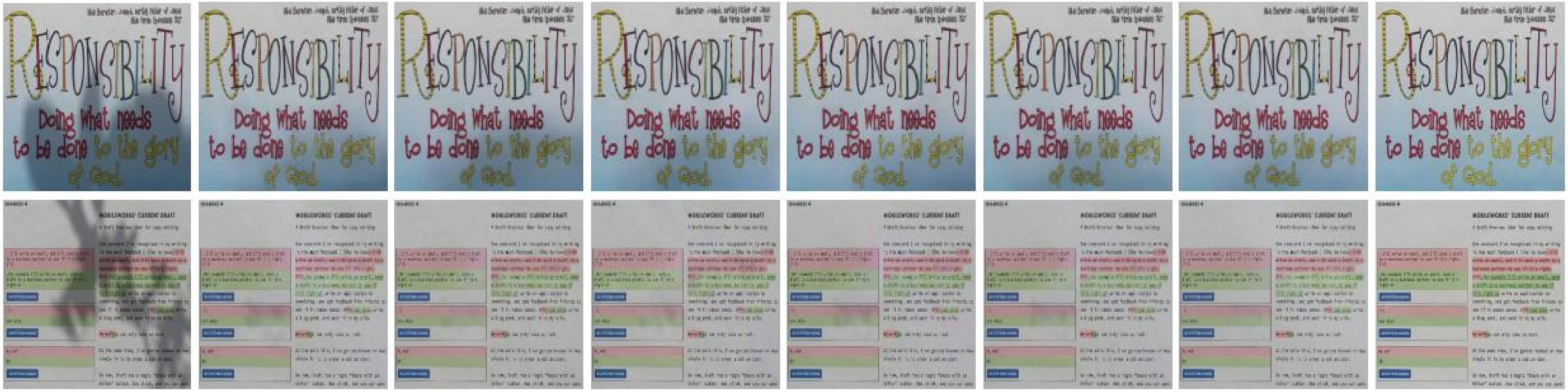
Ablation study-Quantitative results

Methods	RDD			Kligler		
	RMSE ↓	PSNR ↑	SSIM ↑	RMSE ↓	PSNR ↑	SSIM ↑
$BASE_1$	2.942	34.821	0.938	6.253	28.267	0.944
$BASE_2$	2.897	35.976	0.945	5.811	28.895	0.947
$BGShadowNet_1$	2.603	36.052	0.980	5.805	28.371	0.944
$BGShadowNet_2$	2.583	36.135	0.981	5.731	29.035	0.947
$BGShadowNet_3$	2.433	36.681	0.982	5.538	29.180	0.947
$BGShadowNet_4$	2.344	37.049	0.982	5.633	28.840	0.948
BGShadowNet	**2.219**	**37.585**	**0.983**	**5.377**	**29.176**	**0.948**

BASE1: one DenseUnet; **BASE2:** two stacked DenseUnet; **$BGShadowNet_1$:** BGShadowNet without StageII;
$BGShadowNet_2$: BGShadowNet without DEModule and BAModule; **$BGShadowNet_3$:** BGShadowNet without BAModule;
$BGShadowNet_4$: BGShadowNet without DEModule.

Experiments

Ablation study



Input BASE$_1$ BASE$_2$ BGShadowNet$_1$ BGShadowNet$_2$ BGShadowNet$_3$ BGShadowNet$_4$ Our result

BASE1: one DenseUnet; **BASE2:** two stacked DenseUnet; **BGShadowNet$_1$:** BGShadowNet without StageII;
BGShadowNet$_2$: BGShadowNet without DEModule and BAModule; **BGShadowNet$_3$:** BGShadowNet without BAModule;
BGShadowNet$_4$: BGShadowNet without DEModule.

Conclusion

- Dataset: **RDD**
  - The first large-scale real document dataset for shadow removal
- CBENet
  - **Satially varing background** for the shadow image
- BGShadowNet
  - Coarse-to-fine strategy
  - **Task network**: remove shadows in the image

Thanks for watching.

Dataet available at *https://github.com/hyyh1314/RDD*
Code available at *https://github.com/hyyh1314/BGShadowNet*